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The Measurement of University Performance Using Concepts Derived from Data Envelopment Analysis (DEA).

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Abstract of Thesis.

Performance measurement in higher education is examined during this study, in particular university performance indicators are reviewed and discussed. The conclusion is made that appropriate input and output indicators require some form of combination in order to allow practical consideration to be made.

The technique of Data Envelopment Analysis (DEA) is reviewed and found to have a number of conceptual drawbacks. The model is considerably developed within the thesis, primarily by the introduction of weight restrictions on the variables. Taken as a whole the developments, coined the DEAPMAS process, create a technique which can be used to assess cost effectiveness rather than simply efficiency.

Data for two examples of subject areas, defined by recognised accounting units, are applied to the program as inter-university comparison was felt to be impractical at institutional level; due to differing subject mixes. A considerable computer implementation of the developed theory was written and utilised to provide results over a number of data runs for the examples.

It was concluded that the results obtained represented a considerable improvement over separate consideration of numerous performance indicators.

Detailed Table of Contents.

1. DEFINING 'UNIVERSITY PERFORMANCE'.

In the private, or traded, sector, there are a range of straightforward and widely accepted performance measures, including market share, growth in sales, and rates of return on investment. Efforts directed towards such measures are ultimately in order to increase the primary objective, and hence key performance measure, of profit.

It is the absence of such clearly defined objectives, and hence related performance measures, which complicates the assessment of performance in the public sector. In the absence of comprehensive single performance measures, some form of analytical model is necessary. As is the general case, results obtained through the use of any analytical model are directly related to not only the suitability of the model, but the appropriateness of the input data.

In the context of Higher Education, determining the data from which an attempt at measuring performance can be implemented, involves many complex issues. Not least of these issues is definition of just what is meant by the term 'University Performance' itself.

The purpose of this introductory chapter is therefore to examine the concept of performance measurement, whether there are standards against which measurement can be made, and the plethora of terms in use within the topic. Only after this process of clarification can an unambiguous statement of the purpose of the study be produced.

1.1. Performance Measurement.

Taken in isolation, discussion of the 'performance' of any man, machine or system appears to be inevitably open to ambiguity, and hence the creation of controversy. Some simple examples follow which are designed to illustrate this point.

The performance of a track athlete in a particular race is clearly indicated by the time that they take to complete the distance. This may seem clear cut, but if the race were an Olympic final run in appalling weather conditions, then the time becomes of secondary importance. Performance is then measured purely in terms of finishing position, whether or not the athlete finished in a medal winning position.

Now consider the race had simply been a qualifying round in a major championship, then both the time and whether or not the race was won would become irrelevant, the sole performance criteria being whether or not a high enough position was achieved to qualify for the next round.

A high performance car is one which can achieve speeds well in excess of 100 miles per hour, or it is a car which can achieve 0-60 MPH in a just a handful of seconds. Common perceptions about automotive performance suggest concurrent consideration of these performance measures tends to apply. A prospective car owner may alternatively, however, simply seek safe family travel, in which case steering, suspension and safety features define each cars relative performance.

These generally conflicting attributes are not the only possible 'points of view' on car performance; one of the major costs involved in motoring is fuel, there are many, therefore, who would support the notion that a 'high performance' car be judged not on how many miles per hour it can cover, but on how many miles per gallon.

In industry, the performance of a production process may be rated on the number of units produced per hour. Alternatively, the competitive environment may be such that the cost per unit is of greater importance to the company's profitability. If the production process involves the creation of hazardous by-products; then to society as a whole the most important performance criteria is the rate of production of these wastes.

Two main observations can be made from these simple examples. Firstly, there are many different perspectives on performance in any given case, the particular criteria which applies varying according to the requirements of those seeking the assessment. Secondly, there will rarely be one performance criteria of over-riding importance, but more likely a number of, perhaps conflicting, attributes which will require simultaneous consideration.

Whenever performance is being considered, hence, the choice of criteria is influenced by additional information concerning the objectives which the performance measurement is being linked to. Without clear definition of these objectives, any performance measurement is unlikely to adequately reflect the degree to which the subjects of the assessment are fulfilling those very objectives.

At best, this 'mis-match' of performance criteria and objectives would render the results of the performance measurement of little use. At worst, the misleading results produced could lead to misguided decision-making which reduces the degree to which the true objectives are being met.

The next section, therefore, considers the aims of Higher Education and in particular those of the university sector.

1.2. The Goals and Objectives of Universities.

The very broadest level definition of purpose, 'mission statements', have been defined for many individual American universities, but rarely has this been attempted for British universities. Furthermore, a study by Allen (1988) revealed that:

> *"...most British Universities seem to regard their charter as a sufficient statement of their overall aims...The prevailing attitude seems to be 'We all know what a university is, so we don't need to discuss its aims'."* ALLEN (1988).

As Bourke (1986) notes, however, the political and financial climate has changed since the end of the post-Robbins expansion to a degree which brings this attitude into question.

> *"One notable feature of recent British experience...is the absence of specification of goals for single institutions and for the higher education system as a whole. It is a serious problem for British higher education that there is now pressure for quality controls and for evaluation but no agreed statement of system-wide or institutional objectives."*
>
> BOURKE (1986).

A large proportion of universities have a clause within their charter stating that 'The object of the University shall be to advance learning and knowledge by teaching and research.' This is consistent with the mission statement for the university system as a whole put forward by Clarke *et al.* (1984):

> *"Over the centuries of evolution in the University system, the fundamental role has not changed; that is to preserve, transmit and extend knowledge."*
>
> CLARKE *ET AL.* (1984).

The preceding quote is not, of course, the first attempt at defining the raison d'etre of the university system in the UK. As early as 1963 the Robbins Committee laid down the four points quoted below, which it described separately as both 'aims' and 'objectives'. They are still sufficiently general to be deemed mission statements by more current terminology.

> *"1. Instruction in skills suitable to play a part in the general division of labour.*
>
> *2. ...what is taught should be taught in such a way as to promote the general powers of the mind...produc[ing] not mere specialists but rather cultivated men and women.*

> *3. ...the advancement of learning. The search for truth is an essential function of institutions of higher education.*
>
> *4. The transmission of a common culture and common standards of citizenship."*
>
> ROBBINS (1963).

Mission statements such as those quoted above translate into more specific 'goals' of two main types as defined by Romney (1978).

> *"1. Outcome goals, which are the substantive objectives of the institution.*
>
> *2. Process goals, which are the objectives that relate mainly to the internal management and climate of the institution."* ROMNEY (1978).

Precise 'objectives', often quantified or with a set time period, are then derived from the stated 'goals'. These definitions are the most commonly used in university literature, other definitions have been used, but these terms became entrenched by the early 1980's, as confirmed in a study by Fenske (1981).

The resources used by universities, their inputs, process measures and outcomes or outputs, are therefore the three points at which objectives can be set, and hence measured.

The boundary between process measures and outputs has moved in recent years. The production of qualified students was once universally measured as an output, while this is still largely the case in the UK, in the United States it has begun to be regarded as a process. This indicates a wider view of higher education which sees the outcome associated with this 'product', or final process, as the impact that graduates have on commerce and society. This development is illustrated in the work of Nichols and Nichols (1991).

Having reached the stage of discussing tangible, measurable objectives, it is necessary before progressing further to clarify the terminology used in connection with their subsequent measurement. These have become known as the 'three E's' and are discussed in the next section.

1.3. Economy, Efficiency and Effectiveness.

The first of these terms 'economy' is of limited importance in the university context, given that few of the inputs to the system can be readily interpreted in financial terms. Ball and Beckett (1991) defined it as follows:

> *"acquiring resources of appropriate quality for the minimum cost, i.e. not paying over the odds."*
> BALL AND BECKETT (1991).

There are several different versions of the precise meaning of the terms 'effectiveness' and 'efficiency', which are summarised by Halwachi (1985). In simple terms, Norris (1978) stated that;

> *"effectiveness is doing the right thing while efficiency is doing the thing right."*
> NORRIS (1978).

More precisely, Etzioni (1964) offered the following definitions:

> *"The actual effectiveness of a specific organisation is determined by the degree to which it realises its goals. the efficiency of an organisation is measured by the amount of resources required to produce a unit of output."* ETZIONI (1964).

The 'three E's' view of the categories of performance measurement is widely adhered to, but other models do exist. Romney *et al.* (1978) suggest that performance can be viewed as having four facets; commitment, utilization, efficiency and effectiveness. Their approach has been summarised by Calvert (1979) diagrammatically as shown in Figure 1.1.

<u>Figure 1.1. Calvert Performance Model, after Romney *et al.*</u>

Resources allocated	▶▶▶▶▶▶▶▶▶▶▶▶▶▶	*Utilization*	▶▶▶▶▶▶▶▶▶▶▶▶▶▶	*Resources used*
▲ ▲ ▲ ▲				▼ ▼ ▼ ▼
Commitment				*Efficiency*
▲ ▲ ▲ ▲				▼ ▼ ▼ ▼
Objectives	◀◀◀◀◀◀◀◀◀◀◀◀◀	*Effectiveness*	◀◀◀◀◀◀◀◀◀◀◀◀◀	*Outcomes produced*

The model seems conceptually robust, it is useful to bear in mind that these four facets are interdependent. Failure in any one of these performance areas would have a detrimental effect on the institution concerned.

The lack of clear definition of the purposes of higher education makes applying notions such as efficiency and effectiveness in a university context a complex and often controversial task. As pointed out by Blaug (1980):

> *"education serves multiple objectives, some of which involve 'benefits' that cannot be measured in units directly comparable to the resource costs of education."* BLAUG (1980).

This quote suggests that applying concepts such as efficiency and effectiveness to university performance measurement will inevitably involve the use of surrogate measures. This being the case, a clear understanding of the conceptual difference in assessing either university 'processes', or 'outputs' will be important.

1.4. Inputs, Processes, and Outputs.

> *"If an effective institution of higher education is one which achieves objectives which are appropriate to the economic, socio-political, technological, ecological and educational environment in which it operates, then should not its effectiveness be measured in terms of the outcomes/benefits/impacts of its teaching and research programmes on society?"* SIZER (1979).

This rhetorical question clearly calls for the emphasis to be placed on output, rather than process, measures. Continuing this quote, however, highlights the present limitations of performance measurement in this field:

> *"The difficulties involved in developing such measures, and incorporating them into management information systems, should not be underestimated... It is not surprising that to date we have tended to fall back on quantitatively based process measures even though we know these are inadequate where institutional effectiveness is concerned, though many (such as staff-student ratios, and costs per FTE) are relevant to decisions regarding internal planning, and control and resource allocation, and to assessing efficiency as opposed to effectiveness."*
>
> SIZER (1979).

There are appear to be basically three reasons why measures are suggested which predict or surrogate for an institution's output. Firstly, to attempt to find factors that lead to student success that can be identified outwith the institution itself. Secondly, because of a combination of lack of confidence in degree awards and other institutional outputs as measures of performance, and the fact that inputs and processes often involve far more measurability and quantifiability than various forms of analysing outputs. Thirdly, and finally, because surrogate measures, more often than not, focus on expenditure.

Cuthbert and Birch (1979) quote the Anthony *et al.* (1972) definition of management control as:

> *"the process by which managers assure that resources are obtained and used effectively and efficiently in the accomplishment of the organization's objectives."*
>
> ANTHONY *ET AL.* (1972).

This would seem to perfectly define the purpose of measuring university performance. The application of a management control model in this context would, however, be unwise, as the same authors note:

> *"Such models usually assume that:*
> *(i) there is a 'standard' corresponding to effective and efficient performance.*
> *(ii) actual performance can be measured.*
> *(iii) when actual performance is compared with the standard and variance performance is fed back, this information can be used to intervene in the process so as to eliminate unwanted differences.*
> *...Education, particularly higher education, is characterised by widely divergent and strongly held views concerning objectives, an inability to identify and trace all the outcomes, and no real understanding of the relationship between inputs and outputs...This has not prevented serious attempts to force, for example, Planning, Programming Budgeting Systems (PPBS) deeply wedded to the traditional model of control on both sides of the Atlantic."*
>
> CUTHBERT AND BIRCH (1979).

Using inputs to predict outputs has been suggested as having several uses such as questioning the basis for entry to higher education. Entwistle and Wilson (1977) studied in detail the relationship between entry qualifications and degrees awarded; examining school exams, head-teachers reports, age and sex differences, tests of intellectual aptitude, mental health, neuroticism and anxiety, extroversion and sociability, academic motivation, and intellectual climate, in great depth. The summary included the fact that:

> *"In spite of the disappointingly low correlations it is nevertheless possible... to identify a series of variables which have been predictive of academic achievement."* ENTWISTLE AND WILSON (1977).

So whilst evidence was found that characteristics of more successful students were identifiable before entry, it could not be proven that the institution's role was secondary, indeed even if a strong correlation had been found, it is intuitively apparent that the institution must nurture and make full use of those characteristics. Calvert (1978) agrees to this to the extent that he sees the provision of a suitable environment as the key to institutional success, after finding similar results in a study with Birch and Sizer (1977):

> *"The examination marks were fairly uniform across departments, discipline areas and even institutions, despite differences in teaching patterns and use of resources. As a result it was not possible to produce acceptable relationships between the inputs and examination marks by regression analysis...*
>
> *The knowledge and skills developed by the student reflect more his learning curve than the performance of the institution. Indeed, its performance is related more to the provision of educational opportunities".* CALVERT (1978).

It is this measurement of the teaching environment which is the purpose of a large proportion of performance measurement in the university sector, other than that which seems to exist simply to restrain expenditure. It is never clear, however, how various 'measures' should be combined or what their relative importance is, making comparative analysis of large banks of data extremely difficult.

Intuitively, the quality of the teaching environment produced, which extends from sports facilities to quality of teaching, will only accurately show through the extent to which students develop knowledge and skills. This would seem to turn the above quotation into an apparent contradiction.

1.5. Performance Indicators.

The range of 'measures' of the environment and expenditure referred to above are examples of what have come to be known as 'performance indicators'. Although many formal definitions have been put forward as to what constitutes a 'performance indicator', in practice almost any management-related statistic can fall within this category. Elton (1987), referring to the second Committee of Vice-Chancellors and Principals/University Grants Committee (CVCP/UGC) statement on performance indicators of the same year, concluded that the Working Group mistakenly seemed to believe:

> *"whatever is easily measurable becomes a performance indicator."* ELTON (1987).

Perhaps the most practical definition, however, is that put forward by Cuenin (1987), who states the minimum requirements of a performance indicator as:

> *"numerical values which provide a measurement for assessing the quantitative or qualitative performance of a system...when the indicator shows a difference in one direction, this means that the situation is better whereas, if it shows a difference in the opposite direction, then this means that the situation is less favourable."* CUENIN (1987).

The use of performance indicators in the UK university sector has undoubtedly created a great deal of insight into many aspects of university operation. Equally, however, The relevance of many of the statistics involved has created a great deal of controversy.

> *"If objectives are expressed with some precision, usually in terms of quantitative performance indicators, then appraisal can be carried out with corresponding precision. Unfortunately, this advantage is usually bought at a great price, namely that the work appraised shapes itself towards the performance indicators. This would not be a disadvantage if quantitative performance indicators could be devised that correlated strongly with quality. Unfortunately, the opposite is usually the case."* ELTON (1987).

At the very least, the substantial and increasing scope of management statistics which are now being collected, are useful as potential input data for more complex models of institutional performance. A critical stage of such an application of these 'performance indicators', and of any analysis of a set of such data, was highlighted by Ball and Halwachi (1987):

> *"It will be important to distinguish between performance indicators which relate to outcome goals and hence measure how effectively the institution meets the needs of society and those relating to process goals which indicate how well the institution is functioning internally."*
> BALL AND HALWACHI (1987).

A thorough review of the development of performance indicators in the UK, and both the ways in which they have been utilised in their own right and incorporated into other analytical work, is clearly indicated. Such a review is carried out in the second chapter. The point has now been reached, however, at which we can satisfactorily set objectives for the thesis itself and define the purpose of the study.

1.6. Purpose of Study.

In attempting to measure university performance, we are primarily concerned with establishing the extent to which quality, or excellence, exists within these institutions, their externally viewed performance in terms of the degree to which they meet their objectives. This could be construed as indicating that the sole concern is with their effectiveness. But effectiveness at any cost is not acceptable where resources are limited, it is not enough to simply examine effectiveness in isolation of the price paid to achieve objectives.

The amount of any scarce or limited resources which a particular institution consumes, and hence prevents other institutions from consuming, must be taken into account; and hence it is important that not only is effectiveness determined, but simultaneously, consideration is made of efficiency.

The majority of the statistics which have been advocated in the UK as performance indicators do focus on efficiency, equally, however, such consideration of the way available resources are used in the creation of outputs, should not be carried out without consideration of effectiveness.

> *"...work is still being undertaken on effectiveness measures, particularly in the area of research, teaching quality and the longitudinal impacts of teaching outputs. The PI's are, therefore, more useful in assessing efficiency than effectiveness, but, of course, an institution can only be efficient if it is effective."* SIZER (1990).

It would be extremely complex and controversial, if not conceptually impossible, to establish any absolute measures of excellence in higher education, nor any concrete justification of the current university system itself. Laying judgement on the merits of the existing system, therefore, clearly lies outside the remit of the thesis.

When the Joint Working Group of the Committee of Vice Chancellors and Principals and the University Grants Committee released its second statement on performance indicators in 1987, one of the stated objectives was as follows:

> *"providing a means of making comparisons both within and between institutions."*
> CVCP/UGC (1987).

Any comparison between entire universities is likely to be somewhat tenuous as a result of the extent to which subject mixes differ. A more practical approach will be taken, by seeking to establish a basis for making comparisons at particular examples of the UGC's 'cost centre' and 'subject group' levels.

A vital stage in attempting to measure performance at either of these levels will be the identification of a set of appropriate performance indicators that can collectively indicate both effectiveness and take the level of resources used into account.

This approach, however, could simply yield an alternative set to, or sub-set of, the performance indicators produced by the CVCP/UGC (and more recently CVCP/Universities Funding Council). This would clearly be insufficient to allow practical inter-institutional comparison, as this would still require comparison to be based upon a large number of statistics, with no ranking or guidance to the relative importance of each individual performance indicator.

Additionally, individual comparison of particular indicators would continue to be difficult, as they would inevitably continue to be strewn with caveats pertaining to the preparation of the statistics, that make actual comparison somewhat impractical.

> *"...the reader will need to consider carefully the inferences that can properly and usefully be drawn from the figures...They need to be interpreted with knowledge, understanding and intelligence: knowledge especially of the definition of the statistics, understanding of the organisation of the relevant part of the University and the range of variation throughout the sector, and intelligence to recognise when other figures need to be considered simultaneously. It must never be assumed that University A is 'better' than University B just because one figure is bigger or smaller than the corresponding one. It may be better, or it may not - it may just be different."* CVCP/UGC (1987).

The purpose of the study will therefore be to provide a methodology, or model, which utilises appropriate and available performance indicators, by presenting the information within these selected indicators in a more tangible and practical form, which enables comparison between similar areas of different universities.

> *"The point is made that measures of performance implicitly relate to some concept of the process that turns inputs into outputs."* CALVERT (1978).

As has been discussed, one of the major problems in university performance measurement is unawareness of the nature of this process of conversion from input to output. Ideally, therefore, a model is required which considers both inputs and outputs, but requires no definition of the processes between.

There is a technique which fulfils these requirements, a model designed to indicate relative efficiency using incommensurate inputs and outputs. This is a relatively new technique called 'Data Envelopment Analysis', and this is introduced in Chapter Three.

The methodology for comparing university performance developed within the thesis will be applied to an example of both universities which participate in a particular cost centre, and universities active in a particular subject group.

It may be, particularly in view of the limited data currently available for manipulation, that the technique put forward will become more appropriate over time as more performance indicators become available, particularly those relating to 'long-term' output measures. An improvement on existing practice is not overly ambitious, however, there being no previous published attempts at reducing the UGC, and now UFC's, diverse and numerous university performance indicators to more manageable information.

> *"...it should always be remembered that it is better to be nearly right than precisely wrong."*
> PORTER (1978).

An improvement on simply providing lists of performance indicators would better inform the allocation process for the element of government funding to higher education which is based on merit. An indication of comparative 'excellence' between the provision of particular subjects at different universities could also help to replace subjective attitudes formerly based on tradition and image, and as such, be an aid to potential students, bodies wishing to sponsor research, and many other groups.

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2. THE DEVELOPMENT OF UNIVERSITY PERFORMANCE INDICATORS IN THE UK.

The concept of performance indicators was introduced in Chapter One, the purpose of this chapter is to review the development of these measures in the context of higher education in the UK, and in particular within the university sector.

The term 'performance indicator' was introduced to higher education as a result of early attempts to apply production theory within the public sector. Although it is difficult to attach a date to the first use of the term in the context of universities, doing so would by no means mark the first use of statistical information in the management of higher education. As the Vice-Chancellor of Reading University noted:

> *"Statistics describing some aspects of a University have been circulating within individual Institutions for as long as I can remember. More than 30 years ago every Head of a Department in the University in which I then served received annually a statement of student/staff ratios, student/technician, students/clerical staff, and similar figures for every Department."* PAGE (1989).

Such statistics were largely limited to internal use within the institutions, however, with inter-university comparison very tenuous due to inconsistencies in the basis of their calculation.

The setting up of the Universities Statistical Record (USR) in 1968 by the Committee of Vice-Chancellors and Principals (CVCP) and the University Grants Committee (UGC) marked the beginning of a steady increase in the availability of such data.

> *"The USR contained a great deal of information about numbers of students and staff, of money spent and money received, but it was very clear there was little which could be said actually to measure the performance of a university or part of it."*
>
> PAGE (1989).

Interest in institutional comparisons remained limited until the eighties, by which time the change of Government had led to calls for increased accountability throughout the public sector. In 1984, the then Education Secretary, Sir Keith Joseph, sought studies into the efficiency of Universities. The CVCP responded swiftly to this request, with the report of the studies it commissioned becoming commonly known as the 'Jarratt Report' after its Chairman, Sir Alex Jarratt. The contents of this important document which relate to performance measurement are reviewed in Section 2.1.

Within a year of the 'Jarratt Report' being published the term 'performance indicator' was being coined, albeit somewhat incorrectly, in regard to virtually all statistics relating to universities. Ewan Page was also the chairman of the 'Performance Indicators Steering Committee' set up by the CVCP and UGC after the Jarratt Report, and later commented that:

> *"The term 'performance indicators' was...not one with which the group was very happy. By this time, however, the term had entered into the vocabulary of politicians and press and it was not likely to be abandoned."* PAGE (1989).

Expanding on the definitions quoted in Chapter One, Dochy and Segers (1990) define performance indicators in terms of three requirements.

> *"A first requirement is that they should be clearly related to the defined functions of the institution. A second requirement is the recognition that they are only what their name states, indicators of the extent to which the institutional goals are achieved. A third requirement is that they should be a valid operationalization of what they intend to indicate and that they can be measured and interpreted in a reliable and correct way."*
> DOCHY AND SEGERS (1990).

Sizer, who later became a member of the CVCP/UGC 'Working Group on Performance Indicators' suggested as early as 1979 that the key attributes of performance indicators are as follows:

> *"RELEVANCE:*
> *The indicator must be useful to those concerned with managing that activity;*
>
> *VERIFIABILITY:*
> *qualified individuals working independently of one another should be able to develop essentially similar measures from examination of the data;*
>
> *FREEDOM FROM BIAS:*
> *the indicator must be shown to be free from both statistical and personal bias;*

QUANTIFIABILITY:
(although we are warned not to give greater weight to quantifiable but less relevant indicators than to non-quantifiable but relevant ones);

ECONOMIC FEASIBILITY:
the benefit derived from the use of the performance indicator must outweigh the cost of development;

INSTITUTIONAL ACCEPTABILITY:
individuals using performance indicators must accept that the basis on which they are derived is relevant and fair." SIZER (1979).

2.1. The Jarratt Report.

The Steering Committee for Efficiency Studies in Universities was appointed by the CVCP in 1984, its terms of reference were as follows:

> *"To promote and co-ordinate, in consultation with the individual institutions which it will select, a series of efficiency studies of the management of the universities concerned, and to consider and report...on the results with such comments and recommendations as it considers appropriate; provided that the commissioned studies will not extend to issues of academic judgement nor be concerned with the academic and educational policies, practices or methods of the universities."*
> CVCP (1985).

The Committee commissioned studies in six universities and a seventh study of the use nationally of data relating to the university system. The Committee's report (The Jarratt Report), stated that the objectives for universities provided by the Robbins Committee were 'still generally accepted' (see Section 1.2), and defined the functions of a university as follows:

> *"The prime function of a university is the attainment of these [Robbins] objectives through teaching and research. In addition universities have important cultural roles in their communities. The efficient performance of teaching and research involves essential secondary functions such as the provision and maintenance of plants and buildings, many forms of support for students (for example, residences and careers guidance), administration and forward planning."* CVCP (1985).

Hence it was clear that any performance measures proposed would be likely to include a high proportion of process measures. Universities were reminded that the Committee's work was not, however, purely for academic study.

> *"The Universities had hoped that the three years of cuts after July 1981 would be followed by a period of 'level funding' but this was not to be...by 1984 the universities were being told that they would be provided with less than level funding and would be expected to compensate for this by increased efficiency."* CVCP (1985).

The case was made that 'efficiency' would be prioritised over 'effectiveness' primarily because of uncertainties over effectiveness measurement in universities, thus demonstrating the infancy of 'performance indicators' at this stage.

> *"The UGC has no present intention of taking into account quality of teaching, because it has no reliable way of assessing it- whereas peer review*

can be used to assess quality of research. This may change when satisfactory performance indicators for teaching are developed." CVCP (1985).

The report makes the point that statistical information was already supporting subjective assessment within universities, but notes the emphasis was very much on administrative, rather than managerial, utilisation.

"Quantitative performance measures play some part in the [resource] allocation in most institutions. These measures usually merely supplement the qualitative judgements made by colleagues on performance and views about short term political pressures...Plenty of information is collected and that relating to students and staff is seen as being of good quality. But much of it is 'raw' data which is not effectively analysed, brought together and presented. It is currently used for administration and not for management." CVCP (1985).

To improve planning within universities, the report made a number of recommendations, the last of which was as follows:

"There is a recognised need for reliable and consistent performance indicators. These need to be developed urgently for universities as a whole and for individual universities as an integral part of the planning and resource allocation process."
CVCP (1985).

It was noted that the existing data which could be used as performance indicators at that time, held by the Universities Statistical Record, had restricted access because of fears over the comparisons for which it could be used.

"the universities are reluctant to allow the USR to release to anyone except the UGC, data which would enable individual institutions to be put in 'league table' order. This has the effect of limiting the extent to which proper management comparisons of performance can be made by institutions within the university system."
CVCP (1985).

In the 'Summary of Recommendations', however, the Committee clearly dismisses such fears over comparison, unequivocally calling for the development of university performance indicators:

"A range of performance indicators should be developed, covering both inputs and outputs and designed for use both within individual universities and for making comparisons between institutions."
CVCP (1985).

Referring to the more detailed interpretation the Committee constructed from its terms of reference, the danger of performance indicators potentially being applied simply as tools to control expenditure by, is raised by the final objective:

"achieve optimum value for money as a clear objective of policy, and to identify any obstacle to that end." CVCP (1985).

The final appendix of the report (Appendix G), consists of a summary of potential performance indicators which portrays the sort of statistics the committee envisaged being developed. These performance indicators were categorised into three types, 'operating' (process and administrative measures), 'external' (output measures), and 'internal'. The internal performance indicators are a mixture of what would be deemed input, process and output measures by more recent terminology.

> *"(a) Internal performance indicators include*
>
> *- market share of undergraduate applications (by subject)*
> *- graduation rates and classes of degrees*
> *- attraction of masters and doctoral students*
> *- success rate of higher degrees (and time taken)*
> *- attraction of research funds*
> *- teaching quality*
>
> *(b) External performance indicators include*
>
> *- acceptability of graduates (postgraduates) in employment*
> *- first destination of graduates (postgraduates)*
> *- reputation judged by external reviews*
> *- publications by staff and citations*
> *- patents, inventions, consultancies*
> *- membership, prizes, medals of learned societies*
> *- papers at conferences*
>
> *(c) Operating performance indicators include*
>
> *- unit costs*
> *- staff/student ratios*
> *- class sizes*
> *- course options available*
> *- staff workloads*
> *- library stock availability*
> *- computing availability"* CVCP (1985).

Shortly after the Jarratt Report was published, the British Government presented its Green Paper 'The Development of Higher Education into the 1990s'. Given that Central Government ultimately controls the purse-strings of higher education, the views of the Department of Education and Science were naturally of crucial importance in the development of performance measurement in higher education. The relevant contents of the Green Paper are therefore reviewed in the next section.

2.2. The 1985 Government Green Paper on Higher Education.

The Government chose to make as the first statement of its Green Paper 'The Development of Higher Education into the 1990s', a statement of its concern that economic benefits be derived from higher education.

> *"The Government believes that it is vital for our higher education to contribute more effectively to the improvement of the performance of the economy... unless the country's economic performance improves, we shall be even less able than now to afford many of the things that we value most- including education for pleasure and general culture and the financing of scholarship and research as an end in itself."* DES (1985).

The paper comments on the findings of the Jarratt report noting that, with classic understatement:

> *"The establishment of specific objectives for whole institutions and for their separate faculties and departments, and the monitoring and evaluation of their achievement, are demanding management tasks."* DES (1985).

Strong backing is then given to the call within the Jarratt Report for the development of university performance indicators, but more emphasis appears to be put on output measures, reflecting effectiveness, than was the case within the Jarratt Report.

> *"Sound management is based not only on efficient use of resources (inputs) but also on the effectiveness of results achieved (outputs). this argues the need to develop and use measurements of performance...The government believes there would be advantage in the regular publication of a range of unit costs and other performance indicators by institution and by department."*
>
> DES (1985).

The intention to integrate the consideration of performance indicators into the allocation process used in central government funding of the university sector appears to be indicated by this quote from the same paragraph as the previous extract:

> *"The development of such indicators will be important for the internal management of institutions and for the development of a policy on the allocation of resources more generally."*
>
> DES (1985).

An annex of the paper is devoted specifically to performance measurement in higher education. This commences with an expansion on the 'cost control' aspect of performance measurement:

> *"The essential purposes of performance measurement in education are to introduce...*

concrete information on the extent to which the benefits expected from education expenditure are actually secured, and to facilitate comparisons in terms of effectiveness and efficiency...the effort has to be made if the government is to pursue its objectives of controlling public expenditure and of making the most effective use of the taxpayers' money." DES (1985).

The three main outputs of higher education are identified in the annex as being; 'highly qualified manpower', 'research', and 'other social benefits'. After calling for a switch in emphasis from performance measures for higher education as a whole, to their calculation for individual departments and institutions in order to allow comparative analysis; the document concludes with a statement on the 'other social benefits'.

"These include the cultural benefits of higher education and the preservation of the stock of knowledge. Such items are not amenable to measurement with any pretensions to objectivity but it is important that their existence should always be kept in mind." DES (1985).

The next section reviews developments between the higher education Green Paper and the proposals to publish the first volume of university performance indicators, including discussion of the main output measures available at that time.

2.3. Background to the Introduction of the First Set of 'University Performance Indicators' in the UK.

As a result of the Jarratt Report, and in reaction to the higher education Green Paper, a joint working group was established jointly by the CVCP and UGC into performance indicators in universities.

The working group released two statements on their findings, the second statement, which is a precursor to the publication of the first volume of performance indicators, is discussed in Section 2.4.

The first statement, in 1986, inevitably contained a further suggested refinement to the definition of a performance indicator.

> *"- they must relate to stated objectives of the organisation; in the case of universities we have taken these to be primarily teaching and research. But there are many activities of universities which underpin their primary roles, or even peripheral to them. We propose that indicators relating to all aspects of a university's activities be developed as soon as practicable;*
>
> *- they must be specific, quantifiable and standardised so that the information can be used for making valid comparisons within and between institutions;*
>
> *- they must be as simple as possible consistent with their purpose;*
>
> *- they must be acceptable and credible in the sense of being free from systematic bias;*

- they must be useful and capable of acting as signposts to areas where questions concerning operations can and should be asked."
CVCP/UGC (1986).

The distinction between 'internal', 'external' and 'operating' performance indicators made in both the Jarratt Report and the higher education Green Paper is also refined to a distinction still in common use now:

"- Input indicators have to do with the resources, human and financial, employed by universities.

- Process indicators relate to the use of resources by universities; to the management effort applied to the inputs and to the operation of the organisation.

- Output indicators are about what has been achieved; i.e. the products of the university."
CVCP/UGC (1986).

The statement sounds a cautious note on the use of performance indicators, warning against over-reliance by noting that:

"The use of performance indicators is an aid to good judgement and not a substitute for it. The numbers will not and never can 'speak for themselves'. Mere inspection is not enough; interpretation is always necessary. It cannot be assumed that even a wide variation from a central value for a single indicator is either desirable or undesirable." CVCP/UGC (1986).

The working group were also concerned about the wider implications of the introduction of performance indicators, the consequences of establishing 'norms' or 'target values' for particular indicators.

> *"Performance indicators should not be used to impose standardisation either within an individual institution or more widely. The diversity of the higher education system is one of its strengths. An attempt to use performance indicators to impose uniformity is likely to destroy excellence."*
> CVCP/UGC (1986).

At this stage the working group proposed the introduction of sixteen performance indicators for teaching and research, and in addition eight administrative ratios which could loosely be regarded as process indicators.

No guidance as to the level at which the performance indicators would be calculated was given, but it was suggested that the teaching and research indicators would be utilised at departmental level, with some also at cost centre level and/or institutional level, and that the administrative ratios, except one relating to staff, would be solely utilised at institutional level.

Table 2.1 lists these indicators with, additionally, an indication of the implementation timescale proposed for the measures. This differentiates between those available immediately (Group A), those which could easily be calculated (Group B), and those which would only be feasible in the longer term (Group C).

Table 2.1. Performance Indicators Selected by the CVCP/UGC Working Group in the First Statement.

	GROUP		
	A	B	C
Teaching and Research.			
Cost per FTE student	X		
Research income	X		
Contribution to postgraduate and professional training	X		
Submission rates for research degrees	X		
Number of research and sponsored students	X		
Occupation of graduates after 12 months	X		
Undergraduate wastage rates		X	
Occupation of graduates after 5 years			X
Analysis of publications/patents/agreements/copyrights			X
Citations			X
Peer review			X
Editorship of journals/officers of learned bodies			X
Membership of research councils			X
Costs per graduate			X
FTE students to FT academic staff	X		
Equipment costs per FT academic staff	X		
Others.			
Administrative costs per FTE student	X		
Premises costs per FTE student	X		
Library costs per FTE student	X		
Careers services costs per FTE student	X		
Medical services costs per FTE student	X		
Sports facilities costs per FTE student	X		
Other central costs per FTE student	X		
Ratio of support staff to academics	X		

The table makes many references to 'FTE', full-time equivalent, a commonly used administrative technique involving conversion of part-time numbers pro-rata to full-time units. The purpose of this calculation is to simplify statistics by enabling the use of single figures to represent student numbers, or other data which would otherwise be represented by a number of different categories of participation.

In a conference paper after the working group's first statement, Sizer (1986) summarised the work of the Working Group up to that point as follows:

> *"In view of the already widespread and well-established use of performance indicators within universities the working group saw its principal task as being to draw on this experience to standardise existing practice by formulating common definitions and developing an agreed list for use by all universities. It decided to concentrate attention initially on the main university activities of teaching and research which posed the working group with difficulties associated with the intangible nature of the outputs and it has not yet proved possible to resolve all these difficulties."* SIZER (1986).

There was clear evidence of these difficulties within the statement, it was felt, for example, that data should not be published on the classification of honours degrees, yet the reasoning used could be interpreted as ruling out any comparison on the basis of qualifications.

> *"some indicators which are used within institutions are inappropriate for making comparisons between*

> *institutions...the working group has excluded the classification of honours degrees awarded as an indicator of teaching quality. Degree class reflects not only the quality of teaching which students have received but also their own abilities, and we see no valid way to separate out the relative contributions of these two factors."* CVCP/UGC (1986).

There are a number of authors who have expressed a lack of confidence in degree awards as indicators of an institution's performance. Oppenheim *et al.* (1967), developed a list of assumptions about the use of examinations, which are still central to most degree awards. These number twenty in all, which evidence the problems involved in regarding paper certificates as final outputs, these five points are perhaps the most crucial:

> *"1. The assumption that university examinations can include some so-called imponderables such as 'quality of mind', 'independent critical thinking','breadth' etc. in their assessment.*
> *2. The assumption that 'quality' of academic performance is rateable on a single continuum from first class honours to failure.*
> *5. The assumption that each examinee should have individual responsibility for his own performance; we do not expect collaboration or teamwork, no matter how common this may be in real life performance.*
> *11. The assumption that the use of external examiners prevents bias.*
> *12. The assumption that forced regurgitation of knowledge under stress is predictive of future performance."* OPPENHEIM *ET AL.* (1967).

This lack of faith in degree awards as measures of institutional or individual 'success' is backed up by the Confederation of British Industry:

"Paper qualifications are no guarantee of suitability or success." CBI (1986).

One solution to this problem is to use performance indicators beyond the 'factory gate' reflecting the suitability/employability of graduates. In practice the only practical way of doing this is through the use of 'First Destination Surveys' which categorise the success of graduates a fixed period after graduation. Categories used vary but commonly include, those in full-time employment, short term employment, those in further education or training, and those still seeking employment.

The working groups first statement proposed the use of such data twelve months, and five years, after graduation. As will be seen in Section 2.4, practical restrictions resulted in the time period being amended to just six months after graduation, by the time performance indicators were actually being published.

Research has a longer record of output performance measurement than teaching, though the traditional method is no less controversial. 'peer review' has been used to assess research effort for many years, its application being in the funding of future research. Research has continued to be assessed by peer review both within and parallel to the 'new' performance indicators.

In an article in the Times Higher Education Supplement, Hall (1986) defined the peer review process as it is commonly applied in funding procedures:

"At its simplest, peer review is a process whereby a research proposal is subject to the scrutiny of a chosen group of scientists, usually a research council committee, at least one of whom has expert knowledge about the field of research. The proposal has usually been sent out to several referees who supply written comments to the committee. When the committee meets, the expert member introduces the application, giving his or her own views on the quality of the science and providing some of the necessary background knowledge. The committee then assesses the proposal in the light of the expert's comments and the referees' reports."

HALL (1986).

Hall notes that this process has become more complicated as a result of increasing, and encouraged, cooperation with industry.

"Industry is being encouraged to invest in university research and that makes evaluation even more complicated. Joint university-industry projects which are partially supported by Government departments have to be assessed not for only scientific merit but also for commercial potential. Ideally a company's ability to develop a successful product should also be evaluated." HALL (1986).

Brennan (1990) summarised the advantages and disadvantages of peer review as follows:

"<u>ADVANTAGES</u>

1 recognises the subjective elements of quality;
2 provides basis for dialogue with those being assessed;
3 judgements made by 'experts';

4 can accommodate multi-dimensionality of quality and diversity of purpose.

DISADVANTAGES

1 selecting the 'right' peers;
2 objectivity can be questioned (cosiness v vendettas);
3 knowledge base for comparisons might be absent;
4 legitimacy of decisions may be questioned."
BRENNAN (1990).

When the Government presented its higher education White Paper in 1987, there were a number of major changes from the Green Paper which had preceded it, as reviewed by O'Leary (1987). The views displayed on performance measurement, however, did not significantly alter between the two papers. One fresh point, was the suggestion that peer review be coupled with quantitative measures in the assessment of research efforts.

> *"...assessment of the outcomes of research is a complex business which cannot sensibly be based exclusively or even mainly on simple quantitative measures. However, used as an adjunct to the traditional means of assessment- peer review- quantitative measures may shed useful light on certain aspects of performance."* DES (1987).

In a study into performance measurement in institutions of higher education throughout Europe, Wagner (1987), confirmed that 'value for money' had become the paramount concern in higher education.

> *"The key productivity questions in the 1980's have been whether higher education is giving value for money, and whether and how its productivity can be*

improved so that the same or even a little more can be provided with less." WAGNER (1987).

Wagner notes that 'quality issues' were not developing separately from concepts of 'productivity', offering the following explanation for this phenomenon:

> *"The lead in answering these questions of the 1980's has been taken, not by academic economists but by accountants and management consultants at the behest of governments and planning bodies. It is not surprising, therefore, that the narrower question of productivity of the higher education system and its component parts has become intertwined with broader issues concerning the quality of the system, its accountability and its relevance to the needs of society. Nor is it surprising that productivity measurements have become linked with performance indicators and evaluation issues."*
> WAGNER (1987).

One of the conclusions of the report voiced concern over the philosophy behind the developments in performance indicators, both in the UK and throughout Europe.

> *"...most performance indicators concentrate either on inputs or on outputs (unit cost or staff-student ratio indicators being the exception). The danger is that managers, administrators and decision-makers will seek ever more sophisticated measures of outputs <u>or</u> inputs separately and believe, wrongly, that they are learning something about productivity or efficiency. It is the performance of outputs and inputs together that determines the efficiency of an activity."* WAGNER (1987).

With this background, Section 2.4 examines the second statement by the CVCP/UGC Working Group on Performance Indicators in Universities, issued in 1987, which heralded the publication of the first volume of university performance indicators later the same year.

2.4. The Second Statement by the CVCP/UGC Working Group on Performance Indicators in Universities.

The CVCP/UGC working group's second statement, one year after the first, began by reviewing the reaction of universities to their first statement. Clearly, discontent still existed over the definition of performance indicators, let alone the use to which they could be put:

> *"It was pointed out that statistical information, by itself, does not constitute an indicator of performance unless it is subject to some kind of interpretation: 'there is a need to avoid confusion between management information and performance indicators as such; the former will include the latter, but will also take account of underlying assumptions, such as viable size of departments, economies of scale etc."* CVCP/UGC (1987).

The universities had welcomed the idea that performance indicators be used to aid decision-making, but were against any more formal application of such data. One, unnamed, university was quoted as follows:

> *"Performance indicators do not themselves provide solutions to planning problems; they represent a spectrum of measures, integrated into a coherent set*

of management data, to serve as a basis for measuring and assessing the nature of areas of the university's activities, as an indicator of the effectiveness or efficiency of activities... and as a guide which when tempered by informed academic judgement will aid decision about the planning and disposition of the university's human, physical and financial resources." CVCP/UGC (1987).

The danger of over-reliance on easily quantifiable performance indicators to the exclusion of more relevant, but difficult to quantify, factors was recognised by the working group.

"Because certain factors can be measured accurately, they may eventually be regarded as all important, with only lip service being paid to the more illusive and subjective judgements of quality that are central to the evaluation of universities." CVCP/UGC (1987).

A further danger, or unintended consequence, of utilising performance indicators is the possibility of universities working towards the performance indicators rather than their institutional objectives. Naturally, the poorer defined are the objectives, and hence less relevant are the associated performance indicators, the more serious would be this problem.

"There is an obvious need to strike a balance so that activities do not become 'indicator led', creating disincentive for innovation and risk taking. Performance indicators should be evaluative not prescriptive, and 'should not be goals in themselves.'" CVCP/UGC (1987).

The working group went further than this, however, almost to the extent of suggesting that comparison using these figures would be impossible:

> *"...the reader will need to consider carefully the inferences that can properly and usefully be drawn from the figures...They need to be interpreted with knowledge, understanding and intelligence: knowledge especially of the definition of the statistics, understanding of the organisation of the relevant part of the University and the range of variation throughout the sector, and intelligence to recognise when other figures need to be considered simultaneously. It must never be assumed that University A is 'better' than University B just because one figure is bigger or smaller than the corresponding one. It may be better, or it may not - it may just be different."* CVCP/UGC (1987).

The decision was taken not to add student entry qualifications to the indicators listed in the first statement, the working group opting to reconsider the area of admission indicators prior to the second volume of performance indicators due in 1988.

> *"The working group gave very careful consideration to the suggestion that indicators giving 'A' level entry scores should be included and some sympathy was expressed for this view...the working group, however, was very sensitive to the current political interest in widening access to university courses... It may be the case that candidates with non-'A' level qualifications could weaken the primacy of 'A' levels. Also it has to be remembered that the relationship between 'A' level entry score and degree class is blurred even within students who have received the same teaching."*
> CVCP/UGC (1987).

A list was provided of indicators which required 'further work' at this stage, this is reproduced as Figure 2.2. With the exception of admission indicators, this table in fact consisted entirely of no less than eleven of the sixteen teaching and research performance indicators listed in the first statement. None of the surviving five could be regarded as output measures, and only two of these surviving indicators could be regarded as input indicators. Clearly the emphasis in the first published set of performance indicators was to be placed very heavily on process measures.

Figure 2.2. 'Future' Indicators in the CVCP/UGC Working Group's Second Statement.

Contribution to postgraduate and professional training
Submission rates
Occupation of graduates after 18 months (12 months in first statement)
Occupation of graduates after 5 years
Undergraduate completion rates (wastage in first statement)
Analysis of publications/patents/copyrights (also agreements in first statement)
Citations
Peer review
Editorship of journals (also officers of learned bodies in first statement)
Membership of research councils
Cost per graduate
Admission indicators

The working group also noted the scope for work on 'continuing education indicators, distinction between gross and net costs and the measurement of research income'.

Five of the eight ratios grouped as 'other performance indicators' in the first statement were to be retained, the exceptions being the two relating to medical services and sports facilities, and that relating to 'other central costs'. It was decided that, despite these measures apparently having been identified as relevant and significant, that the range of values obtained in each case was unacceptably large.

> *"Medical services costs showed a bizarre variation in values which reflected the widely varying medical care practices in universities. Meaningful comparisons could not therefore be made. Sports facilities costs were also rejected for this reason. Other central costs appeared to be a collection of miscellaneous expenditure items which were of little practical use."* CVCP/UGC (1987).

The final list of initial indicators totalled 39, though many of these consisted of the same budget area presented as a number of different ratios. Only nine indicators were to be provided at cost centre level, four of these were also provided at institutional level and the other 29 were provided only at institutional level, the exception being the first destination data which was not converted from its originating form of subject group, and primary classification. These 39 'performance indicators', which include just one output measure, are reproduced as Table 2.3.

Not surprisingly, reaction within the academic community was swift and largely critical to the proposed indicators, this could only have been exacerbated by the wholesale difference between the mixture of performance indicators proposed in the first statement and the plethora of process measures which it was now

Table 2.3. The 39 Performance Indicators to be published in 1987.

1. Expenditure per FTE student
2. Expenditure per FTE academic staff
3. Expenditure on support staff per FTE academic staff
4. Expenditure on Equipment per FTE academic staff
5. Research income per FTE academic staff

6. Research postgraduates as a % of FTE students
7. Taught postgraduates as a % of FTE students
8. All postgraduates as a % of FTE students
9. Ratio of FTE students to FTE academic staff

10. Central admin expenditure as a % of Grand Total expenditure
11. Central admin pay expenditure as a % of central admin expenditure
12. Central admin expenditure per FTE student
13. Central admin expenditure per FTE academic staff

14. Library expenditure as a % of general expenditure
15. Publications expenditure as a % of library expenditure
16. Library pay expenditure as a % of library expenditure
17. Library expenditure per FTE student
18. Library expenditure per FTE academic staff
19. Book expenditure per FTE student
20. Periodicals expenditure per FTE student

21. Computer services expenditure as a % of general expenditure
22. Computer services pay expenditure as a % of computer services expenditure
23. Computer services expenditure per FTE student
24. Computer services expenditure per FTE academic staff

25. Total premises expenditure as a % of total general expenditure
26. Premises pay expenditure as a % of premises expenditure
27. Heat, water and electricity expenditure as a % of total general expenditure
28. Cleaning and custodial services expenditure as a % of total general expenditure
29. Repairs and maintenance as a % of total general expenditure
30. Telephone expenditure as a % of total general expenditure
31. Total premises expenditure per FTE student
32. Premises pay expenditure per FTE student
33. Heat, water and electricity expenditure per FTE student
34. Cleaning and custodial services per FTE student
35. Repairs and maintenance expenditure per FTE student
36. Telephone expenditure per FTE student

37. Careers services expenditure per FTE student
38. Student unions and societies expenditure per FTE student
39. Occupations of graduates after 6 months.

disclosed the first volume of 'University Management Statistics and Performance Indicators' was to contain. The reaction to the working group's second statement is covered in the next section, Section 2.5.

2.5. Reaction to the Second Statement of the CVCP/UGC Working Group.

Cameron (1988) commented on the relationship between Government and Higher Education in both Australia and the United Kingdom, noting that:

> *"There is an uneasy acceptance in higher education that the golden rule of financing will prevail (that the one with the gold makes the rules)..."*
>
> CAMERON (1988).

That reality accepted, some of the views and criticism which followed the second statement are documented in this section, with those which followed the actual publication of the first set of performance indicators included in Section 2.6.

Kirkwood (1989) presented a conference paper in which he dismisses the usefulness of the CVCP/UGC working groups efforts in terms of effectiveness.

> *"The performance indicators listed by the CVCP are wholly administrative, as they concentrate on factors that relate to efficiency in the utilisation of resources rather than to educational quality and standards. Academic questions of quality in university teaching, learning and research have hardly been addressed... If institutions of higher education are increasingly to be regarded as*

'production enterprises', we must be clear what the 'products' are, or risk producing- with great efficiency- a totally inappropriate output."

KIRKWOOD (1989).

Elton (1987) was equally unimpressed by the second statement, contrasting it with the guidelines laid down in the first statement as follows:

"Performance indicators must relate to stated objectives. (The word objectives is not mentioned in the second statement.)

The objectives for universities are primarily teaching and research. (Of the 39 performance indicators in the second statement only one is directly related to research and none to teaching. Several others are related indirectly, but these must be largely discounted since it is exactly in the proper use of such indicators that the first statement issued cautions...

The need to categorise indicators as input, process or output. (Not mentioned in the second statement.)

...A set of questions against which each performance indicator should be tested. (This was not done for the indicators listed in the second statement.)"

ELTON (1987).

Elton then concludes that, in terms of the objectives stated in the first statement, the performance indicators listed in the second statement will not indicate performance:

"The second statement gets around the problem of devising performance indicators for teaching and research by almost omitting them and concentrating on what is easily quantifiable... No less than 33 of

the 39 are concerned purely with the expenditure of money. One cannot help concluding that the principle behind this list is that whatever is easily measurable becomes a performance indicator."

ELTON (1987).

2.6. The First Two Editions of CVCP/UGC Performance Indicators.

The first edition of University Management Statistics and Performance Indicators was published by the CVCP and UGC in the Autumn of 1987. In addition to the warnings about inappropriate comparisons contained in the second statement of the CVCP/UGC Working Group, two new 'cautions' appeared.

"Mere inspection is not enough; interpretation is always necessary. It cannot be assumed that even a wide variation from a central value for a single indicator is either desirable or undesirable... It is essential therefore to build up a range of data, none of which should be seen as paramount, to cover the full sweep of an institution's activities."

CVCP/UGC (1987.2).

In the foreword, the Chairman of the Performance Indicators Steering Committee, Ewan Page, concluded with the now infamous statement that:

"Again, we consider it more important to allow some valid comparisons now, even at the risk of exposing the possibility of making some invalid ones. This publication should bear the following warning to all users, whether in government, universities or elsewhere: uncritical use of these indicators may seriously damage the health of your university." CVCP/UGC (1987.2).

The volume presents the 39 indicators first disclosed in the second statement of the CVCP/UGC working group in eight tables, each of which had both caveats and definitions attached.

Figures were provided for the academic years 1984-85 and 1985-86, with the exception of the first destination survey data, which was provided for the graduates of those years as at the end of 1985 and 1986 respectively.

The 'health warning' contained in the foreword was picked up by Elton (1987), who cleverly extended the analogy.

> *"The smoking analogy is a telling one. An obvious similarity is that smoking can damage not only the health of the smokers themselves, but also that of the society which they are consequently less able to serve and to which they may even become a burden. Similarly, most academics would contend that the uncritical use of performance indicators in universities may damage the health not only of the universities, but also of the society which they serve."* ELTON (1987).

Gray (1987) described the publishing of the first volume of performance indicators are a 'step in the right direction', pointing out that:

> *"If education resources are to be managed efficiently, then suitable 'performance indicators' are required to assist decision makers. Better information can lead to better performance."*
> GRAY (1987).

Gray found a whole series of what he called 'idiosyncratic' findings for statistics of a number of different universities. Some of these he believed to be linked to the nature of information provision to the USR by certain universities, but clear examples supported his hypothesis that:

> *"Whatever the obvious merits of performance indicators, however, there are always dangers in publishing statistics. The most obvious is that the naive and uninformed reader will ignore the various caveats that accompany them and plunge straight into misleading interpretations."* GRAY (1987).

When the second volume of 'University Management Statistics and Performance Indicators' was published in 1988, it opened with a defence of the earlier volume.

> *"several reviewers and critics of the 1987 volume commented, some acidly, to the general effect that 'arrays of numbers did not become performance indicators just by being so called'. The members of the group which produced the volume were well aware of that and had hoped that the many warnings included in the foreword and in the caveats would have communicated that message."*
> CVCP/UGC (1988).

The foreword also reiterated the need for concurrent consideration of a number of the indicators for any practical comparison to be feasible, though guidance on just which figures should be simultaneously considered, and how, remained conspicuously absent.

"League tables, beloved of much of the press, will almost always be misleading. There are very few important characteristics of a university that can be described by a single number; most require several numbers to give even a partial picture and still leave significant features omitted."

CVCP/UGC (1988).

A number of additional performance indicators were introduced in the 1988 volume, covering first destinations of first degree graduates, completion rates and entry qualifications.

Some of the first destination survey data was supplied for the first time by university; the total number of graduates of known destination, and the number of these graduates who were unemployed or in short-term employment. Additionally, various calculations on this data were provided, the numbers that would be expected to be unemployed or in short-term employment if national averages applied, and the subsequent difference between expected and actual figures.

Now that the CVCP/UGC volume of statistics was in its second edition, perhaps the most obvious performance indicator of all, the number of graduates, was included for the first time. 'Successful leavers' was included, along with the associated completion rates, the length of courses (three or four year by percentage), the average terms of attendance, and how this final statistic compares with the nominal length of the course.

Five admission indicators were included, despite the earlier misgivings of the working group regarding entry qualifications. The number of 'A' levels of entrants to all universities, and Highers in Scottish universities, a 'mean score' calculation on the same basis, and finally the numbers with main qualifications other than 'A' levels in English and Welsh universities, or 'A' levels and Highers in Scottish universities.

2.7. Interpreting and Utilising Performance Indicators.

More important than understanding or applying the results of performance measurement, is the recognition of the consequences of their very existence, as Elton (1988) observes:

> *"The very act of measuring any human activity is almost certain to alter that activity- not necessarily for the better."* ELTON (1988).

Elton had earlier made the same point in the context of the trade-off between validity and reliability:

> *"What is important in complicated human activities can frequently be assessed only qualitatively while for assessment to be reliable it has generally to be quantitative. Thus there is often a conflict between high validity and high reliability. Since those who are being assessed tend to adjust their work towards their assessment, forms of assessment which sacrifice validity for reliability can distort work."*
> ELTON (1987.2).

One obvious example of this is explained by Page (1989), referring to one of the performance indicators highlighted by the CVCP/UGC working group for further study.

> *"One topic on which our current attitude is one of scepticism is citation counting. We certainly do not want to encourage the formation of 'citation clubs', whose members cite each others papers by arrangement. Nor do we wish to present a measure which undervalues the production of a seminal paper, uncited for years while disciples recognise its worth. However we know that these techniques have their advocates and we will consider them further."*
>
> PAGE (1989).

Cuenin (1987) reported the findings of an international study on the use of performance indicators in universities which was carried out in 1985. The study covered fifteen countries and 70 institutions.

Around 50% of citations of performance indicators in use were for operating, or process, indicators; an average which is unlikely to have dropped in subsequent years, noting the British experience of the following two years (between 75% and 90% of the performance indicators in the first published set were process measures, depending on interpretation).

Over 70% of the cited performance indicators related to research with around a quarter relating to teaching, a small quantity could be applied to either teaching or research. Again, the CVCP/UGC indicators were in completely different proportions with just two of the 39 in the 1987 data relating to research and four at most, directly relating to teaching.

Booth and Booth (1989) pointed out that the difficulties associated with attempting to utilise performance indicators far outweigh any effort involved in their production.

> *"Producing a listing of this kind is easy. The difficult part is translating it into anything of use to an institution or a funding body."*
> BOOTH AND BOOTH (1989).

It is difficult to determine the extent to which UK university funding has taken performance indicators into account, however, what is clear is that the research component of recurrent grants was to be based on an increasingly competitive basis from 1986/87 onwards. In this process, consultation of performance indicators, probably peer review and research income, would be directly involved in resource allocation in order to implement:

> *"a more systematic and selective approach to the allocation of general funds for research."*
> UNIVERSITY GRANTS COMMITTEE (1984).

One particular area of difficulty, and continuing controversy, associated with a particular set of performance indicators lies in the concept of 'value-added' in teaching. This approach has much credence in America, but to date has had only academic discussion in Britain. Astin (1982) explained that:

> *"The basic argument underlying the value-added approach is that true quality resides in the institution's ability to affect its students favourably, to make a positive difference in their intellectual and personal development."* ASTIN (1982).

Cave *et al.* (1988) in a thorough examination of the value-added approach, explained the concept very concisely:

> *"The concept of value-added is simple. We consider two individuals identical in every respect until the decision to enter higher education is taken. One goes on to take a degree of a given quality; the other does not. The value-added by the degree is the difference in the contributions made to the welfare of society by the two individuals."*
> CAVE *ET AL.* (1988).

As part of a report by the Centre for Higher Education Studies, 'value-added' was examined, but it was felt that:

> *"...despite some useful conceptualisations there is little to suggest how the concept might be used in practice. Various value-added systems are currently in use in the USA. These systems are complex, costly and depend on a well-developed national testing industry and ethos."*
> CENTRE FOR HIGHER EDUCATION STUDIES (1989).

Cave *et al.* (1988) agree that the concept could never, in practice, be fully implemented:

"We lack the ability to perform a controlled experiment with two individuals, and the capacity to measure the benefits... Most attempts to implement the value-added approach do so by comparing the academic attainment of students entering the institution with their attainment on graduation; the assumption is that either all or a given proportion of the increase is associated with the educational process..." CAVE *ET AL.* (1988).

The report by the Centre for Higher Education Studies goes on to conclude that the value-added concept is of some importance, but that as an analytical technique it requires information that may not be available in the foreseeable future.

"The value added aspect of conceptual change and perspective transformation may be highly significant but it is not easy to record it nor to attribute change to particular aspects of the students experience. If it is to be given the prominence it deserves there may need to be new ways of assessing students..."
CENTRE FOR HIGHER
EDUCATION STUDIES (1989).

Cave *et al.* (1988) agree that the difficulties involved in developing a satisfactory system will remain unsurmountable for some time, concluding that:

"research in this area is still in its infancy and by no means at a stage where we can say value-added measures can or cannot be made operational at some level." CAVE *ET AL.* (1988).

As with the majority of performance indicators, the arguments for and against pivot on issues of measurability and practicality, and their apparent inverse relationship with the appropriateness and validity of the statistics obtained. With continuing determination by Government bodies to adopt consideration of performance indicators into resource allocation processes, Wagner (1987) makes an observation that the academic community would perhaps be wise to heed:

> *"However while it is important to remember that one should not necessarily value only that which can be measured it may be considered somewhat disingenuous to argue that one should value most only that which cannot be measured."*
> WAGNER (1987).

2.8. The Future of Performance Indicators in Higher Education.

While there has been considerable work carried out in the field of performance measurement in the last decade and in particular on the development of performance indicators. The comprehensive review of these carried out by the Centre for Higher Education Studies (1989) concluded that relatively little had actually been achieved, in particular:

> *"The literature on performance indicators of teaching quality has not progressed far beyond the rehearsal of arguments for and against a few obvious indicators and the development of more elaborate theoretical models with little empirical content."*
> CENTRE FOR HIGHER EDUCATION STUDIES (1989).

A competitive basis will continue to be used, to an increasing extent, in the allocation of both Government and Research Council funding, a process which is planned to continue to at least the end of the decade. The literature indicates that performance indicators will undoubtedly continue to be involved in this process.

> *"All this is not to say that quantitative performance indicators should not be used at all since, without them, accountability may well become a pointless exercise."* ELTON (1988.2).

The influence that these increases in accountability will ultimately have on the 'fitness for purpose' of the university system remains open to debate, as Sizer (1990) surmised in a recent paper:

> *"It remains to be seen whether the moves in the UK to a market economy in higher education accompanied by executive styles of management will improve or impair effectiveness."* SIZER (1990).

The problem of analysing performance indicators is increasingly been seen as a question of how to consider distinct indicators concurrently. Reliance on single indicators having been almost universally rejected. Dochy and Segers (1990) suggested a need to introduce some form of weighting into the analysis:

> *"Every institution has to define its objectives in connection with the centrally stated goals and in connection with its individual mission. Interpretation and relative weighting of performance indicators have to take account of this mission."*
> DOCHY AND SEGERS (1990).

Elton (1988.3) also noted that some form of calculation would be required if practical and justifiable consideration were ever to be made of the existing performance indicators.

> *"A way in which at least some qualitative judgement can be incorporated within a scheme of quantitative performance indicators is through attaching different weights to different indicators. Although the weights themselves are numerical and hence quantitative, decisions on their size require qualitative judgement."* ELTON (1988.3).

The need to identify a rationale on which such concurrent consideration of performance indicators could be based, and hence on which weighting could be established, was an issue which remained to be resolved.

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3. METHODOLOGIES FOR INCREASING THE PRACTICALITY OF PERFORMANCE INDICATORS.

Supplying multiple, related performance indicators implicitly introduces some form of subjective analysis, by anyone considering the information, of the relative significance of each of the measures, and of other issues such as the effect of caveats.

Given over fifty separate statistics to consider for each institution, as is the case in recent editions of the CVCP/UFC 'Management Statistics and Performance Indicators in the UK', this becomes a task which is, realistically, completely impractical.

The second chapter concluded by identifying the need to introduce qualitative judgement into the consideration of performance indicators in a more formal manner, and the purpose of this chapter is, therefore, to examine the possible approaches that could be adopted.

Chapter One established that any technique which attempted to indicate performance by relating inputs to outputs would be difficult to justify.

> *"...Education, particularly higher education, is characterised by... no real understanding of the relationship between inputs and outputs."*
> CUTHBERT AND BIRCH (1979).

It was noted that a major problem in university performance measurement is a poor understanding of the process of conversion from input to output. The conclusion was that a crucial requirement of any analytical model would be that it considers both inputs and outputs but requires no definition of the processes between.

Two entirely distinct approaches have been identified which meet this requirement. The first approach focuses on the outputs of higher education, and only considers inputs specifically in order to explain some of the differences in the output statistics that are observed. This technique has been pioneered by Johnes and Taylor (1990), and is reviewed in Section 3.1.

The second approach is that of Data Envelopment Analysis (DEA), which utilises Linear Programming concepts, considering a range of inputs and outputs, but requiring no definition of the relationship between them, thus allowing the processes within universities to be treated as a 'black box'. Data Envelopment Analysis is introduced in Section 3.2.

3.1. Contrasting Actual Outputs against Calculated 'Expected' Outputs.

Johnes and Taylor (1990) explain that if performance indicators are to be used for inter-university comparisons then it must be ensured that like is compared with like. The philosophy of this approach is that differences attributable to particular factors other than the effectiveness of the institution, must be allowed for before a true picture of effectiveness can be gained.

> *"The basic procedure is very simple. Instead of comparing each university's outputs with (say) the average for all universities, each university's outputs should be compared with the outputs that we would expect each university to produce given its particular mix of inputs."*
>
> JOHNES AND TAYLOR (1990).

A very general form of production function is offered for the case of the production of a single homogenous commodity, which is reproduced here as Figure 3.1.

Figure 3.1. General Form of Production Function, after Johnes and Taylor (1990).

$$y = f(l,k,t,c,r)$$

where		(general case)	(university context examples)
y	=	output	teaching and research
l	=	labour inputs	academic and non-academic staff
k	=	capital inputs	buildings and equipment
t	=	technical knowledge	knowledge of academic staff
c	=	consumables	heating and telephones
r	=	raw material	students

Naturally, as these authors have not been alone in pointing out, the problem with applying production theory in the university context lies on the left-hand side of the equation, the fact that universities produce several outputs which cannot readily be combined.

This difficulty is expanded upon, with the need to view educational processes as a 'black box' stated in the introduction to this chapter being reiterated:

> *"inputs are often used to produce more than one output and there is no obvious way of attributing specific inputs to specific outputs... Since research output and teaching output cannot be added together in any meaningful way, this makes it difficult to estimate input and output relationships for specific outputs."*
>
> JOHNES AND TAYLOR (1990).

An illustration of the application of this approach is now examined, taking a teaching output as the example.

3.1.1. Actual and Expected University Degree Results.

The philosophy of the approach used by Johnes and Taylor is re-stated in the specific context of degree results:

> *"...any performance indicator based on degree results will have to be 'corrected' to allow for inter-university differences in degree results which are due to factors unrelated to the teaching process-since it is the effectiveness of the teaching process which degree results are supposedly measuring."*
>
> JOHNES AND TAYLOR (1990).

A 'score' is produced for each university using a weighting system across the different categories of degree awards as shown in Figure 3.2.

The number of graduates in each class is multiplied by the weighting factor, with the result divided by the total number of graduates.

These weights are obviously subjective, the only justification provided being a high correlation with a second 'model' based on the percentage that 'firsts' and 'upper seconds' contribute to the total number of degree awards less 'undivided seconds'.

Figure 3.2. Weights used to Rationalise Degree Results to a Single 'Score'.

Degree Class	Weighting
first class honours degree	75
upper second class honours degree	65
undivided second class honours	60
lower second class honours degree	55
third class honours degree	45
pass or ordinary degree	40

Student-related and university-related factors which affected the level of degree awards were identified by multiple regression methods. Six factors were included which together accounted for over 80% of the differences. These factors are shown in Figure 3.3.

A particularly strong correlation was found between 'A' level scores and degree results for universities as a whole.

<u>Figure 3.3. Factors Used to Explain Differences in Degree Results.</u>

1. the mean A level score of entrants.
2. the percentage of students who live at home.
3. library expenditure as a percentage of total expenditure.
4. whether or not a university is an ex-college of advanced technology.
5. whether or not a university is one of the new greenfield universities established in 1964/65.
6. whether or not a university is located in Scotland.

Using the coefficients for each of the factors identified as significant in the regression analysis, expected values were then calculated for each university which could be compared with the actual results.

The 'actual versus expected' approach was also applied to a number of other areas of university output; unit costs, non-completion rates, first destinations of new graduates, and research activity.

The results across these five areas were then compared, and it was observed that the rankings of universities varied widely for each.

> *"The importance of considering the performance of a university across several indicators is vividly demonstrated... any individual university['s] relative performance varies considerably depending upon which indicator is selected. The variation in each university's performance between the five indicators is substantial for <u>all</u> universities. No university has performed either consistently well or consistently badly across all indicators."*
>
> JOHNES AND TAYLOR (1990).

Hence the approach advocated by Johnes and Taylor may considerably improve the extent to which differences between institutions for individual performance indicators, after adjustment, can be considered as significant. Differences are not homogenous across different performance indicators, however, so this technique has not been able to progress to combining output measures.

In their conclusions, Johnes and Taylor (1990) point out that:

> *"This book has focused almost entirely on whole institutions... this level of aggregation is inappropriate, however, for managing resources within institutions. Cost Centres are more relevant for this purpose... more attention should therefore be devoted to inter-university comparisons at the cost centre level."*
>
> JOHNES AND TAYLOR (1990).

Analysis on the basis of, or close to, subject level would undoubtedly increase the range of indicators over which valid comparisons could be made. In terms of 'drawing together' different performance indicators to a single overall measure, these authors suggest that:

> *"In the last resort, decisions will have to be made about the weight to be attached to each available indicator of performance."*
>
> JOHNES AND TAYLOR (1990).

One approach to doing this which it is suggested by Johnes and Taylor merits further study is that of Data Envelopment Analysis, and this is introduced in Section 3.2.

3.2. The Farrellian Efficiency Model and the Theory of Data Envelopment Analysis (DEA).

Interest has rapidly gained in the technique of Data Envelopment Analysis in recent years. It stems from a method originally put forward by Charnes (1978). Their work was based on a definition of efficiency stated by Farrell as early as 1957, then developed by Farrell and Fieldhouse (1962), before being dormant until the late seventies.

In the Farrellian Efficiency Model, one or more distinct units, referred to as 'Decision-Making Units' (DMU), are assessed. The efficiency of one of these units is then defined as a ratio of the weighted sum of the outputs to the weighted sum of the inputs. In these terms, the efficiency of the jth DMU would be as shown in Figure 3.4.

Figure 3.4. The Farrellian Efficiency Model.

$$\text{efficiency} = \frac{\sum_{r=1}^{r=s} O_r OQ_{rj}}{\sum_{i=1}^{i=m} I_i IQ_{ij}}$$

with

OQ_{rj} = the quantity of DMU j's rth output.
O_r = the rth output's weight.
IQ_{ij} = the quantity of DMU j's ith input.
I_i = the ith input's weight.

The logical step from this which Charnes (1978) took was to define the relative or pareto efficiency of one of a set of such 'Decision-Making Units'. This involves treating the weights O_r and I_i as variables, and thus maximising the efficiency ratio of any particular DMU. For this an arbitrary constraining limit must be set and a value of one, unity, has come to be used exclusively in this topic. The efficiency of a DMU j_0 would hence be obtained by solving the model shown in Figure 3.5, all definitions are as before.

Figure 3.5 Charnes Relative Efficiency Model.

$$\text{MAXIMISE } h_0 = \frac{\sum_{r=1}^{r=s} O_r OQ_{rj0}}{\sum_{i=1}^{i=m} I_i IQ_{ij0}}$$

$$\text{SUBJECT TO} \quad \frac{\sum_{r=1}^{r=s} O_r OQ_{rj}}{\sum_{i=1}^{i=m} I_i IQ_{ij}} \leq 1 \quad j = 1 \ldots j_0 \ldots n$$

$$\text{WITH} \quad O_r \text{ AND } I_i > \varepsilon \text{ FOR ALL } r \text{ AND } i$$

In other words, each DMU is allowed to adopt the set of weights that shows it in the most favourable light by maximising the pareto efficiency of that DMU (j_0), subject to all efficiencies (for all DMU) being feasible, that is, less than or equal to one, by selecting the best weights (O_r,I_i) for the particular Decision-Making Unit (j0). All these weights (O_r,I_i) must be positive, implemented by the restriction that they be greater than or equal to some small constant 'ε', epsilon. 10^{-5} is used throughout to represent epsilon.

It would be useful to introduce a fictional example at this point in order to demonstrate the above model. In Table 3.6, fictional data is presented which is based on the traffic divisions of eight 'Scottish Police Forces'.

The same seven statistics are presented for each of these 'traffic divisions', consisting of two inputs and five outputs. The inputs are firstly, the total budget of the DMU, and secondly the number of 'operational patrol units'. Including the second input ensures that recognition can be made of the varying levels of resource draining administrative costs and other overheads that may exist, which could not be represented by examining total budget alone.

Three categories of output were included, offences statistics (positive breath tests and moving vehicle offences), basic traffic policing activities (speed monitoring hours and total road hours), and finally special traffic police activities (escort mileage).

Note that these measures are incommensurate, one input is in millions of pounds, the other simply a count; different outputs are measured in hours, occurrences and miles. The mathematics of DEA are such that this does not represent any problem. Equally the varying scale of the figures is of no significance as the technique is not scale sensitive.

Table 3.6. Fictional Example Based upon Scottish

Police Forces Traffic Divisions.

Output/Input DMU	O1	O2	O3	O4	O5	I1	I2
1 STRATHCLYDE	18.7	8.7	36.0	46.8	22.8	36.1	7.8
2 LOTHIAN&BORDERS	11.8	4.8	23.5	27.6	13.8	16.1	4.6
3 GRAMPIAN	7.6	3.3	14.7	18.6	8.8	12.5	3.1
4 TAYSIDE	5.1	2.4	9.8	11.4	5.9	7.9	1.9
5 CENTRAL SCOTLAND	3.8	1.2	6.8	8.4	4.9	5.4	1.4
6 FIFE CONSTABULARY	3.2	1.1	6.8	7.2	2.9	4.9	1.2
7 DUMFRIES&GALLOWAY	1.8	0.7	3.2	4.2	2.4	3.3	0.7
8 NORTHERN	2.1	0.9	2.9	4.0	1.7	3.2	0.7

key:
- O1 Speed monitoring hours (10,000's)
- O2 Positive breath tests (10,000's)
- O3 Road hours (100,000's)
- O4 Moving vehicle offences (10,000's)
- O5 Escort mileage (10,000's)

- I1 Budget (£millions)
- I2 Units (100's)

(Fictional Data)

From the data of Table 3.6, the DEA formulation for the Decision-Making Unit 'STRATHCLYDE' would then be as shown in Figure 3.7. In both this figure and Figure 3.8, a double-asterisk, '**', denotes the constraint line of the subject DMU.

Equally, the Data Envelopment Analysis formulation for the DMU 'LOTHIAN&BORDERS' would be as shown in Figure 3.8, with the same constraint lines as for 'STRATHCLYDE', but with the 'LOTHIAN&BORDERS' data forming the objective function.

Figure 3.7. Data Envelopment Analysis Formulation

for the DMU 'STRATHCLYDE'.

MAXIMISE

$$\frac{18.7\ O_1 + 8.7\ O_2 + 36.0\ O_3 + 46.8\ O_4 + 22.8\ O_5}{36.1\ I_1 + 7.8\ I_2}$$

SUBJECT TO

$$\frac{18.7\ O_1 + 8.7\ O_2 + 36.0\ O_3 + 46.8\ O_4 + 22.8\ O_5}{36.1\ I_1 + 7.8\ I_2} \leq 1 \quad **$$

$$\frac{11.8\ O_1 + 4.8\ O_2 + 23.5\ O_3 + 27.6\ O_4 + 13.8\ O_5}{16.1\ I_1 + 4.6\ I_2} \leq 1$$

$$\frac{7.6\ O_1 + 3.3\ O_2 + 14.7\ O_3 + 18.6\ O_4 + 8.8\ O_5}{12.5\ I_1 + 3.1\ I_2} \leq 1$$

$$\frac{5.1\ O_1 + 2.4\ O_2 + 9.8\ O_3 + 11.4\ O_4 + 5.9\ O_5}{7.9\ I_1 + 1.9\ I_2} \leq 1$$

$$\frac{3.8\ O_1 + 1.2\ O_2 + 6.8\ O_3 + 8.4\ O_4 + 4.9\ O_5}{5.4\ I_1 + 1.4\ I_2} \leq 1$$

$$\frac{3.2\ O_1 + 1.1\ O_2 + 6.8\ O_3 + 7.2\ O_4 + 2.9\ O_5}{4.9\ I_1 + 1.2\ I_2} \leq 1$$

$$\frac{1.8\ O_1 + 0.7\ O_2 + 3.2\ O_3 + 4.2\ O_4 + 2.4\ O_5}{3.3\ I_1 + 0.7\ I_2} \leq 1$$

$$\frac{2.1\ O_1 + 0.9\ O_2 + 2.9\ O_3 + 4.0\ O_4 + 1.7\ O_5}{3.2\ I_1 + 0.7\ I_2} \leq 1$$

WITH

I1, I2, O1, O2, O3, O4, O5 $\leq \varepsilon$

Figure 3.8. Data Envelopment Analysis Formulation

for the DMU 'LOTHIAN&BORDERS'.

MAXIMISE

$$\frac{11.8\ O_1 + 4.8\ O_2 + 23.5\ O_3 + 27.6\ O_4 + 13.8\ O_5}{16.1\ I_1 + 4.6\ I_2}$$

SUBJECT TO

$$\frac{18.7\ O_1 + 8.7\ O_2 + 36.0\ O_3 + 46.8\ O_4 + 22.8\ O_5}{36.1\ I_1 + 7.8\ I_2} \leq 1$$

$$\frac{11.8\ O_1 + 4.8\ O_2 + 23.5\ O_3 + 27.6\ O_4 + 13.8\ O_5}{16.1\ I_1 + 4.6\ I_2} \leq 1 \quad **$$

$$\frac{7.6\ O_1 + 3.3\ O_2 + 14.7\ O_3 + 18.6\ O_4 + 8.8\ O_5}{12.5\ I_1 + 3.1\ I_2} \leq 1$$

$$\frac{5.1\ O_1 + 2.4\ O_2 + 9.8\ O_3 + 11.4\ O_4 + 5.9\ O_5}{7.9\ I_1 + 1.9\ I_2} \leq 1$$

$$\frac{3.8\ O_1 + 1.2\ O_2 + 6.8\ O_3 + 8.4\ O_4 + 4.9\ O_5}{5.4\ I_1 + 1.4\ I_2} \leq 1$$

$$\frac{3.2\ O_1 + 1.1\ O_2 + 6.8\ O_3 + 7.2\ O_4 + 2.9\ O_5}{4.9\ I_1 + 1.2\ I_2} \leq 1$$

$$\frac{1.8\ O_1 + 0.7\ O_2 + 3.2\ O_3 + 4.2\ O_4 + 2.4\ O_5}{3.3\ I_1 + 0.7\ I_2} \leq 1$$

$$\frac{2.1\ O_1 + 0.9\ O_2 + 2.9\ O_3 + 4.0\ O_4 + 1.7\ O_5}{3.2\ I_1 + 0.7\ I_2} \leq 1$$

WITH

I1, I2, O1, O2, O3, O4, O5 $\leq \varepsilon$

Similarly, models could be composed for the remaining six DMU. As can be seen from the figures, to make any DMU the subject of the optimisation, all that is required is to duplicate the left hand side of the constraint line for that particular DMU as the objective value.

The technique can therefore be used to bring together incommensurate inputs and outputs, without any requirement to define their relationship to each other. Furthermore as stated, Data Envelopment Analysis is not scale sensitive.

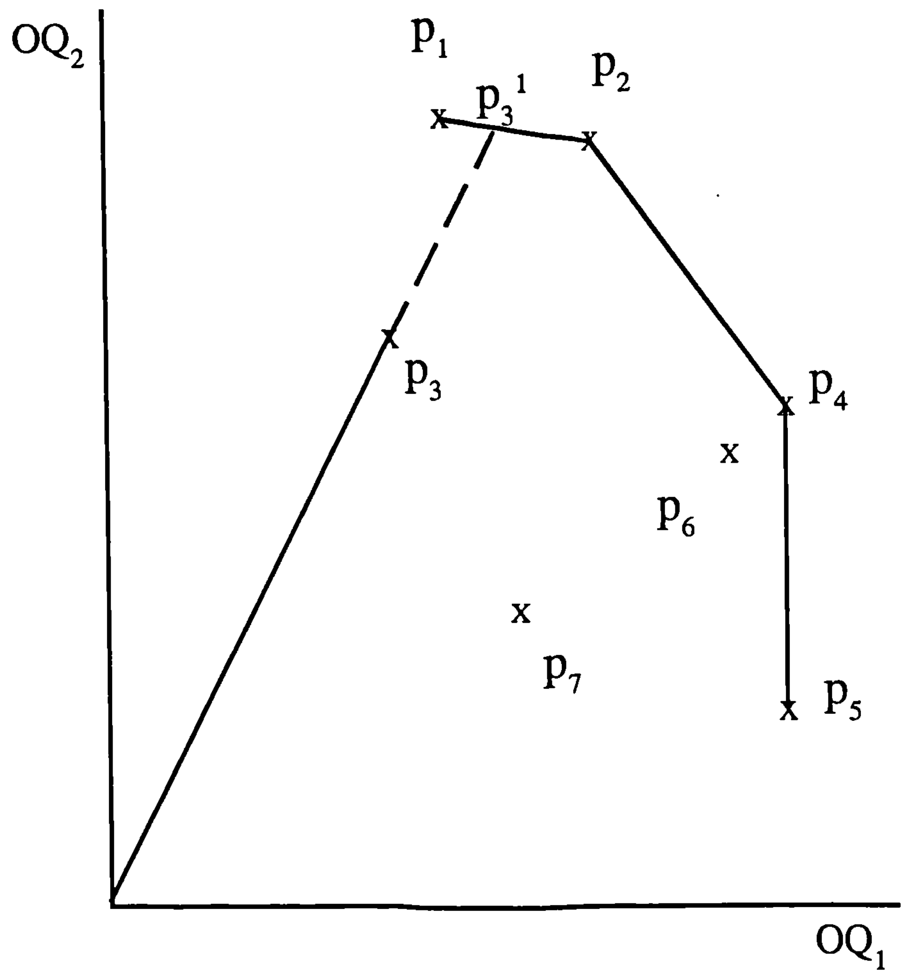
The above model is known as the 'Conceptual' or 'Primal' model of DEA, which is a fractional linear program. Naturally a linear program can be derived from this fractional linear program. To obtain pareto efficiency ratings for all of a set of DMU will, therefore, require the optimisation of a suite of very similar linear programs.

It should be noted that there is an alternative model known as the 'Computational' or 'Dual' model which many DEA implementations utilise. The advantages of this, more mathematically complex, dual model are purely computational; as such, further discussion of this or another derivation known as the 'side model' would not make any contribution to an understanding of the central theory of DEA.

Before progressing further, it would be appropriate at this point to explain the concept behind Data Envelopment Analysis and indeed where the title originates from.

Consider a set of units P_1, P_2,...,P_7, each consuming the same quantity of a single resource (input), but producing different amounts of outputs OQ_1 and OQ_2 as shown in Figure 3.9.

Figure 3.9. Illustration of The Pareto Efficient Frontier or 'Data Envelope'.



P_3, P_6, and P_7 are pareto inefficient DMU which could become pareto efficient by increasing output so that they reach the 'data envelope' or 'pareto efficient frontier' formed by the Pareto efficient units P_1, P_2, P_4 and P_5.

P_3^1 is the target point that can be immediately generated by the model, but it is important to note that by different combinations of increased outputs, P_3 could become pareto efficient by moving to any point on the envelope. The use of a 'target point' also, somewhat unrealistically, assumes P_3 could have the opportunity of moving to a pareto efficient position while the other DMU remain static. In reality whilst P_3 would attempt a move towards the pareto efficient frontier, the other units would also be attempting to remain relatively efficient and hence in the next time period the frontier itself will undoubtedly have changed.

In order to carry out an implementation of Data Envelopment Analysis, carefully considered input and output sets would be defined, the data would then be applied to a suite of linear programs, one per DMU, with each linear program being optimised to provide the pareto efficiency ratings for the particular DMU.

Of the possible approaches to measuring performance in universities, it seems that Data Envelopment Analysis may offer the most potential for achieving significant and practical results. There are a number of conceptual problems which would need to be overcome, however, and discussion of the technique is limited without the aid of more detailed practical illustration.

The justification is clearly provided, therefore, to carry out a thorough examination and critical analysis of Data Envelopment Analysis. This will be the subject matter of Chapter Four, and will include the application of DEA to the fictional 'traffic police' data set, and an attempt at overcoming the conceptual problems identified.

Quotations from the findings of other authors will be introduced and discussed, where appropriate, throughout the chapter. These can additionally be regarded as serving as a literature review of the technique of Data Envelopment Analysis, a topic which has received relatively little attention to date. Taken together with the work referenced in this section; sufficient of the major contributions on Data Envelopment Analysis are covered to enable an understanding of the existing theory to be gained. There are, however, a number of other significant works which could be studied were a fuller picture of the development of the existing theory desired, and an extended bibliography of some of the contributions not referenced within the thesis have therefore been included as Appendix A.

References for Chapter Three.

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4. AN INVESTIGATION OF DATA ENVELOPMENT ANALYSIS.

In the previous chapter, Data Envelopment Analysis (DEA) was identified as having a number of attributes which make it potentially suitable as a model into which existing university performance indicators could be incorporated in order to produce a single overall measure of performance.

The purpose of this Chapter is, therefore, to carry out a thorough investigation into this technique, which has the principal attraction of being able to incorporate incommensurate inputs and outputs, without requiring any definition of the productive relationship involved between these inputs and outputs.

4.1. Efficiency and Effectiveness Measurement using DEA.

The use of the term 'efficiency', entirely divorced from 'effectiveness', raises the most obvious doubts about the technique of Data Envelopment Analysis. Anxieties which are only increased when the terms are used interchangeably in some articles. It seems clear, however, that as long as the correct outputs and resources (inputs) are chosen for inclusion, then, using Data Envelopment Analysis, it should be possible to obtain an indication of relative performance. To help avoid confusion, whilst other authors have simply used the term 'efficiency', here the fuller term 'pareto efficiency' will be used throughout.

The inclusion of an element of effectiveness for the study of performance in UK universities seems essential, hence it is crucial to any practical use of results obtained using the technique that only important and relevant factors are chosen, and that all important and relevant factors are included.

There remains, however, some debate about the importance of including all relevant factors. In a keystone paper by Thanassoulis *et al.* (1987), they argue that:

> *"Should an input be omitted, the relative efficiencies determined will not reflect the performance of units in terms of their effective (or otherwise) use of that resource. Similarly, the omission of some output would mean the assessment ignores the performance of units on that output."*
>
> THANASSOULIS *ET AL.* (1987).

This is, of course, hardly unique to Data Envelopment Analysis, as with any technique; if you use inappropriate data, you will inevitably get inaccurate, or misleading results. They continue, however, to put forward an argument that intuitively seems to contradict this basic philosophy:

> *"In principle, all inputs and outputs relevant to the function of the units should be included. However, the larger the number of inputs and outputs in relation to the number of units being assessed, the less discriminatory the method appears to be... This tendency will, in general, be true because the larger the number of inputs and outputs for a given number of units being assessed, the greater the chance that a unit can find weights for some subset of the inputs and outputs that show it efficient. Thus the number of inputs and outputs included in a DEA assessment should be as small as possible, subject*

> *to their reflecting adequately the function performed by the units being assessed."*
> THANASSOULIS *ET AL.* (1987).

The argument here seems to suggest that if a situation may occur where a large percentage of the Decision-Making Units (DMU) would be shown to be pareto efficient, then the results should be manipulated by excluding factors almost arbitrarily, in order to yield results with a lesser number of pareto efficient units. Were this to amount to simple 'marking-down' or 'under-valuing' across the board, then it would matter little. It does, however, appear that the true picture of relative performance is likely to be hidden at times purely for the sake of statistical convenience, the creation of a clearly ranked 'league table'.

Fortunately this approach to choosing inputs and outputs for inclusion does not seem to carry favour elsewhere. One method advocated by Thanassoulis *et al.* (1987) to reduce variable numbers is to exclude highly correlated factors, with only one of any such correlated variables remaining within the implementation. As Nunamaker (1985) states, however;

> *"Our analysis...indicates that for selected DMU's, addition of a highly correlated variable may alter substantially the DEA efficiency evaluations. Just because a variable is redundant within a regression model does not mean it is redundant within DEA. Addition of a correlated variable to a regression model will add little to the mean square accounted for by the existing independent variables. DEA, however, is not based on any 'squared distance from the mean' notions."* NUNAMAKER (1985).

Examining the model of DEA, adding a highly-correlated additional variable would double the 'opportunity' to apply weight to the correlated activities. Where a DMU had a large weight already applied to the particular variable, such a re-run of the analysis would be most likely to result in a higher rating being achieved.

It is generally accepted by the majority of authors that inputs and outputs are included if and only if they are relevant to the performance assessment in question and excluded if and only if they are not. This may result in few pareto efficient DMU or in many, but should provide pareto efficiencies which far more accurately reflect performance in terms of the objectives of the set of DMU.

The principal advantage with DEA, over ad-hoc weight application is that Decision-Making Units will have their weights decided to their best advantage by the program, not simply with static weights, but by optimisation for each individual DMU. Hence there can be no criticism of the results obtained in terms of bias or subjectiveness in the choice of weights. The way in which these pareto efficiency ratings are actually achieved can be best explained by demonstration; by returning to our simple fictional example, in Section 4.2.

4.2. An Implementation of Data Envelopment Analysis.

In the last chapter, Section 3.2 introduced the theory and technique of Data Envelopment Analysis. A set of fictional data was presented to demonstrate the way in which input and output statistics are introduced into the model to provide pareto efficiency ratings for each of a set of Decision-Making Units.

Utilising the fictional data set, for the purposes of examination, Data Envelopment Analysis is now implemented for a fictional example. The data was as given in Table 3.6, reproduced here as Table 4.1.

Table 4.1. Fictional Data of Table 3.6, Scottish Police Forces Traffic Divisions.

Output/Input DMU	O1	O2	O3	O4	O5	I1	I2
1 STRATHCLYDE	18.7	8.7	36.0	46.8	22.8	36.1	7.8
2 LOTHIAN&BORDERS	11.8	4.8	23.5	27.6	13.8	16.1	4.6
3 GRAMPIAN	7.6	3.3	14.7	18.6	8.8	12.5	3.1
4 TAYSIDE	5.1	2.4	9.8	11.4	5.9	7.9	1.9
5 CENTRAL SCOTLAND	3.8	1.2	6.8	8.4	4.9	5.4	1.4
6 FIFE CONSTABULARY	3.2	1.1	6.8	7.2	2.9	4.9	1.2
7 DUMFRIES&GALLOWAY	1.8	0.7	3.2	4.2	2.4	3.3	0.7
8 NORTHERN	2.1	0.9	2.9	4.0	1.7	3.2	0.7

key:
- O1 Speed monitoring hours (10,000's)
- O2 Positive breath tests (10,000's)
- O3 Road hours (100,000's)
- O4 Moving vehicle offences (10,000's)
- O5 Escort mileage (10,000's)

- I1 Budget (£millions)
- I2 Units (100's)

(Fictional Data)

Clearly, a visual examination of these statistics reveals no obvious information as to the relative performance of the DMU involved. Recall that the implementation model for 'STRATHCLYDE' given in Figure 3.7, was formulated as shown in abbreviated form in Figure 4.2 .

Figure 4.2 DEA Formulation for DMU 'STRATHCLYDE' (Abbreviated).

MAXIMISE

$$\frac{18.7\ O_1 + 8.7\ O_2 + 36.0\ O_3 + 46.8\ O_4 + 22.8\ O_5}{36.1\ I_1 + 7.8\ I_2}$$

SUBJECT TO

$$\frac{18.7\ O_1 + 8.7\ O_2 + 36.0\ O_3 + 46.8\ O_4 + 22.8\ O_5}{36.1\ I_1 + 7.8\ I_2} \leq 1$$

$$\frac{11.8\ O_1 + 4.8\ O_2 + 23.5\ O_3 + 27.6\ O_4 + 13.8\ O_5}{16.1\ I_1 + 4.6\ I_2} \leq 1$$

$$\vdots$$

$$\frac{2.1\ O_1 + 0.9\ O_2 + 2.9\ O_3 + 4.0\ O_4 + 1.7\ O_5}{3.2\ I_1 + 0.7\ I_2} \leq 1$$

WITH

$$I1, I2, O1, O2, O3, O4, O5 \geq \varepsilon$$

The formulation in Figure 4.2 is a fractional linear program, to solve this as a linear program, its numerator was set equal to the figure chosen as the 'maximum' efficiency, unity, and the denominator minimised, subject to the total product for any DMU, of all inputs and their weights never being exceeded by the total product of the outputs and their weights. More formally, this provides an implementation model for DEA as shown in Figure 4.3, derived from the conceptual model of Figure 3.5.

Figure 4.3. Implementation Model for DEA, Derived from Relative Efficiency Model (Figure 3.4).

MINIMISE $$h_0 = \sum_{i=1}^{i=m} I_i IQ_{ij0}$$

SUBJECT TO $$\sum_{r=1}^{r=s} O_r OQ_{rj0} = 1$$

$$\sum_{i=1}^{i=m} I_i IQ_{ij} - \sum_{r=1}^{r=s} O_r OQ_{rj} \geq 0 \quad j = 1 \ldots j_0 \ldots n$$

WITH O_r AND $I_i > \varepsilon$ FOR ALL r AND i

From this model, linear program coding can be directly created, the actual program used for the fictional example is shown in Figure 4.4; written using the LINDO (Linear, Interactive and Discrete Optimizer) linear programming package (LINDO Systems, Inc.).

Naturally the same results could have been achieved by setting the denominator equal to the constant and maximising the numerator, the choice is purely arbitrary, and was made subject simply to convenience when using this particular package.

Figure 4.4. 'LINDO' Linear Program Coding for Data of Figure 4.1.

```
MIN A1 + A2
SUBJECT TO
CONSTANT) B1 + B2 + B3 + B4 + B5 = 1
 STRATHC) 36.1 I1 +  7.8 I2 - 18.7 O1 - 8.7 O2 - 36.0 O3 - 46.8 O4 - 22.8 O5 >= 0
 LOTHIAN) 16.1 I1 +  4.6 I2 - 11.8 O1 - 4.8 O2 - 23.5 O3 - 27.6 O4 - 13.8 O5 >= 0
 GRAMPIA) 12.5 I1 +  3.1 I2 -  7.6 O1 - 3.3 O2 - 14.7 O3 - 18.6 O4 -  8.8 O5 >= 0
 TAYSIDE)   7.9 I1 +  1.9 I2 -  5.1 O1 - 2.4 O2 -  9.8 O3 - 11.4 O4 -  5.9 O5 >= 0
 CENTRAL)  5.4 I1 +  1.4 I2 -  3.8 O1 - 1.2 O2 -  6.8 O3 -  8.4 O4 -  4.9 O5 >= 0
 FIFECON)   4.9 I1 +  1.2 I2 -  3.2 O1 - 1.1 O2 -  6.8 O3 -  7.2 O4 -  2.9 O5 >= 0
 DUMGALL) 3.3 I1 +  0.7 I2 -  1.8 O1 - 0.7 O2 -  0.2 O3 -  4.2 O4 -  2.4 O5 >= 0
 NORTHER) 3.2 I1 +  0.7 I2 -  2.1 O1 - 0.9 O2 -  2.9 O3 -  4.0 O4 -  1.7 O5 >= 0
  VIRI1)   - 36.1 I1 + A1 = 0
  VIRI2)    - 7.8 I2 + A2 = 0
  VIRO1)  - 18.7 O1 + B1 = 0
  VIRO2)    - 8.7 O2 + B2 = 0
  VIRO3)  - 36.0 O3 + B3 = 0
  VIRO4)  - 46.8 O4 + B4 = 0
  VIRO5)  - 22.8 O5 + B5 = 0
  EPSI1)  I1 >= 0.00001
  EPSI2)  I2 >= 0.00001
  EPSO1)  O1 >= 0.00001
  EPSO2)  O2 >= 0.00001
  EPSO3)  O3 >= 0.00001
  EPSO4)  O4 >= 0.00001
  EPSO5)  O5 >= 0.00001
 END
```

Note also, however, that DEA models involving maximisation will yield the pareto efficiency, whilst those involving minimisation will yield the inverse of the pareto efficiency.

The program is largely self-explanatory, the extra variables A1, A2 and B1...B5 become necessary at a later stage, and have been included in this initial program, which will be referred to as program 'DEA1', simply to enable easy comparison with later versions. They do, however, with this particular package, make the adaptation to the programs for other DMU extremely simple; only the lines named 'VIRI1' to 'VIRO5' needing alteration to move from the implementation for one DMU to another.

The result of this particular minimisation, for 'STRATHCLYDE', is an objective function value of 1.000.

As already indicated, with a minimisation implementation, the inverse of this must be taken to convert the figure to a pareto efficiency. For 'STRATHCLYDE' this is, of course, still 1.000. Pareto efficiency ratings are commonly given in percentages of unity, hence 'STRATHCLYDE' rates 100% pareto efficient (100% PE). The full results for all the DMU are laid out in Table 4.5, along with the weights chosen by the program in each case.

Table 4.5. Pareto Efficiency Ratings and Variable Weights After Implementation of Program DEA1 for all DMU.

DMU	PARETO EFFICIENCY	INPUT WEIGHTS I1	I2	OUTPUT WEIGHTS O1	O2	O3	O4	O5
1 STRATHCLYDE	100%	ε	.12817	ε	ε	ε	.02136	ε
2 LOTHIAN&BORDERS	100%	ε	.21736	ε	ε	ε	.03623	ε
3 GRAMPIAN	100%	ε	.32255	ε	ε	ε	.05376	ε
4 TAYSIDE	100%	ε	.52627	ε	ε	ε	.08771	ε
5 CENTRAL SCOTLAND	100%	.02170	.63060	ε	.01088	.09618	ε	.06794
6 FIFE CONSTABULARY	100%	.05506	.60851	.21086	.03769	.03769	ε	.00947
7 DUMFRIES&GALLOWAY	100%	ε	1.42857	.16393	ε	ε	.16393	ε
8 NORTHERN	100%	.19362	.54346	.47305	.00733	ε	ε	ε

The weights applied to each variable will be dependent upon the scale of magnitude of the particular variable. Given, therefore, that the data for the DMU covered a large range, it would be more useful to present the product of each variable and its associated weight. This yields the 'virtual' outputs and inputs.

This can be stated more formally after recalling the terminology already introduced in the last chapter; summarised here as Figure 4.6.

Utilising the terminology of Figure 4.6, in place of input I_i, the product of weight and variable; IQ_{ij} X I_i would be the virtual input of the ith input and equally OQ_{rj} X O_r would be the virtual output of the rth output. These are, in fact, the definitions of the variables A1, A2 (virtual inputs) and B1...B5 (virtual outputs) used in the program DEA1 and shown in Figure 4.4.

Figure 4.6. Data Envelopment Analysis Terminology

Adopted in Formal Model of Figure 3.4.

OQ_{rj}	:	the quantity of DMU j's rth output.
O_r	:	the rth output's weight.
IQ_{ij}	:	the quantity of DMU j's ith input.
I_i	:	the ith input's weight.

Table 4.7 presents the results of Table 4.5, but with virtual inputs and outputs instead of the actual variable weights. Examining the distribution of these figures, it can be seen that half of the units have achieved pareto efficiency by placing all their weights onto just one output and one input, effectively ignoring all other variables.

The constraint that each variable must be greater than or equal to epsilon does ensure the creation of a virtual input or virtual output for all variables across all DMU, but at the minimum level this would be wholly insignificant to the calculation of the pareto efficiency rating.

Figure 4.7. Pareto Efficiency Ratings of Figure 4.5. with Virtual Inputs and Virtual Outputs Replacing Variable Weights.

DMU	PARETO EFFICIENCY	A1	A2	B1	B2	B3	B4	B5
		VIRTUAL COMPONENTS						
1 STRATHCLYDE	100%	0.00	1.00	0.00	0.00	0.00	1.00	0.00
2 LOTHIAN&BORDERS	100%	0.00	1.00	0.00	0.00	0.00	1.00	0.00
3 GRAMPIAN	100%	0.00	1.00	0.00	0.00	0.00	1.00	0.00
4 TAYSIDE	100%	0.00	1.00	0.00	0.00	0.00	1.00	0.00
5 CENTRAL SCOTLAND	100%	0.03	0.97	0.00	0.06	0.55	0.00	0.39
6 FIFE CONSTABULARY	100%	0.08	0.92	0.71	0.13	0.13	0.00	0.03
7 DUMFRIES&GALLOWAY	100%	0.00	1.00	0.50	0.00	0.00	0.50	0.00
8 NORTHERN	100%	0.26	0.74	0.98	0.02	0.00	0.00	0.00

Additionally, this form of breakdown of the components of the pareto efficiencies reveals that even where more than two variables are involved there are examples of high levels of concentration of weighting. Variables which were identified as involved in the calculation of the pareto efficiencies in Table 4.5, are now revealed as in some cases contributing only six, three or just two per cent of the total input or output product.

Were this more than simply a fictional example, such degrees of selectivity in weight application would undoubtedly raise questions about the significance of results produced in this manner. The technique shows each DMU in the best possible light, but by doing so, entirely disregards less desirable aspects of the DMU's activities. Unfortunately, this potentially includes simply 'sweeping under the carpet' aspects which could indicate severe failings in the operation of particular DMU.

Very few authors have discussed this problem, which effectively is one of being unable to 'force' DMU to take into account, that is place significant weights on, any particular sub-set of variables. In conversation with R.G. Dyson in 1988 at an Operational Research Society Tutorial event on DEA, at Warwick University; the suggestion that some form of limitation on the flexibility of weight application was perhaps indicated, produced the response that 'anything other than complete flexibility would destroy the integrity of the technique'. In a subsequent paper with E. Thanassoulis (1988), however, they accepted that:

> *"Unfortunately...the assessment model can assign such low weights to some inputs and/or outputs as effectively to exclude them from the assessment of the target DMU. As a result, the relative efficiency of a DMU may not really reflect its performance on the inputs and outputs taken as a whole. In the extreme, this can lead to classifying a certain DMU as relatively efficient simple because its ratio for a single, possibly minor, output to one input is the highest in comparison to the equivalent ratio for the other DMU's, while the rest of the inputs and outputs are effectively ignored. By the same token, relatively inefficient DMU's may be even more inefficient than they first appear, were it not for the fact that their worst performance aspects have been all but ignored in their assessment."*
>
> DYSON AND THANASSOULIS (1988).

There is nothing to lead us to believe that the above results are in any way 'wrong' or that the model has 'failed' in some way, the results simply reflect the fact that, with the given data, all eight DMU can select weights in a way which shows each of them to be pareto efficient, under the conditions imposed. This in itself in some situations may be a satisfactory conclusion.

The fact that the results show all eight DMU to be pareto efficient, is not entirely surprising when it is considered that there are five outputs and two inputs for the weights to be distributed upon, and only the eight DMU. Some authors have even suggested that a 'rule of thumb' be adopted whereby there should be a minimum number of DMU per variable. Whilst this may ensure a degree of discrimination between the units, it is difficult to see any practical rationale for adherence to such a rule.

It would seem, intuitively, that any number of variables could be used with any number of DMU and the results will accurately reflect the data as provided, perhaps it is the formulation of the data itself which should be questioned. Clearly there is no consideration of the relative merits of production of different outputs or use of different inputs. This is a crucial point which will be returned to, and examined further, in Section 4.3.

It is clear that variable choice is absolutely crucial; logically the objective in choosing variables should be to involve all inputs and outputs which have a bearing of any sort on the operation of the DMU.

> *"Should an input be omitted, the relative efficiencies determined will not reflect the performance of units in terms of their effective (or otherwise) use of that resource. Similarly, the omission of some output would mean the assessment ignores the performance of units on that output.*
>
> *In principle, all inputs and outputs relevant to the function of the units should be included".*
>
> THANASSOULIS *ET AL.* (1987).

This unfortunately has not been thought practical in the past in light of the mathematics of the technique. Firstly, Data Envelopment Analysis views all inputs as equal in relevance and equally views all outputs as having identical status.

> *"DMU's should be expected to argue for inclusion of those variables which permit them to appear as efficient as possible.*
>
> *At the extreme, DMU's would prefer the largest variable set imaginable, since the more variables considered, the greater the likelihood a given DMU will become Pareto-dominant and rated efficient.*
>
> *This observation underscores a subtle yet important weakness of the Pareto efficiency criterion used by DEA. In one sense, the Pareto criterion regards each separate input and output as being equal in value."* NUNAMAKER (1985).

Secondly, it has troubled authors that such large efficient sets result from assessments involving moderate or large numbers of variables.

> *"...the larger the number of inputs and outputs in relation to the number of units being assessed, the less discriminatory the method appears to be...the larger the number of inputs and outputs for a given number of units being assessed, the greater the chance that a unit can find weights for some subset of the inputs and outputs that show it efficient. Thus the number of inputs and outputs included in a DEA assessment should be as small as possible, subject to their reflecting adequately the function performed by the units being assessed."*
>
> THANASSOULIS *ET AL.* (1987).

This quote appears to directly contradict the previous quote from the same authors, and hence a dilemma appears to exist in applications of DEA. A dilemma involving a trade-off between on the one hand the production of discriminatory results and emphasis on 'key' variables, and on the other, the level of confidence in the results obtained through not having excluded important variables. Tomkins and Green (1988), in similar vein, are more optimistic:

> *"DEA also has the possible disadvantage that one can have a fairly large number of organisations in the efficient set. The likelihood of more members of that set is increased as the number of input and output is increased. There is then a practical limit on the extent that DEA can be used to incorporate multiple variables. The findings in any actual application,...[and] in this paper, that scores stabilise with relatively few variables therefore offers considerable encouragement that DEA may be useful in this problem situation."*
>
> TOMKINS AND GREEN (1988).

Just to what extent this stability can be generalised could be argued at length, it is likely that, whilst apparently true, this merely reflects the fact that in many applications by considering just a sub-set of identified variables, the DMU will have formed a ranking amongst themselves which is largely unaltered with each addition of an extra variable into the analysis. Naturally, this could not be put forward as a rule, in particular applications the data could be such that an additional variable significantly raises the rating for one or more particular DMU. The practical implications of this observation would therefore seem somewhat limited.

Nunamaker (1985) in his critical examination of the technique determined the effect that variable addition or disaggregation has, concluding that in both cases an efficient DMU could not become pareto inefficient as a result of such a change, and that a pareto inefficient DMU could only improve its rating. He further established that addition of or disaggregation to, variables that were perfectly correlated would not allow a pareto inefficient DMU to move to a pareto efficient position, but if the correlation was less than perfect then pareto efficiency could be achieved.

Such conclusions may appear to raise further doubts about the conceptual relevance of DEA to the majority of management situations, each can, however, be easily traced to simple general mathematical rules. The following section attempts to overcome the conceptual drawbacks of applying DEA outlined in this section. Additionally, the course of action proposed conveniently renders the Nunamaker rules completely redundant.

4.3. Restricting the Flexibility of Weight Application in DEA.

> *"However, before the units identified by DEA as efficient can be used as examples of good operating practices or in setting performance targets, they must be investigated further to gain better insight into their performance...A unit whose efficiency rating is based fairly evenly on all its outputs and inputs can be said to show well-rounded performance. An efficient unit with well-rounded performance is relatively efficient when all aspects of its performance are taken into account rather than just a small subset of them."*
>
> THANASSOULIS *ET AL.* (1987).

The above quote, despite the year of publication, represents one of the earliest points at which the practicality of Data Envelopment Analysis is, if indirectly, brought into question. The basic theory of DEA allows the pareto efficiency to be based upon any number of variables from those provided, including just one output and one input (given that a weighting of epsilon is insignificant).

The introduction of the idea of 'well-rounded' performance, as above, suggests that 'ignoring' a number of variables may be undesirable. But although on occasion it may be desirable to simply take account of all variables, there can be envisaged applications where a number of variables were clearly more important than the remainder.

The concept of 'well-rounded' performance is also problematic mathematically, any Linear Program stops when the optimisation is completed, regardless of how many variables are involved. A DMU which is pareto efficient using just one input and output, may also be pareto efficient were it forced to use more, or all, of the variables. Clearly there are an infinite number of possible scenarios and hence simply looking for 'well-rounded' performance is not in itself sufficient to produce confidence in results obtained using DEA.

Ideally the DEA model should be able to handle all the possible permutations of rank between variables, the exact details of each of which will depend on the nature of the activities of the set of DMU in question. In some cases it may be perfectly reasonable for a DMU to base its rating on just one output and input, or simply a basic level for all variables may be indicated. It is far more likely, however, that variables can be identified as having an importance relative to each other, and that too little or too much weight on some or all of the variables is unacceptable. An aspect of this problem was pointed out by Tomkins and Green (1988):

> *"It is also clear that DMU's adopting extreme policies of specialisation can make themselves a hundred per cent efficient, simply because no-one else is competing in that niche of activity."*
>
> TOMKINS AND GREEN (1988).

The notion of a decision-making unit with a number of outputs and inputs showing itself to be as efficient as possible by putting a heavy weighting onto a particular pairing of input and output and placing weights of close to zero on others does not seem attractive, certainly in the field of higher education.

The possibility that, for example, one university could have a weighting of close to 100% on one possibly minor aspect of its activity, linked to an unrelated single input such that it is rated pareto efficient clearly would raise doubts about the significance of the results. That same university could be glaring ineffective at all the major objectives of the higher educational sector, but these bad aspects would be simply ignored, completely cast aside.

Some form of provision for limitation on the values that can be taken by weights for each DMU would seem highly desirable. This would seem to suggest an extra stage in the formulation of Data Envelopment Analysis. Section 4.3.1. discusses the possible approaches to effecting limitation on the variable weights, the subsequent sections then follow through a fictional example, setting weight limits for the example (Section 4.3.2.), and then obtaining pareto efficiency ratings with these in place (Section 4.3.3.).

4.3.1. Approaches to Establishing Weight Limits.

After those seeking the assessment have agreed on all the inputs and outputs that are involved for their purposes, regardless of how trivial some may be, a minimum and maximum level which each input and output is permitted to contribute could be set, in the range of zero to 100%. This would then reflect the way in which the resource use and activities of the DMU correspond to their governing objectives, their 'raison d'etre'.

By placing limits in this way a 'performance profile' is hence established, introducing a framework of variable weight limits, to reflect both the relative effectiveness as well as the relative efficiency of the DMU. In this way, an entirely objective model can be utilised, within the constraints of subjective limitations, which are themselves derived from the careful definition of performance with regard to the particular application.

Naturally, this can still allow a considerable degree of flexibility, but flexibility without the attendant disadvantages of complete freedom of weight distribution. The drawbacks involved with fixed weights, as discussed in Section 4.2, are still avoided.

Forming a range of permissible weights for application to each variable would seem to be far more logical and justifiable than either of the alternative extremes; using fixed weights, or omitting to set any restriction at all. As a model based on linear programming is being utilised there should not be any practical drawbacks in adopting such an approach.

Despite the earlier opposition of R.G.Dyson to reducing weight flexibility in DEA already referred to, a paper by Dyson and Thanassoulis (1988) discusses some of the means by which this could be achieved. The paper attempts to avoid any loss in the 'integrity of the technique' by adopting statistically generated measures.

> *"Few would argue against reducing weight flexibility in DEA, since doing so would ensure that the subsequent assessment not only cannot effectively ignore any inputs or outputs but also would assign weights to inputs and outputs more in line with some general view of their perceived importance...Hence a DMU's assessment should not reflect its performance on individual aspects of its function on an equal footing, but should weigh individual aspects relative to their importance in the context of its overall function."*
>
> DYSON AND THANASSOULIS (1988).

It is argued in the paper that constraint of the weights be on an arbitrary basis, except in the single input situation where two approaches are offered. But subjective constraint of the contribution made by outputs and inputs is far from arbitrary; the variables and their relative significance will vary across different topics. It would be, logically, incorrect were there not some point at which a degree of subjective assessment of the relative significance of the variables involved in an application took place.

Such assessment would undoubtedly strengthen, rather than undermine, the usefulness of a technique which after this subjective assessment of relative variable importance, would then entirely objectively manipulate the data provided in a way which would yield no bias towards any individual DMU, or group of DMU.

Dyson and Thanassoulis (1988) argue that, in single-input cases:

> *"the weight on each output in the DEA model can be related to the amount of resource the DMU may be deemed to consume per unit of that output."*
> DYSON & THANASSOULIS (1988).

It is suggested that an 'average' value for each of these output weights may be determined either by consensus or by regression analysis. These having been determined, they propose that an agreed set of lower bounds on the weights is then obtained and used to modify the DEA model.

It could be questioned, however, if an 'average' value is relevant to the limitation of weights. This approach intuitively seems to work against the principle of each DMU adopting different sets of weights.

Whilst undoubtedly it is necessary to consider weight restriction in any application, to limit all output weights after consideration of some 'average' value does not seem an appropriate course of action. It would involve running the program twice, but more importantly, would be open to distortion by extreme values present as a result of specialisation by a number of DMU onto a particular activity. Hence this activity may then have a high average value, causing its 'importance' for all DMU to be exaggerated and an inappropriate lower bound imposed.

It is also suggested that the 'consensus' approach could be assisted by examining activities in a pareto efficient unit in order to determine the minimum amount of resource necessary to support a unit of output; this seems, however, somewhat self-defeating as it is suggested that the pareto efficient DMU is identified by an unconstrained DEA assessment!

Clearly, any technique which can only be used in applications where there is unquestionably only a single significant input will have very limited application. Furthermore, an approach which cannot be used universally is unlikely to be adopted on a wide scale if alternative approaches exist which do have universal application.

These points do not detract from the potential benefits which could be obtained by the imposition of weight limits to create a 'performance profile', but there remains the practical problem of how such weight limitations would be developed if not by the 'Dyson and Thanassoulis' approaches outlined.

These approaches place emphasis on attempting to preserve the objectivity of the technique, the key to the 'performance profile' approach is that subjectivity is deliberately introduced, the lower and upper limits on each variable being achieved by subjective analysis. This is necessary if pareto efficiency ratings are to be produced which are also able to reflect the effectiveness of the DMU. Once these subjective limits have been established, the linear program based DEA would then entirely objectively establish the ratings from the data provided, within the limits imposed.

It is the virtual inputs and outputs, as already defined, on which the weight limits will be set and the performance profile hence created, rather than simply the variable weights. It is worth re-emphasizing the relevance of these virtual inputs and virtual outputs before progressing further, their contribution is well explained by Thanassoulis *et al.* (1987):

> *"A larger weight for an output or input does not necessarily mean that that unit produces the corresponding output or utilizes the corresponding input more efficiently than outputs and inputs with lower weights. This is because the magnitude of each weight is also dependent on the scale of measurement of the corresponding input or output...The virtual inputs and outputs attributable to each input and output show exactly how the efficiency rating of the corresponding unit is derived."* THANASSOULIS *ET AL.* (1987).

To demonstrate the way in which a performance profile is constructed, and the consequent effect its use has on the results, it would be useful to return to the

'Scottish Police Force Traffic Divisions' fictional example originally introduced in Table 3.6 of the previous chapter.

4.3.2. Creation of a Performance Profile for the Data of Table 3.6.

The 'Traffic Divisions' fictional example introduced in the previous chapter portrayed an application with two inputs and five outputs. These statistics were applied to Data Envelopment Analysis Section 4.2 with the weight limits unconstrained. In this section a performance profile for this same application will be produced. The definition of the variables of this example are reproduced in Figure 4.8.

'I2', the number of patrol units, was included to take into account the fact that total budget (I1) alone, would fail to register the varying degrees to which the forces divide their resources between patrol units deployed and other resource application such as administrative effort. The total budget is of course nevertheless of great importance being the major indicator of total resources used.

Figure 4.8. Definition of Variables in Table 3.6.

I1: BUDGET (£M)
I2: PATROL UNITS (100's)

O1: SPEED MONITORING HOURS (10,000's)
O2: POSITIVE BREATH TESTS (10,000's)
O3: ROAD HOURS (100,000's)
O4: MOVING VEHICLE OFFENCES (10,000's)
O5: ESCORT MILEAGE (10,000's)

Considering the resource use which each of these inputs represents, it would seem appropriate to prevent the DMU from adopting too great an imbalance between these two statistics, this would be ensured by limiting their relative contribution to a maximum ratio of 3:1 in either direction. This would be implemented by limiting each of the virtual inputs (A1, A2) to a maximum of 75%.

The outputs fall into three broad categories; basic traffic policing activities (O1, O3); offences statistics (O2, O4); and special traffic policing activities (O5). The first two areas include variables which are all highly relevant and which, therefore, the DMU should not have the option of excluding. This indicates a minimum level be set for each of these four outputs, care must be taken, however, that an inappropriately large proportion of the total virtual outputs do not become 'fixed' rather than free for allocation in the process of optimisation.

For this number of variables, a minimum of ten percent of the total virtual outputs on each of the four would create a fixed element of weighting totalling 40%, the remaining 60% being 'flexible'. Similarly, it seems reasonable to ensure that no single output makes up more than half of the total virtual outputs.

Escort mileage (O5) is expensive and time consuming in its nature, but can be regarded as a comparatively minor variable and as such no minimum level will be imposed, allowing the DMU to adopt the minimum weighting of epsilon,'ε'. This variables lack of importance relative to the others suggests that the maximum level should not be far in excess of the minimum level for the other outputs, a figure of 15% of total virtual outputs being adopted.

The preventative effect of O1 and O3 should not be overshadowed by the statistics of 'O2' and 'O4', but these latter pair are, nevertheless, the tangible 'evidence' of traffic police effectiveness. As such it would seem appropriate to ensure that they, combined, account for at least half of the weighting, the total virtual outputs. There is no reason to effect different bounds for these two so a minimum for each of 25% of total virtual outputs is indicated by this reasoning.

This automatically sets a maximum of 50% of total virtual outputs (TVO) on the remaining virtual outputs combined. This would also set a maximum of 50% for 'O1' and 'O3' combined, possible when a weighting of epsilon is adopted for 'O5'. Individually, the maximum possible for either 'O1' or 'O3' is 40% TVO, as the minimum of 10% TVO for the other is added to the 25% TVO minimum stipulated for both 'O2' and 'O4'. Again to emphasis the importance of effectiveness, however, the variable which simply represents total road hours (O3) could be further restricted to a lower maximum of, say, 30% TVO.

This results in a total fixed element for the outputs of 70% TVO, leaving 30% of total virtual outputs free for optimisation. It is unlikely that the fixed element for any application would ever be much in excess of this, clear definition of objectives in this example having been made over a relatively small set of variables.

Obviously the process of setting such limits in any real application would be more drawn out with considerable consultation taking place. The key to the size of the fixed element for both inputs and outputs should always be, however, linked to the definition of objectives for the application, care being taken that the fixed element does not rise simply with the number of variables involved.

Special, perhaps short-term, emphasis can be placed with such performance profiles. For example, it could be argued that detecting drunk drivers is more important than other moving vehicle offences, this is already indicated by its inclusion as a separate variable, but in addition it could have been given extra status by its virtual output being allowed a higher upper bound than that for moving vehicle offences.

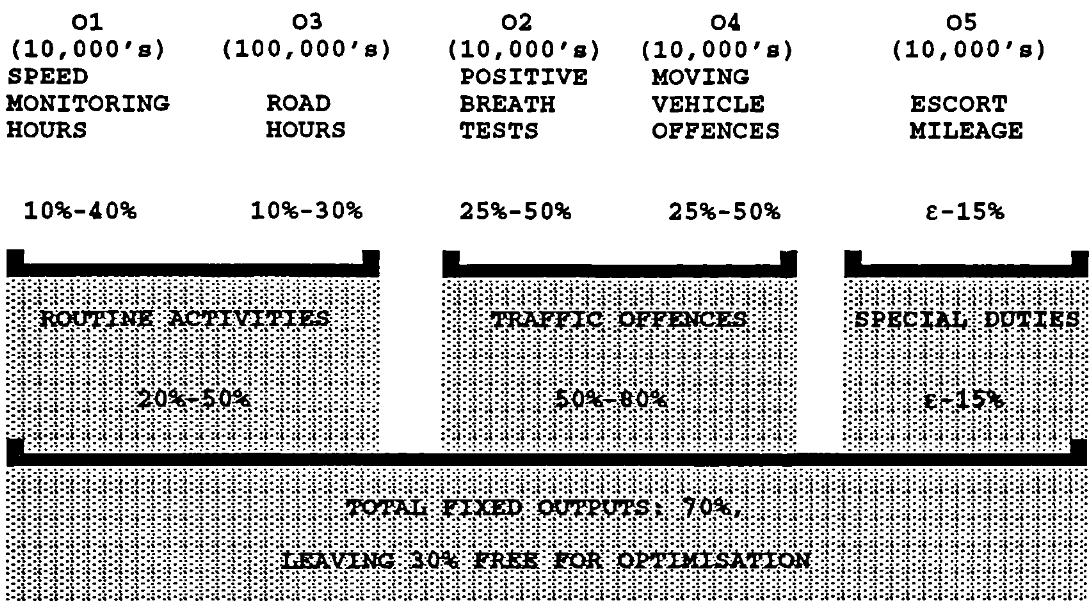
This sets the weight limits for each variable as shown in Figure 4.9, note the degree of development involved in establishing these limits even for our trivial example. This is, of course, in direct contrast with the complete lack of discrimination under the unrestrained DEA model.

Figure 4.10 displays the output side of the performance profile, showing not just the weight limits on individual outputs, but also those in effect on the three groups of outputs identified earlier, and the total proportion of fixed output weights. It would seem that the weight limits in place on 'groups' of variables will often be of at least equal significance to those on individual statistics.

Figure 4.9. Weight Limits For 'Scottish Police Force Traffic Divisions' Example.

		MINIMUM	MAXIMUM
VIRTUAL INPUTS.	A1:	25%	75%
	A2:	25%	75%
VIRTUAL OUTPUTS.	B1:	10%	40%
	B2:	25%	50%
	B3:	10%	30%
	B4:	25%	50%
	B5:	ε	15%

Figure 4.10. Performance Profile (Output Side) for 'Scottish Police Traffic Divisions' Example.



All that remains to implement this performance profile is to make the necessary changes to the program version 'DEA1', to take account of these limits. This is very straight forward, each minimum or maximum requires an additional constraint line enforcing the restriction by algebraic means. A full explanation of this methodology can be found in Section 5.3.

4.3.3. Results of DEA Implementation With Restrained Weights.

With the additional constraints introduced, the LINDO program version 'DEA2' is then as shown in Figure 4.11, the particular version shown has 'STRATHCLYDE' as the subject DMU. This coding is identical to that of program 'DEA1' (Figure 4.4.) except for the introduction of these new constraint lines.

The results of the eight variations of 'DEA2', one per DMU, are shown in Table 4.12. Just two of the DMU have succeeded in maintaining 100% pareto efficiency (PE), namely 'LOTHIAN&BORDERS' and 'TAYSIDE', with the remaining six achieving ratings ranging from 98.7% PE ('NORTHERN') to 90.8% PE ('DUMFRIES&GALLOWAY').

As would be expected with a linear program optimisation, for each DMU the virtual outputs and virtual inputs tend to be at the extremes, either the required minimum or the permitted maximum. This is particularly the case in this example for the virtual outputs, although three of the eight DMU adopted the extreme virtual input balance of 75%/25%.

Figure 4.11. LINDO Coding for Program Version 'DEA2', an Implementation of DEA with Weight Restriction.

```
DEA2(STRATHC)

MIN A1 + A2
SUBJECT TO
CONSTANT) B1 + B2 + B3 + B4 + B5 = 1
 STRATHC) 36.1 I1 + 7.8 I2 - 18.7 O1 - 8.7 O2 - 36.0 O3 - 46.8 O4 - 22.8 O5 >= 0
 LOTHIAN) 16.1 I1 + 4.6 I2 - 11.8 O1 - 4.8 O2 - 23.5 O3 - 27.6 O4 - 13.8 O5 >= 0
 GRAMPIA) 12.5 I1 + 3.1 I2 -  7.6 O1 - 3.3 O2 - 14.7 O3 - 18.6 O4 -  8.8 O5 >= 0
 TAYSIDE)  7.9 I1 + 1.9 I2 -  5.1 O1 - 2.4 O2 -  9.8 O3 - 11.4 O4 -  5.9 O5 >= 0
 CENTRAL)  5.4 I1 + 1.4 I2 -  3.8 O1 - 1.2 O2 -  6.8 O3 -  8.4 O4 -  4.9 O5 >= 0
 FIFECON)  4.9 I1 + 1.2 I2 -  3.2 O1 - 1.1 O2 -  6.8 O3 -  7.2 O4 -  2.9 O5 >= 0
 DUMGALL)  3.3 I1 + 0.7 I2 -  1.8 O1 - 0.7 O2 -  3.2 O3 -  4.2 O4 -  2.4 O5 >= 0
 NORTHER)  3.2 I1 + 0.7 I2 -  2.1 O1 - 0.9 O2 -  2.9 O3 -  4.0 O4 -  1.7 O5 >= 0
 A1MAX75) - 0.33333 A1 + A2 >= 0
 A2MAX75)   A1 - 0.33333 A2 >= 0
 B1MIN10) - 9 B1 + B2 + B3 + B4 + B5 <= 0
 B1MAX40) - 1.5 B1 + B2 + B3 + B4 + B5 >= 0
 B2MIN25)   B1 - 3 B2 + B3 + B4 + B5 <= 0
 B2MAX50)   B1 - B2 + B3 + B4 + B5 >= 0
 B3MIN10)   B1 + B2 - 9 B3 + B4 + B5 <= 0
 B3MAX30)   B1 + B2 - 2.33333 B3 + B4 + B5 >= 0
 B4MIN25)   B1 + B2 + B3 - 3 B4 + B5 <= 0
 B4MAX50)   B1 + B2 + B3 - B4 + B5 >= 0
 B5MAX15)   B1 + B2 + B3 + B4 - 5.66666 B5 >= 0
   VIRI1) - 36.1 I1 + A1 = 0
   VIRI2)  - 7.8 I2 + A2 = 0
   VIRO1) - 18.7 O1 + B1 = 0
   VIRO2)  - 8.7 O2 + B2 = 0
   VIRO3) - 36.0 O3 + B3 = 0
   VIRO4) - 46.8 O4 + B4 = 0
   VIRO5) - 22.8 O5 + B5 = 0
   EPSI1) I1 >= 0.00001
   EPSI2) I2 >= 0.00001
   EPSO1) O1 >= 0.00001
   EPSO2) O2 >= 0.00001
   EPSO3) O3 >= 0.00001
   EPSO4) O4 >= 0.00001
   EPSO5) O5 >= 0.00001
END
```

Table 4.12. Results from DEA2 (Weight Limitation).

	PARETO			COMPONENTS				
DMU	EFFICIENCY	A1	A2	B1	B2	B3	B4	B5
1 STRATHCLYDE	91.9	25	75	10	25	10	50	5
2 LOTHIAN&BORDERS	100.0	59	41	10	50	10	30	0
3 GRAMPIAN	94.5	34.7	65.3	15	25	10	50	0
4 TAYSIDE	100.0	32.3	67.7	15	25	10	50	0
5 CENTRAL SCOTLAND	93.6	44.2	55.8	25	25	10	25	15
6 FIFE CONSTABULARY	94.3	39.2	60.8	10	25	30	35	0
7 DUMFRIES&GALLOWAY	90.8	25	75	10	25	10	40	15
8 NORTHERN	98.7	25	75	40	25	10	25	0

The way each DMU allocated weights to obtain its virtual inputs and virtual outputs can be seen more clearly with the aid of Table 4.13. This table displays the same results as Table 4.12, but with the actual virtual input or virtual output for each variable, replaced with an indication of the position in the possible range of percentages.

Table 4.13 shows whether a DMU has adopted the set minimum (MIN) or maximum (MAX) possible virtual input or virtual output. Relevant to inputs only; whether it has created the majority (MAJ), short of the maximum, of its total virtual inputs from a particular input, and finally, for both inputs and outputs, if the particular variable contributes simply the remaining, or residual (RES) amount.

Table 4.13. Results of Table 4.12, Showing Each Variables Optimised Contribution Relative to its Permissible Range of Values.

	DMU	PARETO EFFICIENCY	A1	A2	COMPONENTS B1	B2	B3	B4	B5
1	STRATHCLYDE	91.9	MIN	MAX	MIN	MIN	MIN	MAX	RES
2	LOTHIAN&BORDERS	100.0	MAJ	RES	MIN	MAX	MIN	RES	MIN
3	GRAMPIAN	94.5	RES	MAJ	RES	MIN	MIN	MAX	MIN
4	TAYSIDE	100.0	RES	MAJ	RES	MIN	MIN	MAX	MIN
5	CENTRAL SCOTLAND	93.6	RES	MAJ	RES	MIN	MIN	MIN	MAX
6	FIFE CONSTABULARY	94.3	RES	MAJ	MIN	MIN	MAX	RES	MIN
7	DUMFRIES&GALLOWAY	90.8	MIN	MAX	MIN	MIN	MIN	RES	MAX
8	NORTHERN	98.7	MIN	MAX	MAX	MIN	MIN	MIN	MIN

Table 4.13 reveals more about the six pareto inefficient DMU than the two which did achieve 100% PE. This is because the linear program will stop when the optimal rating is achieved. It may well be, therefore, that there are many

other combinations of weights which could have been adopted by 'LOTHIAN&BORDERS' and 'TAYSIDE' with which they would still rate pareto efficient. In the case of pareto inefficient DMU, the optimisation never reaches unity, and therefore the rating achieved is only likely to be possible with these particular weights.

Examining the virtual outputs for each DMU it can be seen how, under the performance profile imposed, each adopts the maximum permissible virtual output for one output and the minimum for all others, with the exception of a single residual application beyond the required minimum in the case of all DMU except 'NORTHERN'. This 'residual' application can be viewed as the DMU's 'second-best' activity, behind that which it applied the maximum possible virtual output to.

These results appear to have a practical significance beyond that which could ever have been achieved with an unconstrained implementation. It would seem, therefore, that it is a development from Data Envelopment Analysis which would be of most use in the context of university performance rather than the original, unconstrained technique.

Before these developments can be formalised (Chapter Five), however, there remain other areas of the application of DEA which require examination. Section 4.4 looks at the first of these, the consideration of environmental influences on the set of DMU.

4.4. The Consideration of Environmental Factors in DEA.

In the majority of applications, even in a situation with a set of identically operating DMU, carrying out the same mix of activities with identical objectives; there is likely to be a number of factors outwith the control of each DMU which affect the relationship between their inputs and outputs, and hence their pareto efficiency ratings.

These external influences, often the effect of geographic or demographic variations, are commonly known in this context as 'environmental factors'. The consideration of such factors has been fairly limited, firstly because there is no firmly established method by which they can be included into an application of DEA, and secondly because in many fields such data is extremely elusive.

Section 4.4.1 examines the way in which the influence of environmental factors has been accounted for by other authors, the subsequent sections then examine the effect of alternative approaches by utilising a simple example.

4.4.1. The 'Contextual Input Variable' Approach to Environmental Factor Inclusion in DEA.

Although consideration of environmental factors in DEA has been somewhat limited; Thanassoulis *et al.* (1987) discuss an approach to their inclusion within an implementation of Data Envelopment Analysis.

> *"The inputs are first the resources used to produce the outputs, and secondly any environmental factors present which affect the outputs. For example, if schools are the units to be assessed, the inputs might include the number of teachers, the quality of the pupils on entry and the social class of parents."*
> THANASSOULIS *ET AL.* (1987).

Clearly these authors view environmental factors as simply additional inputs, indeed later in the same paper they are referred to as 'contextual input variables'. As the following quotes demonstrate, the logic behind such a view is initially attractive.

> *"...to determine...the outputs of their function and what environmental factors and resources (inputs) affect those outputs."*
> THANASSOULIS *ET AL.* (1987).

> "...the tasks undertaken by a rates department [for example]...clearly depend on factors such as the prosperity of the local community...To the extent... that such contextual variables might affect the administrative effort required to handle a given output level, then such environmental factors should feature in the analysis. For example, the proportion of the local community whose first language is not English might affect the effort required to process rate rebates." THANASSOULIS *ET AL.* (1987).

Earlier, Charnes *et al.* (1981), had already used this same approach of including environmental factors as part of the set of inputs, when examining an experiment in remedial primary education.

> *"We might, as an illustrative case in point, refer to 'self-esteem' as one of the 11 desired outputs, and to "parental attention to children" as one of the 25 inputs designated as important for evaluating the results of the Program Follow Through Experiment."* CHARNES *ET AL.* (1981).

This approach of regarding environmental factors as part of the set of inputs appears, however, to have a number of drawbacks. To view the relevant factors, the inputs and outputs, in terms of "cause and effect", may well provide information on the operation involving a DMU, but it does not necessarily assess the DMU itself. This is because an assessment of a DMU calculated on such a basis will be affected by, or may even be dominated by, statistics which are entirely independent of the DMU and over which it has no control.

A variable, and hence the resultant pareto efficiency, could conceivably become more or less advantageous over time, regardless of the activities of the DMU. A DMU could hence remain or become pareto efficient by virtue of a heavy weighting on an environmental factor which changes advantageously, largely independently of its reaction to that very change, due to that DMU placing a very low weighting on the outputs and other inputs which the particular environmental factor influences.

It is quite conceivable that it is then possible that as a result of an advantageous change in a highly weighted environmental factor and a DMU's poor reaction to that change in environmental influence only affecting variables with very low weighting, that the DMU which in reality has become less relatively efficient, would appear pareto efficient or more pareto efficient.

It is very easy from the following quote to envisage a situation such as that already outlined, where the relative efficiency of a particular environment which includes a DMU is assessed, rather than the DMU itself.

> *"These input values were selected from among a set of 25 as follows:*
>
> x_1: *Education level of mother as measured in terms of percentage of high school graduates among female parents.*
>
> x_2: *Highest occupation of a family member according to a pre-arranged rating scale.*
>
> x_3: *Parental visit index representing the number of visits to the school site.*
>
> x_4: *Parent counselling index calculated from data on time spent with child on school-related topics such as reading together, etc.*
>
> x_5: *Number of teachers at a given site.*
>
> *CHARNES ET AL. (1981).*

In this example four of the five 'designated inputs' appear to be environmental factors, leaving just x_5 as the sole input which actually refers directly to the resource use of the DMU. Undoubtedly with 25 of the 70 DMU in this example being pareto efficient despite there being only 3 outputs used for analysis (from an originally identified eleven), it is not necessary to examine the results to realise that in some cases x_5 will have been given a negligible value. This creates exactly the situation described, with misleading results more likely than possible.

This could be viewed as another example of the advantage of producing a performance profile for the application. If such a profile were produced, x_5 would undoubtedly receive a significant minimum restriction. Hence, the limiting of weights in the above example, even if unusually flexible, would largely eliminate the possibility of a move to a less relatively efficient position appearing in the analysis as the opposite, as well as less extreme disparities.

More significantly, however, the creation of a performance profile would highlight the problems in treating environmental factors in this way. The limits would seem generally to be more difficult to arrive at for inputs than they are for outputs, but looking again at the five 'inputs' above, such a task would clearly be difficult, with the conclusions likely to be open to question.

Whilst the factors represented by x_1 to x_4 need to be considered, this would consequently effect a maximum far below 100% for the only actual resource input to the DMU. Thus rather than using a performance profile to guarantee inclusion at a significant level of x_5, imposing restrictions on x_5 in order to guarantee the inclusion of the environmental factors would, however intuitively incorrect, be inevitable.

This 'contextual variable' approach assumes that environmental factors affect only outputs, in some cases such factors may have a direct effect on the resources used. At best this would lead to a form of 'double-counting' of an input, which alone, however, could yield a completely misleading pareto efficiency. Additionally, it is not necessarily the outputs affected by the environmental factors that will be linked to them by DEA, hence they may affect the pareto efficiencies by virtue of their relationship with variables completely independent of those very environmental factors.

The final problem identifiable with the 'contextual input variable' approach is the fact that such environmental factors tend, for a range of DMU, to include extreme values completely out of proportion to their influence on any of the variables associated with the particular DMU. Again this will, either advantageously or disadvantageously, affect the pareto efficiencies obtained in the analysis.

If such environmental factors are not best treated as additional inputs, then this leaves the problem of how to include their influence, for clearly such factors do need to be taken into account. Section 4.4.2 returns to the fictional 'traffic divisions' example to examine the possible approaches.

4.4.2. The Identification of an Environmental Factor for the 'Scottish Police Force Traffic Divisions' Fictional Example.

Returning to the fictional example, first introduced as Table 3.6, one environmental factor which clearly affects the operation of a police traffic division is the amount of traffic on roads within the jurisdiction of each force.

For example, a 'speed trap' in a city centre street in Glasgow is likely to have far more passing vehicles, and hence offending motorists in any given time period than a quiet road through a small Sutherland town.

Whilst not impossible to establish, clearly such statistics are beyond the scope of this simple introductory example. Use can be made, however, of a simple substitute measure which is likely to be closely related to this factor. This is shown in Table 4.14 and is developed from figures in the 1981 census (Scotland).

Table 4.14. Population Density Within the Jurisdiction of Scottish Police Forces; An Environmental Factor.

	DMU	(A) HECTARES[2] (10,000's)	(B) POPULATION (1,000's)	(C) POP. DENSITY (B)/(A)	(D) 10 X POP.DENSITY^{-1} 10 X (1/(C))
1	STRATHCLYDE	135.4	2584	19.1	0.52
2	LOTHIAN&BORDERS	64.2	812	12.6	0.79
3	GRAMPIAN	87:0	440	5.1	1.98
4	TAYSIDE	74.9	398	5.3	1.88
5	CENTRAL SCOTLAND	26.3	245	9.3	1.07
6	FIFE CONSTABUL.	13.0	320	24.6	0.41
7	DUMFRIES&GALL.	63.7	146	2.3	4.36
8	NORTHERN	253.9	164	0.6	15.48

Columns A and B show figures developed from the Census data for the Regions of Scotland, these have been scaled simply for convenience. As pointed out in the third chapter (Section 3.2), this is unimportant as DEA, being based on linear programming principles, is not scale sensitive.

Column C shows the population densities calculated from these figures. Naturally, these are simple averages and hence provide no information about variation within the jurisdiction of a particular force.

If a more serious calculation were considered for this topic there are many alternatives which could be considered, for example; calculations based on figures for the different Districts within the jurisdiction of each force or, somewhat more complex, the number of square miles above or below a particular population density.

The purpose of the figures in column D become clear at a later stage, but note that each is in fact the inverse of the corresponding figure in column C, each multiplied by a factor of ten, again simply for convenience.

First, the population densities as calculated above will be used as an additional input to represent 'traffic level' (the higher the figure the less 'rural' the area, and hence the higher the traffic level is likely to be), following which other ways of taking the environmental factor of 'traffic level' into account will be explored.

4.4.3. Including Population Density as an Environmental Factor in DEA.

By treating the population density statistic as an additional input, a third input variable is being added to the two present in the program 'DEA2', this additional input will carry the name 'I3'. The value for this input for each DMU will be that of column C of Table 4.14. In Section 4.3 the values of the virtual inputs 'A1' and 'A2' were restricted to a maximum of 75% each of the total virtual inputs (A1+A2), this effectively also set a minimum of 25% TVI for each.

It is difficult to provide a rationale by which such limits should be adjusted as the result of the inclusion of an environmental factor.

The purpose of this environmental factor is to provide a possible explanation for, and as a result provide a means by which to compensate for, certain aspects of performance by the DMU which adversely affect its pareto efficiency rating. It would seem logical, therefore, to make consideration of this factor optional by setting no minimum for its corresponding virtual input (A3).

Additionally, there would undoubtedly be little justification for allowing any DMU to ascribe a higher virtual input to the environmental factor than to either of the measures of resource use. Hence, a maximum for 'A3' of 25% of the total virtual inputs will be utilised, matching the minimum levels for 'A1' and 'A2'.

The adaptation from the program 'DEA2', which takes account of the new input variable as detailed above, program version 'DEA3', is shown in Figure 4.15, the subject again being the DMU 'STRATHCLYDE', as will be used throughout to allow the easiest possible comparison between program versions.

Note that the minimum level of 25% of total virtual inputs has now to be actually set for 'A1' and 'A2', previously with just two inputs this was unnecessary.

Figure 4.15. Program version 'DEA3'; DEA with Weight Restriction and a Contextual Input Variable.

```
DEA3(STRATHC)

MIN A1 + A2 + A3
SUBJECT TO
CONSTANT) B1 + B2 + B3 + B4 + B5 = 1
 STRATHC) 36.1 I1 + 7.8 I2 + 19.1 I3 - 18.7 O1 - 8.7 O2 - 36.0 O3 - 46.8 O4 - 22.8 O5 >= 0
 LOTHIAN) 16.1 I1 + 4.6 I2 + 12.6 I3 - 11.8 O1 - 4.8 O2 - 23.5 O3 - 27.6 O4 - 13.8 O5 >= 0
 GRAMPIA) 12.5 I1 + 3.1 I2 +  5.1 I3 -  7.6 O1 - 3.3 O2 - 14.7 O3 - 18.6 O4 -  8.8 O5 >= 0
 TAYSIDE)  7.9 I1 + 1.9 I2 +  5.3 I3 -  5.1 O1 - 2.4 O2 -  9.8 O3 - 11.4 O4 -  5.9 O5 >= 0
 CENTRAL)  5.4 I1 + 1.4 I2 +  9.3 I3 -  3.8 O1 - 1.2 O2 -  6.8 O3 -  8.4 O4 -  4.9 O5 >= 0
 FIFECON)  4.9 I1 + 1.2 I2 + 24.6 I3 -  3.2 O1 - 1.1 O2 -  6.8 O3 -  7.2 O4 -  2.9 O5 >= 0
 DUMGALL)  3.3 I1 + 0.7 I2 +  2.3 I3 -  1.8 O1 - 0.7 O2 -  3.2 O3 -  4.2 O4 -  2.4 O5 >= 0
 NORTHER)  3.2 I1 + 0.7 I2 +  0.6 I3 -  2.1 O1 - 0.9 O2 -  2.9 O3 -  4.0 O4 -  1.7 O5 >= 0
 A1MIN25) - 3 A1 + A2 + A3 <= 0
 A1MAX75) - 0.33333 A1 + A2 + A3 >= 0
 A2MIN25)   A1 - 3 A2 + A3 <= 0
 A2MAX75)   A1 - 0.33333 A2 + A3 >= 0
 A3MAX25)   A1 + A2 - 3 A3 >= 0
 B1MIN10) - 9 B1 + B2 + B3 + B4 + B5 <= 0
 B1MAX40) - 1.5 B1 + B2 + B3 + B4 + B5 >= 0
 B2MIN25)   B1 - 3 B2 + B3 + B4 + B5 <= 0
 B2MAX50)   B1 - B2 + B3 + B4 + B5 >= 0
 B3MIN10)   B1 + B2 - 9 B3 + B4 + B5 <= 0
 B3MAX30)   B1 + B2 - 2.33333 B3 + B4 + B5 >= 0
 B4MIN25)   B1 + B2 + B3 - 3 B4 + B5 <= 0
 B4MAX50)   B1 + B2 + B3 - B4 + B5 >= 0
 B5MAX15)   B1 + B2 + B3 + B4 - 5.66666 B5 >= 0
   VIRI1) - 36.1 I1 + A1 = 0
   VIRI2)  - 7.8 I2 + A2 = 0
   VIRI3) - 19.1 I3 + A3 = 0
   VIRO1) - 18.7 O1 + B1 = 0
   VIRO2)  - 8.7 O2 + B2 = 0
   VIRO3) - 36.0 O3 + B3 = 0
   VIRO4) - 46.8 O4 + B4 = 0
   VIRO5) - 22.8 O5 + B5 = 0
   EPSI1) I1 >= 0.00001
   EPSI2) I2 >= 0.00001
   EPSI3) I3 >= 0.00001
   EPSO1) O1 >= 0.00001
   EPSO2) O2 >= 0.00001
   EPSO3) O3 >= 0.00001
   EPSO4) O4 >= 0.00001
   EPSO5) O5 >= 0.00001
END
```

The program was modified and run for each of the eight DMU, the resulting pareto efficiencies, along with the virtual inputs and virtual outputs, are shown in Table 4.16.

Table 4.16. Results Obtained From Program 'DEA3'.

DMU	PARETO EFFICIENCY	COMPONENTS A1	A2	A3	B1	B2	B3	B4	B5
1 STRATHCLYDE	92.9	25	67.6	7.4	10	25	10	50	5
2 LOTHIAN&BORDERS	100.0	30.2	59.6	10.2	10	25	15	50	0
3 GRAMPIAN	99.7	59.6	25	15.4	10	25	25	25	15
4 TAYSIDE	100.0	33.2	50.8	16	10	25	25	25	15
5 CENTRAL SCOTLAND	93.6	44.2	55.8	0	25	25	10	25	15
6 FIFE CONSTABULARY	94.3	39.2	60.8	0	10	25	30	35	0
7 DUMFRIES&GALLOWAY	90.8	25	75	0	10	25	10	40	15
8 NORTHERN	100.0	25	70.8	4.2	10	25	10	40	15

It can be seen from these results that 'NORTHERN' has joined the pareto efficient set, joining the DMU 'LOTHIAN&BORDERS' and 'TAYSIDE'. 'GRAMPIAN' has also moved to a position of very slight pareto inefficiency with a virtual input 'A3' at 15.4% second only to the figure for 'TAYSIDE' (16%). The pareto efficiencies of 'CENTRAL SCOTLAND', 'FIFE CONSTABULARY' and 'DUMFRIES&GALLOWAY' are unchanged, having been unable to make any improvement in their ratings by using the extra input, and hence having allocated no significant weight to it.

'NORTHERN' has joined the pareto efficient set, joining the DMU 'LOTHIAN&BORDERS' and 'TAYSIDE'. 'GRAMPIAN' has also moved to a position of very slight pareto inefficiency with a virtual input 'A3' at 15.4% second only to the figure for 'TAYSIDE' (16%). The pareto efficiencies of 'CENTRAL SCOTLAND', 'FIFE CONSTABULARY' and 'DUMFRIES&GALLOWAY' are unchanged, having been unable to make any improvement in their ratings by using the extra input, and hence having allocated no significant weight to it.

Whilst it is true that the DMU covering the area with the lowest population density has improved from a rating of 98.7% to pareto efficiency, it should also be noted that 'DUMFRIES&GALLOWAY', clearly the second most 'rural' DMU, has failed to improve its rating by this methodology, yet at the same time the most 'urban' DMU has remained pareto efficient and DMU covering the area with the second highest population density, 'STRATHCLYDE', has actually recorded an increase in its rating.

As an alternative to introducing an additional input as above, an attempt was made at providing compensation for the effect of the environmental factor by direct adjustment of one or more variables. Just as the extra input approach used a substitute measure, rather than an exact representation of the environmental factor, so will any adjustment of variables be equally imprecise. This approach has the advantage, however, that adjustments are being made to actual statistics directly involved in the analysis, a variable is hence utilised which is derived from the actual statistic, adjusted by the substitute measure. In this way the disadvantage of using an entirely 'fabricated' variable is avoided.

The first of these approaches was to adjust the budgets of the DMU to make allowance for the increased costs that the environmental factor imposes on the DMU. This was achieved by subtracting a percentage from all of the budgets (I1) of the eight DMU. The subtracted percentage in this case being the inverse of the population density, as shown in column D of Table 4.14. Clearly, adding a percentage to each budget and hence increasing the level of resources used, as would be the case were the original population densities (column C of Table 4.14) used, would be inappropriate.

The program version, 'DEA4', is identical to that of 'DEA2' in Figure 4.11, therefore, with the figures for 'I1' altered as shown in Table 4.17.

Table 4.17. 'BUDGET (I1)' Adjusted Using Inverse of Population Density.

DMU	10 X POP.DENSITY^{-1} 1/(1,000's Hectare^2)	UNADJUSTED I1 £M	ADJUSTED I1 £M
1 STRATHCLYDE	0.52	36.1	35.91
2 LOTHIAN&BORDERS	0.79	16.1	15.97
3 GRAMPIAN	1.98	12.5	12.25
4 TAYSIDE	1.88	7.9	7.75
5 CENTRAL SCOTLAND	1.07	5.4	5.34
6 FIFE CONSTABULARY	0.41	4.9	4.88
7 DUMFRIES&GALLOWAY	4.36	3.3	3.16
8 NORTHERN	15.48	3.2	2.70

The results for the eight optimisations of 'DEA4' are shown in Table 4.18. Only two of the eight DMU did not have a higher virtual input (A1) for the budget variable, for its run of 'DEA4' than for its run of 'DEA2', these were both static with 'STRATHCLYDE' showing a very slight reduction in pareto efficiency, but 'DUMFRIES&GALLOWAY' nevertheless recording a slight increase.

The set of pareto efficient DMU is identical to that for the runs of program version DEA3, 'NORTHERN' joining 'LOTHIAN&BORDERS' and 'TAYSIDE'.

Table 4.18. Results Obtained from Program 'DEA4'.

	DMU	PARETO EFFICIENCY	COMPONENTS A1	A2	B1	B2	B3	B4	B5
1	STRATHCLYDE	91.7	25	75	10	25	10	50	5
2	LOTHIAN&BORDERS	100.0	75	25	10	44	10	36	0
3	GRAMPIAN	94.6	36.8	63.2	14.6	25	10.4	50	0
4	TAYSIDE	100.0	43.5	56.5	10	34.1	10	45.9	0
5	CENTRAL SCOTLAND	93.4	46.8	53.2	23.2	25	10	26.8	15
6	FIFE CONSTABULARY	93.7	42.1	57.9	10	25	30	35	0
7	DUMFRIES&GALLOWAY	91.3	25	75	10	25	10	40	15
8	NORTHERN	100.0	38.2	61.8	31.8	25	10	25	8.2

'FIFE CONSTABULARY', the DMU with the area of highest population density, records the only significant fall in pareto efficiency between 'DEA2' and 'DEA4' (94.3% to 93.7%), with 'STRATHCLYDE' and 'CENTRAL SCOTLAND' dropping very slightly. 'GRAMPIAN' remains virtually unchanged and 'DUMFRIES&GALLOWAY', the DMU with the area of second lowest population density records an increase from 90.8% to 91.3%.

The changes are, in general, more modest than those from 'DEA2' to 'DEA3', and more importantly follow a pattern that seems intuitively more appropriate.

In larger scale applications, and here in the case of 'STRATHCLYDE' and 'DUMFRIES&GALLOWAY', the optimum weightings for a DMU may well involve minimising the virtual output that is adjusted. Such allocation may result in a DMU which is affected, possibly severely, by an environmental factor, receiving less compensation than would be 'planned'. A possible way round this would be to adjust all the inputs. Where there are several or more inputs this would doubtless create a far too strong compensatory affect. In this case, there is only one additional input (I2); program version 'DEA5' differs only from 'DEA4' in that, additionally, the same percentages that were deducted from the input 'I1' are also deducted from 'I2'. The adjustment to the eight 'I2' figures is shown in Table 4.19, with the results from 'DEA5' shown in Table 4.20.

The effect of this 'double-counting' of the environmental factor is to place such relative advantage upon 'NORTHERN' that, in comparison with 'DEA2', all the other DMU record significant falls in pareto efficiency with the exception of 'LOTHIAN&BORDERS' which remains pareto efficient, joined by 'NORTHERN'. There are also some changes in overall ranking with 'NORTHERN' rising from third to joint highest rating, replaced in third place by 'TAYSIDE'. 'STRATHCLYDE' drops to the lowest rating, behind 'DUMFRIES&GALLOWAY' and, finally, 'CENTRAL SCOTLAND' and 'FIFE CONSTABULARY' switch fifth and sixth places.

Table 4.19. 'PATROL UNITS (I2)' Adjusted Using Inverse of Population Density.

DMU	10 X POP.DENSITY^{-1} 1/(1,000's Hectare^2)	UNADJUSTED I2 100's	ADJUSTED I2 100's
1 STRATHCLYDE	0.52	7.8	7.76
2 LOTHIAN&BORDERS	0.79	4.6	4.56
3 GRAMPIAN	1.98	3.1	3.04
4 TAYSIDE	1.88	1.9	1.86
5 CENTRAL SCOTLAND	1.07	1.4	1.39
6 FIFE CONSTABULARY	0.41	1.2	1.20
7 DUMFRIES&GALLOWAY	4.36	0.7	0.67
8 NORTHERN	15.48	0.7	0.59

Table 4.20. Results Obtained from Program 'DEA5'.

DMU	PARETO EFFICIENCY	A1	A2	B1	B2	B3	B4	B5
		COMPONENTS						
1 STRATHCLYDE	84.4	25	75	10	25	25	25	15
2 LOTHIAN&BORDERS	100.0	75	25	10	30	10	50	0
3 GRAMPIAN	91.4	54	46	10	25	25	25	15
4 TAYSIDE	98.2	52.8	47.2	10	25	25	25	15
5 CENTRAL SCOTLAND	90.9	59.9	40.1	10	25	25	25	15
6 FIFE CONSTABULARY	89.9	66.4	33.6	10	25	30	35	0
7 DUMFRIES&GALLOWAY	86.6	25	75	10	25	25	25	15
8 NORTHERN	100.0	47.7	52.3	10	25	25	25	15

This approach appears to have many potential problems, however, as already stated; altering only one input may not adequately affect certain DMU, due to the DMU's optimum weight allocation. In addition, because of the extreme nature of environmental factors, adjusting multiple inputs will have an undesiredly biased effect, in the example above, there were only two inputs adjusted, but one DMU was able to take absolute advantage over the other six.

It could be reasoned that as adjustment to particular variables is carried out prior to any optimisation in order to take account of 'unfair' differences in the data, that this is the full extent of consideration of an environmental factor which is required. The weight which a particular DMU has applied to adjusted variables within the LP optimisation is then entirely irrelevant.

There remains one other possible type of direct variable adjustment, which, unlike 'DEA3', 'DEA4' or 'DEA5', does not deal exclusively with the input side. This, statistically, has all the potential drawbacks of input adjustment, but a more logical basis which may minimise the problems.

Rather than introducing new variables or making 'across the board' adjustments to existing variables, the final program version, 'DEA6', requires the identification of the variables which are actually affected by the environmental factor. These identified variables are then adjusted, be they inputs, outputs or a combination of the two.

In the fictional 'Traffic Divisions' example, the environmental factor was identified as the less efficient use of resources by DMU operating in areas with less traffic and more rural geography. The definition of the variables from the original data in Table 3.6 was summarised in Figure 4.8, and is reproduced here as Figure 4.21.

Figure 4.21. Definitions of Variables in 'Scottish Police Force Traffic Divisions' Example (Figure 4.8).

I1 : BUDGET (£M)
I2 : PATROL UNITS (100's)

O1: SPEED MONITORING HOURS (10,000's)
O2: POSITIVE BREATH TESTS (10,000's)
O3: ROAD HOURS (100,000's)
O4: MOVING VEHICLE OFFENCES (10,000's)
O5: ESCORT MILEAGE (10,000's)

Whilst we can assume that there will be some form of link between the budgets (I1) and the 'work-load' in terms of variables 'O1', 'O3' and 'O5'; it is the 'actions' that the traffic levels will affect.

Hence, variables O2 and O4 were identified as the 'affected' variables by this environmental factor and hence were adjusted for the program version 'DEA6'. In this case the column C figures of Table 4.14 are the appropriate statistic; the actual population densities as opposed to their inverted result, as a percentage is being added to each of the two variables. The results from the eight runs are shown in Table 4.22.

'STRATHCLYDE' registered a slight decrease in pareto efficiency from 'DEA2' to 'DEA6', and kept the same weights throughout, the same can be said of 'DUMFRIES&GALLOWAY', however, yet it registered a slight increase in its relative rating as a result. Three other DMU also kept their percentage split of virtual outputs the same and achieved higher pareto efficiencies. 'GRAMPIAN' and 'TAYSIDE' made an identical switch of 5% of virtual output from one of the altered outputs to the other. 'NORTHERN' became, and 'LOTHIAN&BORDERS' remained, pareto efficient by placing some weight on O5 where previously they had placed only the minimal epsilon.

Table 4.22. Results Obtained from Program 'DEA6'.

DMU	PARETO EFFICIENCY	COMPONENTS						
		A1	A2	B1	B2	B3	B4	B5
1 STRATHCLYDE	91.7	25	75	10	25	10	50	5
2 LOTHIAN&BORDERS	100.0	33.1	66.9	10	25	10	50	5
3 GRAMPIAN	94.6	35.3	64.7	10	25	15	50	0
4 TAYSIDE	100.0	32.8	67.2	10	25	15	50	0
5 CENTRAL SCOTLAND	93.5	46.4	53.6	25	25	10	25	15
6 FIFE CONSTABULARY	93.8	41.4	58.6	10	25	30	35	0
7 DUMFRIES&GALLOWAY	91.2	25	75	10	25	10	40	15
8 NORTHERN	100.0	25	75	31	25	10	25	9

The set of pareto efficient DMU is the same as that for the runs of program version 'DEA3' and 'DEA4', 'NORTHERN' joining 'LOTHIAN&BORDERS' and 'TAYSIDE'. 'FIFE CONSTABULARY', the DMU with the area of highest population density, records the only significant fall in pareto efficiency between 'DEA2' and 'DEA6', with 'STRATHCLYDE' and 'CENTRAL SCOTLAND' dropping very slightly. 'GRAMPIAN' is virtually unchanged and 'DUMFRIES&GALLOWAY', the DMU with the area of second lowest population density records an increase. The changes from 'DEA2' to 'DEA6' are almost identical to those from 'DEA2' to 'DEA4' and as such also follow a pattern that seems intuitively appropriate.

Table 4.23 presents the pareto efficiencies for all eight DMU across the program versions 'DEA2' to 'DEA6', and for reference also repeats the population density statistic.

Table 4.23. Pareto Efficiencies Achieved In Program Versions 'DEA2' to 'DEA6'.

		PARETO EFFICIENCY					POPULATION
	DMU	DEA2	DEA3	DEA4	DEA5	DEA6	DENSITY
1	STRATHCLYDE	91.9	92.9	91.7	84.4	91.7	19.1
2	LOTHIAN&BORDERS	100.0	100.0	100.0	100.0	100.0	12.6
3	GRAMPIAN	94.5	99.7	94.6	91.4	94.6	5.1
4	TAYSIDE	100.0	100.0	100.0	98.2	100.0	5.3
5	CENTRAL SCOTLAND	93.6	93.6	93.4	90.9	93.5	9.3
6	FIFE CONSTABULARY	94.3	94.3	93.7	89.9	93.8	24.6
7	DUMFRIES&GALLOWAY	90.8	90.8	91.3	86.6	91.2	2.3
8	NORTHERN	98.7	100.0	100.0	100.0	100.0	0.6

As already stated, 'DEA4' and 'DEA6' have produced almost identical results. These two are the only data runs to produce generally acceptable results in terms of what would have been 'expected'. The results for 'DEA4' were undoubtedly easier to achieve, but in more complex applications it would not be clear how inputs should be adjusted.

The additional input approach can virtually be dismissed, and additionally 'DEA5' is also unacceptable, a conclusion which could not easily have been forecast. Beforehand, there could have been some debate as to whether the approach of 'DEA4' or 'DEA5' is the more appropriate, with more inputs the problem would simply have multiplied. Affected Variable Adjustment (AVA) therefore seems the most appropriate approach as advanced in 'DEA6'.

This approach is also more practical as can be demonstrated by reference to this quote from a seminar paper by Dyson and Thanassoulis (1988.1). It should first be noted that a 'basic Z-score' is a measure constructed by the Department of the Environment. The larger the value of the index the more social, economic and housing problems an area faces, the statistic can take both positive and negative values. The proposition in this case was that the 'basic Z-score' be included as a 'contextual input variable':

> *"i. The fact that Z-scores can take negative values makes it necessary to add a positive constant throughout to eliminate negative values. The choice of the constant requires caution as its magnitude determines the proportions new Z-score values are of each other.*
>
> *ii. The Z-score is an index. Index values used in DEA always need to be adjusted to reflect the "size" of the respective units.*

iii. Z-scores have a lower value for areas with fewer expected attendance and welfare cases. Thus, a low Z-score implies lower administrative workload. Hence, if the Z-score is treated as an input its values must be inverted or deducted from some preset large constant. (its values can be left as they stand if it is treated as an output.)

DYSON & THANASSOULIS (1988.1).

If, alternatively, the basic Z-score figures had been used to adjust the affected variables, all three of the above points would cease to be a problem. Hence the approach developed here is not only more conceptually correct, but is more practical and statistically robust.

4.5 The Consequences of Average Performance in all Variables.

One of the fundamental principles of proponents of Data Envelopment Analysis, is the belief that given complete flexibility in weight allocation, any DMU which is revealed as inefficient in an unrestricted implementation of DEA, truly is inefficient.

Undoubtedly this principle holds true in as much as no DMU could increase the pareto efficiency rating it achieves in an unrestricted data run, in a subsequent data run with weight limits imposed. This does not mean, however, that unrestricted DEA could be applied simply to find the least efficient DMU of a set. The purpose of this, final, section of Chapter Four is simply to demonstrate this point.

Consider a situation where a set of nine DMU are being assessed, the data consisting of two inputs and four outputs, as shown in Table 4.24.

Table 4.24. Illustrative Nine DMU, Two Input, Four Output, Data Set.

DMU	Inputs I1	I2	Outputs O1	O2	O3	O4
A	9	24	1100	160	220	120
B	28	7	1050	180	240	150
C	8	26	210	1200	200	130
D	24	7	200	1100	260	180
E	9	29	230	200	950	90
F	23	8	225	130	1200	170
G	6	26	240	140	310	990
H	22	6	190	170	290	970
I	13	14	400	340	330	240

As can be seen from the data, DMU 'I' has fairly average values across all six variables, and in particular has neither the smallest or largest value for any of the variables.

When this data is applied to unrestricted DEA, all the DMU rate 100% pareto efficient with the exception of DMU 'I' which achieves 92%. After restricting the weights on each variable, it is mathematically impossible for the inefficient DMU to improve its rating, as there is no combination of weights now available to it which was not previously available.

The other currently pareto efficient DMU could, however, potentially drop to a lower pareto efficiency rating. This is demonstrated by applying the weight restrictions on the virtual inputs and virtual outputs as follows; between 20%

and 80% of total virtual inputs on each of the inputs, and between 10% and 40% of total virtual outputs on each of the outputs.

The results achieved with these weight restrictions in place are shown in Table 4.25.

Table 4.25. Results After Applying Data of 4.24 to DEA with Weight Restriction.

DMU	Pareto Efficiency Rating
G	100%
I	92%
H	82%
D	69%
C	61%
F	61%
A	59%
B	59%
E	50%

From Table 4.25, it can be seen that DMU 'I' is inefficient relative to DMU 'G', but that in relative terms it is now more efficient than all the other seven DMU, and considerably so for nearly all these DMU.

This clearly refutes the generalisation that Data Envelopment Analysis without weight restriction can be used to unequivocally identify 'weaker' DMU. Hence, rather than there being little use for DEA in basic, undeveloped form; there appears to be no practical application possible at all in terms of gaining significant results.

4.6. Target Reference Sets of Pareto Efficient DMU for Use by Pareto Inefficient DMU.

Once pareto efficiency ratings have been established for a group of DMU, it is natural that those governing the activities of the units identified as relatively inefficient will wish to attempt to move the DMU to a more efficient position over time.

Data Envelopment Analysis can readily provide directions as to how this can be achieved, through the use of 'target reference sets' of pareto efficient DMU. These reference DMU are those whose constraint lines in the optimisation for the pareto inefficient unit were 'active', that is to say the set of DMU which, under the model, determined the value for the DMU being assessed with the particular weights which turned out to be the optimal combination.

> *"The reference set of an inefficient unit consists of the units having an efficiency of 1 with respect to the optimal weights for the inefficient unit. These corresponding efficient units are readily identified..."* THANASSOULIS *ET AL.* (1987).

Once identified, the suggestion is that the set of reference DMU can then be viewed as examples of good practice specifically comparable to the pareto inefficient DMU and as targets for performance improvements.

The use of 'reference sets' is part of the established technique and believed to be of significant practical value by a number of authors:

> *"DEA provides..., via the reference set and its associated pseudo-[target]DMU, direct management guidelines for improvement in that a could become relatively efficient by increasing its outputs and/or decreasing its inputs to approach the performance of its pseudo-DMU. This notion of improvement is not towards some theoretical ideal, but towards a comparable level of performance actually being achieved within the population of DMUs being studied."* TOMKINS AND GREEN (1988).

Despite the understandable enthusiasm for the automatic provision of one or more examples of DMU for each pareto inefficient DMU to demonstrate 'how it should be done', there are a number of conceptual problems in the adoption of these 'reference sets'.

A DMU may imitate the activities of one or more of its reference set and succeed in reaching the set target, its desired point on the efficient frontier; but this will only ever be conceptually as on the next DEA assessment as all DMU evolve and attempt to improve, the efficient frontier will undoubtedly have moved.

It could be suggested that even if this occurs in the long-term, in the short-term it provides a distinct and relevant direction on which to focus improvement. But it is at this, fundamental, level where the majority of the conceptual problems lie. A pareto inefficient DMU could attempt to move to any combination of output and input levels which would render it pareto efficient, including those suggested by the reference set, can it be assumed that it is logically and/or practically wiser to utilise the information provided by the reference set?

In undeveloped DEA, a DMU can be efficient by adopting a pattern of weights which ignores all key activities, (Sections 4.1/4.2) placing zero weight on the variables which represent those important activities, this clearly cannot be held up as an example of 'good practice'. This particular problem is eliminated once a performance profile is introduced (Section 4.3), but conceptual problems persist.

Consider a DMU with a PE rating of 64.3%, it may have a reference set of three DMU established as described above, those DMU involved in the calculation of the efficiency figure using the weights which were the optimal combination under the model. An alternative and substantially different weight distribution could have, conceptually, returned a value of 64.2% which would have indicated an entirely distinct reference set, naturally the LP coding will return the greater value.

It would be difficult with knowledge of the 'next best' weight distribution to continue in that example to argue for improvements focused only on the 'optimal' reference set.

It would seem more appropriate that a pareto inefficient DMU attempt to improve its performance in any way which is feasible and practical, armed with information on which of the other DMU were efficient and which inefficient, rather than unnecessarily narrowing its available routes to improved performance based on statistics extrapolated from one point in an evolving process of assessment.

The developments to the theory and application of Data Envelopment Analysis suggested within this chapter, together with additional developments, are formalised in Chapter Five. After this has been completed, university performance indicators can then be considered for the technique to be applied to.

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5. THE DEAPMAS PROCESS; A DEVELOPMENT OF DATA ENVELOPMENT ANALYSIS.

The theory of Data Envelopment Analysis (DEA) was introduced in the third chapter (Section 3.2), and the technique analysed in Chapter Four with the aid of a fictional data set.

Examination of the results of the data runs on the fictional statistics and reference to relevant literature, led to the conclusion that the technique offered potential for the production of significant results from university performance indicators, but that a considerable degree of development to the technique itself would first be required.

DEA in its undeveloped, unrestrained weights form has major inadequacies in terms of its ability to indicate relative efficiency and effectiveness. These range from its implicit requirement for minimisation of the number of variables for inclusion, to the permitting of the proportion of the total input or output products applied to any individual variable to range from insignificant to 100%, regardless of the relative importance of the particular variable.

From the data runs involving restriction of variable weights experimented with in Section 4.3, the imposition of weight limits clearly has a dramatic effect on the principles involved in variable selection and the interpretation of the results obtained.

Restricting the variable weights in DEA appears to have sufficiently beneficial consequence to justify formalising and developing this process rather than continuing the search for an appropriate alternative technique that could be immediately applied.

There are a number of aspects surrounding the use of DEA which need to be further examined, and subsequently have an approach formalised. Section 4.3 studied variable weight limitation, introducing the concept of the performance profile, and Section 4.4 then examined the inclusion of environmental factors.

A cursory examination of available data relating to higher education is sufficient to reveal that some incomplete data sets are going to be present. Additionally, therefore, the question of specialisation amongst variables will need thorough analysis. This complex area could not easily be examined without computer software capable of supporting manipulation of the data.

5.1. The DEAPMAS Computer Program.

Even without introducing a performance profile, for data sets larger than those used in Chapter Four it would become impractical to use LINDO or any other linear programming package in terms of both programming time and the limitations of the packages. To progress further it was therefore necessary to write a computer program capable of carrying out the conversion of raw statistics to linear program, the subsequent data manipulations necessary in

DEA, and the necessary manipulations and calculations for the conceptual developments made.

To clearly distinguish between undeveloped Data Envelopment Analysis and the developments on the theory of DEA, a distinctive title was adopted for both the developed process and the computer coding written to support it. The name 'DEAPMAS' is therefore used in reference to the principles of the developed theory and is the name given to the computer program which was written to support it. DEAPMAS is a acronym of Data Envelopment Analysis; Performance Modelling and Specialisation.

Reviewing the literature on DEA reveals that the majority of practical implementations have been carried out on programs written in the programming language 'FORTRAN' and it was felt therefore, for the purpose of any comparison that may be necessary, that this would be the most appropriate language in which to code the DEAPMAS program.

The original code was written on the University of Stirling VAX, with later editing on both its replacement, a Hewlett-Packard UNIX; and a PRIME of Napier Polytechnic of Edinburgh on which the input data sets for all the data runs reported in Chapter Seven were also prepared. The program is written to meet the particular requirements of the FORTRAN 77 compiler of the HP UNIX.

The primary manipulations of data sets carried out by the DEAPMAS program are not fundamentally different from those of undeveloped DEA; both manipulate the statistics to make each Decision-Making Unit or DMU in turn the subject of an optimisation, effectively running a suite of linear programs, each differing only by a relatively small adjustment on the same data matrix for all of the DMU involved (See Section 4.1).

The major differences lie in the way in which the basic theory is then transformed into a practical technique, by preadjustment of the data, imposition of a performance profile, and the ability of the DMU to specialise amongst the variables where data is incomplete.

The progression from the Farrellian efficiency model (1957) to the Charnes *et al.* constrained model (1978) which yields a fractional linear program was covered in Section 3.2. The conversion from fractional linear program to a linear program for use in the LINDO package was shown in Section 4.2. A more formal development of the actual linear program produced from data read in within the DEAPMAS program is covered in the next section.

DEAPMAS and DEA, therefore, rely on a linear programming algorithm for the calculation of the actual pareto efficiencies, once the data is ready within the program for optimisation. The actual LP optimisation can be treated largely as a 'black box', as only the solution is of importance, the mathematics involved being irrelevant.

Section 5.2. The Linear Program within DEAPMAS.

As stated in Section 5.1, the methodology of the solution of the linear program set up in DEAPMAS is irrelevant and the LP solution can be regarded therefore as a 'black box'. As such the linear programming solution subroutines within DEAPMAS are independent of the remainder of the program and would solve any linear programming problem of the same form. The coding for the linear programming solution subroutines was developed from the standard algorithms of Best and Ritter (1985).

It is therefore the development of the LP model to be optimised, and how the linear program itself is obtained from any data set which is the subject of this section.

The linear program form utilised is based on the simple model problem shown in Figure 5.1.

Figure 5.1. LP Model Problem which DEAPMAS LP Form Utilises.

$$\min \{c'x \mid Ax \leq b\}$$

Recalling the form of the Data Envelopment Analysis model, the Charnes *et al.* (1978) constrained model originally presented in Chapter Three (Figure 3.5), this is reproduced as Figure 5.2. This fractional linear program was solved as a linear program by setting the numerator of the objective equal to one (the figure arbitrarily chosen to represent 'maximum' pareto efficiency) and minimising its denominator.

Figure 5.2. Charnes *et al.* Constrained DEA Model.

MAXIMISE $$h_0 = \frac{\sum_{r=1}^{r=s} O_r OQ_{rj0}}{\sum_{i=1}^{i=m} I_i IQ_{ij0}}$$

SUBJECT TO $$\frac{\sum_{r=1}^{r=s} O_r OQ_{rj}}{\sum_{i=1}^{i=m} I_i IQ_{ij}} \leq 1 \quad j = 1 \ldots j_0 \ldots n$$

WITH O_r AND $I_i > \varepsilon$ FOR ALL r AND i

WHERE
OQ_{rj} = the quantity of DMU j's rth output.
O_r = the rth output's weight.
IQ_{ij} = the quantity of DMU j's ith input.
I_i = the ith input's weight.

The fractional linear program of Figure 5.2 directly converts to the linear program given in Figure 5.3, with all definitions unchanged. Note that a minimisation model is now being dealt with, this switch is unimportant, other than of course meaning that the objective function optimal value obtained will require inversion to obtain a rating of one or less.

Figure 5.3. Linear Program Form of DEA.

MINIMISE $\sum_{i=1}^{i=m} I_i IQ_{ij0}$

SUBJECT TO $\sum_{r=1}^{r=s} O_r OQ_{rj0} = 1$

$\sum_{i=1}^{i=m} I_i IQ_{ij} - \sum_{r=1}^{r=s} O_r OQ_{rj} \geq 0 \quad j= 1 \ldots j_0 \ldots n$

WITH O_r AND $I_i \geq \varepsilon$ FOR ALL r AND i

Recalling the model LP solution of Figure 5.1, the linear program obtained now fits this model with the exception of the constraint which holds the sum of the outputs of j_0 (the particular DMU for which a rating is to be calculated) multiplied by their associated weights equal to one.

With the exception of this one constraint, all constraints regardless of the number of DMU (n), inputs (m) or outputs (s), can be readily expressed as 'less than or equal to' conditions. This being the case the true model problem is, then, as given in Figure 5.4.

Figure 5.4. Model LP Minimisation Problem with Inequality and Equality Constraints.

$$\min \{c'x \mid A_1x \leq b_1, A_2x = b_2\}$$

Any equality, however, can be written as two equivalent inequalities. The equality constraint $A_2x = b_2$ is hence equivalent to the inequality constraints $A_2x \leq b_2$ and $-A_2x \leq -b_2$ when considered concurrently. The actual model problem which requires solving could hence be represented as shown in Figure 5.5, but does not for practical purposes differ from the original conceptual model in Figure 5.1.

Figure 5.5. Model LP Minimisation Problem with Inequality Constraints only.

$$\min \{c'x \mid A_1x \leq b_1, A_2x \leq b_2 , -A_2x \leq -b_2\}$$

It would be useful to introduce a small-scale example to demonstrate both the conversion from data to DEA linear program form and the small manipulation necessary to reconcile our DEA LP model of Figure 5.3 to our model problems of Figures 5.1/5.5. A set of such example statistics is given in Table 5.6.

Table 5.6. Fictional Data Used to Demonstrate Conversion to DEA LP form.

DMU	I_1	O_1	O_2	O_3
A	7	2	1	7
B	7	4	1	3
C	8	3	2	4
D	6	4	2	5

The example features four Decision-Making Units, each with a single input, and three outputs. Pareto efficiency ratings would be obtained for each of these DMU after four linear programs were run, each of the DMU in turn being the subject. To demonstrate, taking 'DMU A' as the subject of the optimisation; the data converts for solution by Data Envelopment Analysis, prior to considering the actual LP implementation, as shown in Figure 5.7.

<u>Figure 5.7. DEA Model for Table 5.6 with 'DMU A' as Subject.</u>

MINIMISE $7I_1$

SUBJECT TO

$$\begin{array}{rcrcrcrcll} & & 2O_1 & + & O_2 & + & 7O_3 & = & 1 & (1) \\ 7I_1 & - & 2O_1 & - & O_2 & - & 7O_3 & \leq & 0 & (2) \\ 7I_1 & - & 4O_1 & - & O_2 & - & 3O_3 & \leq & 0 & (3) \\ 8I_1 & - & 3O_1 & - & 2O_2 & - & 4O_3 & \leq & 0 & (4) \\ 6I_1 & - & 4O_1 & - & 2O_2 & - & 5O_3 & \leq & 0 & (5) \end{array}$$

$$I_1, O_1, O_2, O_3 \geq \varepsilon$$

The way in which DEA actually 'works' was explored in the early sections of Chapter Four, it would be useful at this point, however, to draw upon Figures 5.3 and 5.7 to clarify this. The constraint lines of Figure 5.7 have been numbered in order to aid explanation.

The above problem can be interpreted most simply as follows;

> *'Minimise the input product of 'DMU A' subject to an absolute minimum of unity, using the available weights such that no DMU could apply these same weights and return a figure for its input product which is less than its total output product.'*

Hence, the constraints can be viewed in two groups. The first of these groups defines the absolute minimum for the input product by setting the total output products to unity (constraint 1) and requiring that the input product be greater than or equal to these (constraint 2). The second group consists of one constraint for each of the other DMU (constraints 3,4 and 5), which serve as 'competition'. 'DMU A' can only be pareto efficient if it can adopt weights which would not indicate any other DMU as being more efficient than itself with those same weights, that is, having its input product less than its total output products.

Where the subject DMU cannot reach pareto efficiency, the figure returned will be the lowest possible with one or more of the 'competitive' constraints (3), (4) and (5) being exactly equal to zero. In such circumstances where one of these constraints is 'tight' the input product for the subject DMU will be greater than, not equal to, its total output products and hence the DMU will be pareto inefficient. It is this figure which, once inverted, is the pareto efficiency rating (below unity, and commonly expressed as a percentage).

Note, therefore, that the objective function and constraint (1) will alter for each DMU being assessed, but that the other constraints will not physically alter, only conceptually. To illustrate this conceptual difference, take 'DMU B' as subject, the first group of constraints as described above would consist of a new 'constraint 1' using the output data for 'DMU B', and constraint (3). The second 'competition from other DMU' group would then consist of constraints (2), (4) and (5).

The quasi-LP model of Figure 5.7 would convert for implementation within the DEAPMAS Program by linear programming to that shown in Figure 5.8 with the two inequality constraints replacing the equality constraint.

This simple example will be returned to in the remaining sections of this Chapter to clarify the way in which performance profiles, specialisation amongst variables and environmental factors affect this basic DEA model within the DEAPMAS process.

The linear program problem which the LP solution subroutines solve is, then, an M x N matrix for each of j DMU, where M is always the number of DMU plus N, plus two; and N is the number of variables.

Figure 5.8. Linear Program Problem from DEA model of Figure 5.7.

$$
\begin{array}{llrrrrrrrrrl}
\text{MINIMISE} & & 7I_1 & & & & & & & & & \\
\text{SUBJECT TO} & & & & 2O_1 & + & O_2 & + & 7O_3 & \leq & 1 \\
 & & & - & 2O_1 & - & O_2 & - & 7O_3 & \leq & -1 \\
 & - & 7I_1 & + & 2O_1 & + & O_2 & + & 7O_3 & \leq & 0 \\
 & - & 7I_1 & + & 4O_1 & + & O_2 & + & 3O_3 & \leq & 0 \\
 & - & 8I_1 & + & 3O_1 & + & 2O_2 & + & 4O_3 & \leq & 0 \\
 & - & 6I_1 & + & 4O_1 & + & 2O_2 & + & 5O_3 & \leq & 0 \\
 & - & I_1 & & & & & & & \leq & 0.00001 \\
 & & & - & O_1 & & & & & \leq & 0.00001 \\
 & & & & & - & O_2 & & & \leq & 0.00001 \\
 & & & & & & & - & O_3 & \leq & 0.00001
\end{array}
$$

The net effect of this conversion, therefore, is an increase of just one line, this will always be the case regardless of the number of DMU or variables present.

The other changes are simply multiplications by negative unity to form 'less than' conditions replacing 'greater than' conditions in the formulation.

This being the case, the right hand side of the problem will always be a matrix whose first component is 1, second is -1, and all other entries are zero, except 1.0×10^{-5} (representing epsilon, ε) for the last N entries.

The objective function and the first two constraints will differ for each DMU being assessed, but the 'inputs greater than outputs' and 'variable greater than ?' constraints are unaltered across each of j optimisations. For each optimisation the objective function and first two constraints are derived from these 'fixed' constraints.

In the simplest form (emulating undeveloped DEA), the data is read into a matrix (A), which has dimensions M x N, the matrix is completed, the objective function derived and then the LP solution subroutines return an objective value which is inverted to yield the pareto efficiency rating.

Details of the Subroutines which carry out these steps can be found in Appendix B, which lists the full DEAPMAS program. The subset of subroutines which is involved in an emulation of undeveloped DEA, together with other subroutines as appropriate, are involved for all runs of the program.

When consulting the FORTRAN coding in Appendix B, it should be noted that although a version of the DEAPMAS program was written which operates as described above with M equal to the number of DMU plus (N + 2); for practical purposes, later versions use a matrix with M equal to the number of DMU plus (3N + 2). The requirement for the extra constraints becomes clear in the next section which looks at the placing of weight restrictions on variables through the use of a 'performance profile'.

The explanation of why this affects runs with unrestricted weights is that emulations of undeveloped DEA using the DEAPMAS Program do, to reduce program complexity, use a performance profile. The profile, however, is one in which the minima are all set at 0% and the maxima at 100%. Naturally, this 'default' profile has no effect on the ratings obtained.

5.3. Variable Selection and Weight Restriction; The Performance Profile.

From the analysis of Chapter Four, it has been seen that Data Envelopment Analysis, in its undeveloped form, purports to demonstrate relative efficiency in a completely objective manner. There are, hence, no rules governing variable selection beyond loose concepts that they should be the most important factors, more emphasis being placed on keeping the total number of variables to a minimum rather than ensuring all relevant factors are included.

The degree of objectivity is such that, in addition, no variable is defined as more important than any other, and, perhaps more significantly for a particular DMU, no individual variable is defined as being necessarily more than completely unimportant.

It has to be questioned whether results obtained under such conditions could ever have any practical significance or application. Even the lynch-pin assertion put forward for the undeveloped theory that whatever else, a DMU that rates inefficient under such generous conditions, truly is inefficient has been shown to be conceptually unsafe (Section 4.5).

Subjectivity is introduced to the analysis through the developments contained within the DEAPMAS process. Subjective identification of all relevant factors, and a subjective, but entirely variable, degree of ranking of the importance of those factors. This does not suggest, however, that the problems involved with fixed weighting have been ignored, such a degree of subjectivity will rarely be appropriate.

To define a range of possible weights for each and every resource input and desired output, to have subjective consideration of the limits permissible on each factor by those for whom the results are to be produced, and then to objectively obtain the maximum possible relative rating within those defined limits is very far from adopting fixed weights. Such subjectivity is not only unavoidable in these circumstances, but is fundamentally essential if the results are to provide any practical and justifiable comparison of the units being assessed.

DEA allows analysis to involve incommensurate inputs and outputs, it further requires no definition of the relationship between inputs and outputs. This is its strength, but it is also, in undeveloped form, its weakness. Efficiency is normally defined using single ratios or combinations of single ratios. It is difficult to conceptualise, therefore, a relative measure based on multi-facet efficiency obtained using any permutation of unrelated measures.

Take, for example, university statistics, undeveloped DEA could readily produce a ratio for a particular department with publication rates, citation indices, and consultancy man-hours as the numerator and undergraduate entry qualifications, taught postgraduate numbers and teaching income as the denominator; it is unclear just what significance this figure could have.

Setting limits on the comparative weighting of outputs is to set limits on their relative 'value'. The consequence of this is that the building of a performance profile provides the opportunity to go beyond the indication of relative efficiency to the indication of relative effectiveness.

This outcome would seem highly desirable in itself, but by the same process of placing weight limits on inputs their relative importance or 'scarcity' can be ranked and hence it is not pure effectiveness (regardless of resource use) which would be indicated, but a measure of performance which encompasses both effectiveness and efficiency. Two distinct aspects which ideally should be considered concurrently are brought together within a single relative performance statistic, thus indicating genuine cost effectiveness.

The developments on Data Envelopment Analysis yield a more practical management tool than obtainable using the undeveloped theory. The differences lie not only in the way in which the results are calculated, however, but have additional major implications prior to the calculations; in the variable selection itself. It is for this reason that reference is made to the developments as the DEAPMAS process, rather than as a variation on the technique of DEA. The next sub-section therefore looks specifically at issues surrounding variable selection. The subsequent sub-section (Section 5.3.2) then considers how the limits used are established, and hence the performance profile created.

5.3.1. Variables, Factors and Point of Measurement.

With varying degrees of difficulty, for any set of comparable DMU; a list of variables, or satisfactory surrogates, relating to resource use (inputs) and desired outputs can be ascertained. We have established now, however, through the discussion of the previous section, which draws on the analysis of Chapter Four, the need to associate the relative significance of such variables to the objectives of the DMU.

By design, undeveloped DEA is wholly inadequate in this respect, not only does the undeveloped technique treat all variables as equal, but in practice use of the technique actively discourages the inclusion of all relevant variables in favour of a minimal collection.

Additionally we have seen, however, that the merits of the selected variables cannot be established simply each in isolation against all others, but often 'areas' have to be considered, as without such consideration a predominance of available data, and/or measurable points in one area will lead to an unintentional 'over-weighting'. In the university context, for example, these areas could be 'teaching' and 'research', as will be seen in Chapter Six; statistics which can be related to teaching far outnumber those relating to research.

It is an often voiced and relevant criticism of not only DEA but the topic of performance measurement generally that analysis tends to concentrate on the measurable.

Normally, variables, certainly where many have been identified as contributory, fall into definable groups. These groups could be established at several levels. Continuing the university example, 'teaching' outputs, can be broken down into 'undergraduate' and 'postgraduate' outputs. 'Undergraduate' outputs in turn sub-divide to 'first destination figures' and 'number of graduates', the first destination factor being, in itself, a collection of individual statistics.

The example is sufficient to demonstrate that we can identify 'factors' relevant to the analysis, but that the variables which we actually adopt, reflect either the point of measurement for the statistics or an addition of these 'as-collected' figures.

This is particularly well illustrated by adhering to the general university example for one further illustration. First destination figures, were suggested alongside graduate numbers, but are provided as a number of individual statistics; such as graduates in 'long-term employment', 'short-term employment', and 'further education or training'. At that 'level', therefore, which could equate to the actual variables for analysis, without weight restriction, the first destinations factor is implicitly defined as several times more important than the graduate numbers factor.

This is due to the fact that the undeveloped technique treats all variables as equal, and so there is far more opportunity to place weights on variables within the first destination factor than on the single graduate variable. When using the undeveloped technique, therefore, in any particular application; all variables are equal, but the factors which they represent are most unlikely to be.

The DEAPMAS program is designed to enable information on these variable groups to be output initially, and again whenever a change involving the performance profile occurs. The structure of these variable groups, or 'sets', being an optional part of the input data (mandatory only where specialisation is present).

Further explanation of this part of the program's output is made in the following sub-section, but further details can be found in the program listing in Appendix B by referring to the listing and program documentation for 'PRNGROUP', the subroutine responsible for its formation.

5.3.2. Creating The Performance Profile.

We have seen that Data Envelopment Analysis, in undeveloped form, allows the different variables to have weights applied in whatever proportion is necessary to maximise the DMU's pareto efficiency.

Before considering the form and degree of restriction in weight application between the different variables, it is necessary to clearly define exactly what is being restricted as it cannot simply be the applied weights themselves.

The weight limits are set and the performance profile built, not on the basis of the actual weighting applied to each variable, but on the 'virtual' inputs and outputs created. These virtual inputs and outputs, which were introduced in the previous chapter (Section 4.2), must be considered rather than merely the actual weights because the size of the weight itself will be affected by the magnitude of the particular variable.

DEA, and hence the DEAPMAS process, are designed to handle incommensurate inputs and outputs. One aspect of this lies in the fact that the magnitude of applied weights compensates for the scale of magnitude of the variable, whether it be tens, thousands, millions or any other unit size.

The restriction, therefore, should not be simply on the applied weight, but on the product of variable and associated weight. It is hence the proportion which this product represents, of the total such products, which is being restricted.

More formally;

for each input I ($I_1 \ldots I_j \ldots I_n$), let there be an equivalent virtual input A ($A_1 \ldots A_j \ldots A_n$), such that $A_j = I_j \times IW_j$.

and, likewise;

for each output O ($O_1 \ldots O_j \ldots O_n$), let there be an equivalent virtual input B ($B_1 \ldots B_j \ldots B_n$), such that $B_j = O_j \times OW_j$.

The virtual input of a particular input is hence the product of that input and its associated weight, equally the virtual output of a particular output is the product of that output and its corresponding weight.

The complete flexibility of weight allocation available when using the undeveloped technique could also be considered as allowing each variable to have a weighting attached which creates a virtual input (or output) in the range 0-100% of the total virtual inputs (or outputs).

By setting a lower and upper limit for each virtual input (or output) at any point within this range, this flexibility can be reduced by any chosen extent. The minima set create fixed weighting; the maxima defining for each variable the limit of the remaining, flexible, weighting which can be applied to it. In both cases, the restriction being not on the actual weights (which are linked to the scale of the particular variable), but on the virtual input or output.

Recalling the trivial example utilised in Section 5.2 (Table 5.6), this is reproduced here as Table 5.9 with additionally required minima and maxima included.

The listing and program documentation of the DEAPMAS program subroutine 'PERPROF' can be consulted in Appendix B, to reveal the way in which the program extends the LP matrix constructed to include restrictions on the virtual inputs and virtual outputs. The central algebraic 'rule' developed on which to base the additional constraints, however, is relatively straightforward. This is formalised in Figure 5.10.

Table 5.9. Fictional Data Of Table 5.6 with Weight Limitations Introduced.

DMU	I_1	O_1	O_2	O_3 (£M)
A	7	2	1	7
B	7	4	1	3
C	8	3	2	4
D	6	4	2	5

LIMIT	I_1	O_1	O_2	O_3 (%)
MINIMUM	0	10	10	30
MAXIMUM	100	50	40	80

Figure 5.10. Algebraic Origin of Performance Profile Constraint Lines in LP Matrix Constructed Within the DEAPMAS Program.

V_1 +... -Y%/Z% V_j +... $V_n \leq 0$; IF MINIMUM LIMIT
V_1 +... -Y%/Z% V_j +... $V_n \geq 0$; IF MAXIMUM LIMIT

WHERE:

Z% : The limit being calculated
Y% : 100 - Z%
V_j : The variable on which the limit is placed

FOR:

Limits greater than zero for all Variables $V_1..V_j..V_n$ of the same class (input or output).

To illustrate this in practice, take a situation where we are dealing with an application involving four outputs and wanted a particular output (V_j) set at a minimum of 25% (The virtual output to be at least 25% of the total virtual outputs). Z% would be 25 and hence Y% would be 75 (100-25). Thus the sum of all the other outputs plus -3 x V_j, (75/25) would hence need to be less than or equal to zero to enforce the restriction.

This formula, hence, uses the internal ratio implied by any restriction in order to form the actual constraint line. Above, restricting one virtual output to a minimum of 25%, automatically sets a maxima of 75% for the remainder, the most extreme ratio permitted therefore is 3:1. Enforcement of this restriction in permitted ratio can be achieved by ensuring that the total of the other virtual outputs less three times the virtual output being restricted does not leave a result greater than zero. Equally 10% can be viewed as an internal ratio of 9:1, 30% can be viewed as 7:3, and 50% as 1:1.

In the case of maximum restrictions, from figure 5.10, the formula is simply reversed, so a 75% maximum would represent a ratio of 1:3, the other total virtual outputs less one-third of the restricted virtual output could not be less than zero. A *40% maximum would equate to an internal ratio of 3:2, and 80%* to one of 1:4.

If we now turn to the fictional data of Table 5.9, the DEA problem with the additional constraint lines in place would be as shown in Figure 5.11, selecting DMU A as the subject. Note that these constraint lines form part of the 'fixed' section of the matrix, that which remains completely unaltered across all the optimisations.

Hence for each variable a pair of constraints is necessary, this is where the final matrix size referred to in Section 5.2 originates of M x N, where N is the number of variables and M equals the number of DMU plus (3N + 2). The M x N matrix formed by the DEAPMAS program from the problem of Table 5.9 would then have the dimensions 18 x 4. This linear program which the DEAPMAS program creates (again taking 'DMU A' as the subject of optimisation) is as shown in Figure 5.12.

Figure 5.11. DEA Problem with Performance Profile, Formulated from Data of Table 5.9.

MINIMISE

$$7I_1$$

SUBJECT TO

$$
\begin{aligned}
2O_1 + O_2 + 7O_3 &= 1 \\
7I_1 - 2O_1 - O_2 - 7O_3 &\leq 0 \\
7I_1 - 4O_1 - O_2 - 3O_3 &\leq 0 \\
8I_1 - 3O_1 - 2O_2 - 4O_3 &\leq 0 \\
6I_1 - 4O_1 - 2O_2 - 5O_3 &\leq 0 \\
- 9O_1 + O_2 + O_3 &\leq 0 \\
- O_1 + O_2 + O_3 &\leq 0 \\
O_1 - 9O_2 + O_3 &\leq 0 \\
O_1 - 3/2O_2 + O_3 &\leq 0 \\
O_1 + O_2 - 7/3O_3 &\leq 0 \\
O_1 + O_2 - 1/4O_3 &\leq 0 \\
I_1, O_1, O_2, O_3 &\geq \varepsilon
\end{aligned}
$$

PARETO EFFICIENCY RATING = 1 / MINIMISED $7I_1$

Figure 5.12. Linear Problem Created within the DEAPMAS Program to Establish Pareto Efficiency of 'DMU A'.

MINIMISE

$$7I_1$$

SUBJECT TO

$$
\begin{array}{rrrrrrrrrl}
 & & & 2O_1 & + & O_2 & + & 7O_3 & \leq & 1 \\
 & & - & 2O_1 & - & O_2 & - & 7O_3 & \leq & -1 \\
- & 7I_1 & + & 2O_1 & + & O_2 & + & 7O_3 & \leq & 0 \\
- & 7I_1 & + & 4O_1 & + & O_2 & + & 3O_3 & \leq & 0 \\
- & 8I_1 & + & 3O_1 & + & 2O_2 & + & 4O_3 & \leq & 0 \\
- & 6I_1 & + & 4O_1 & + & 2O_2 & + & 5O_3 & \leq & 0 \\
- & I_1 & & & & & & & \leq & 0 \\
- & 0I_1 & & & & & & & \leq & 0 \\
 & & - & 9O_1 & + & O_2 & + & O_3 & \leq & 0 \\
 & & & O_1 & - & O_2 & - & O_3 & \leq & 0 \\
 & & & O_1 & - & 9O_2 & + & O_3 & \leq & 0 \\
 & & - & O_1 & + & 3/2O_2 & - & O_3 & \leq & 0 \\
 & & & O_1 & + & O_2 & - & 7/3O_3 & \leq & 0 \\
 & & - & O_1 & - & O_2 & + & 1/4O_3 & \leq & 0 \\
- & I_1 & & & & & & & \leq & 0 \\
 & & - & O_1 & & & & & \leq & 0 \\
 & & & & - & O_2 & & & \leq & 0 \\
 & & & & & & - & O_3 & \leq & 0
\end{array}
$$

By setting these lower and upper weight limits across the set of variables present for a particular application, a model of performance can be created which is designed to specifically reflect the objectives of the DMU under assessment.

Hence, before the optimisations take place within the program, three stages of the DEAPMAS process are completed. To ensure significance in the results, these stages must fully involve the appropriate authority, be it owners, governing environment or simply those commissioning the study, depending on the application.

In summary, the first stage is identifying and agreeing the relevant factors to be included in the analysis, with reference to the objectives controlling the DMU.

Secondly, from these factors a list of representative variables is prepared, based in each case on either available statistics or on data collection where the benefit of the information obtained will clearly exceed the costs of collection.

The third stage both improves on and links the previous two, the building of the performance profile. It has been demonstrated that it is the relative balance of the factors which is of paramount importance as opposed to simply the variables utilised. This stage, therefore, is unlikely to be any less involved, and may be far more complex, than the identification stages.

In effect, these restrictions, both on individual variables and, hence, on the 'factors' as defined in the previous section, add effectiveness to what has been previously, at best, an efficiency model.

Beyond introducing effectiveness, the performance profile additionally compensates for the level of the point of measurement of the data, a problem when there is not a satisfactory single variable corresponding to each factor.

For example, activities X, Y and Z may be broadly equal in importance, it may be, however, that there are two available statistics relating to component parts of activity Y, and five distinct but overlapping statistics relating to activity Z. Undeveloped DEA would require that just one statistic for each be included, not only for the purpose of discrimination but also because, in effect, including all the measures could be seen as automatically ranking activity Y as up to twice as important as activity X and activity Z as up to five times as important as activity X.

Alternatively, activities X and Y may in fact be two components of activity XY. Despite being of equal status, activity Z (with only a single measure) could hence be seen as holding as little as half the significance of activity XY.

An implicit ranking of the activities is referred to above, this relative 'importance' definition occurs because the inclusion of multiple variables for one activity would increase the opportunity to apply weights in different ways to that particular activity. This improves the chances of weights being applied to all the variables in such a way as to create a combination of virtual inputs or virtual outputs which increases the pareto efficiency rating that is achieved.

This increase in the opportunity to become pareto efficient exists solely as a function of the number of variables which a particular activity contributes to the analysis. Clearly this demonstrates that the equal status which the undeveloped technique places on individual variables does not extend to the activities or factors which they represent.

Only by restricting each factor to a single variable as suggested above, could such equality be achieved. Restriction to, and hence selection of, a single variable for many factors would either be a complex task or result in unsatisfactory representation.

To aid consideration of the way in which the weight restrictions on individual variables combine to produce restrictions on factors or variable groups at all defined levels, The 'LOTUS 1-2-3' spreadsheet 'DEAPMAS Variable Weight Limit Combiner' was developed. As introduced in the previous sub-section, additionally, any data run involving a performance profile outputs a summary of the profile initially and at various subsequent points. The extent of this information is, of course, linked to the data on the structure of the variable groups that is input to the program.

The relative weights on these factors, or 'groups of variables' may be as important, or more important, as those on individual variables. Hence it is essential to identify not only the variables, which it has been established are not actually a list of contributory factors at all, but merely the actual points of measurement, but also the actual factors themselves at as many levels as have been identified.

As will be seen, this identification of variable groups becomes even more important when, for example, specialisation amongst variables is present. More than the relationship between individual variables, the effect on the relationship between the factors must be monitored during any changes on weight limits resulting from the specialisation, which is introduced in Section 5.4.

The spreadsheet 'DEAPMAS Variable Weight Limit Combiner' was developed to examine the effective factor weights created by setting weight restrictions on the individual virtual inputs and outputs, Figure 5.13 is an example of the way in which this reveals the profile of weight restriction beyond the level of the individual variable to groups of connected variables or factors. These, in turn, can be viewed as sub-divisions of the defined factors of the next level up.

Note that by simply adding the minimum limits on inputs or outputs, an indication of the actual total restriction is obtained. This total fixed weighting, hence reveals the percentage of weighting which is actually flexible. Naturally this figure should not vary merely as a function of the number of variables present. In this particular example there is 60% fixed weighting on inputs leaving 40% free for allocation during optimisation for each DMU. Similarly 55% of the output weights are fixed, leaving 45% flexible.

Figure 5.13. Example of DEAPMAS Variable Weight Limit Combiner Spreadsheet, Based on Variables Used in Australian University Engineering Department DEA Application.

	Academic Staff	Technical Support Staff	Minimum Entry Centile Rank	Avg. Apparent Completion Rates	Total EFTSU	Bachelor Degree Graduates Avg.	Graduate Diploma Graduates Avg.	Higher Degree Graduates Avg.	Research Expenditure Avg.	Relative Publication Rate	Relative Consultancy Rate
	I1	*I2*	*I3*	*O1*	*O2*	*O3*	*O4*	*O5*	*O6*	*O7*	*O8*
MINIMUM	20	20	20	10	0	5	5	5	10	10	10
MAXIMUM	60	60	60	40	10	25	25	25	40	40	40

	STAFF	*I3*	*O1*	*O2*	*GRADUATES*	*RESEARCH*	
MINIMUM	40	20	10	0	15	20	10
MAXIMUM	80	60	40	10	60	65	40

	STAFF	*I3*	*TEACHING*	*RESEARCH & CONSULTANCY*
MINIMUM	40	20	25	30
MAXIMUM	80	60	70	75

	INPUTS	*OUTPUTS*
MINIMUM	60	55
MAXIMUM	100	100

The proportion of fixed to flexible weighting should vary according to analysis of the topic and discussion by the owners, governing environment, or commissioners of the study as appropriate, rather than by the quantity of variables selected.

The maximum limits placed through a performance profile on the virtual inputs and virtual outputs cannot be treated the same way. To provide more than very narrowly defined flexibility, the total of all the individual maxima will usually exceed 100%. When each optimisation takes place, naturally only a subset of virtual inputs or outputs, can reach their set maximum.

When factors are considered, an additional restriction on the maxima may come into effect. This restriction prevents a factor's maximum (its variables' combined maxima) being reached, prior to optimisation. This is due to the total fixed minima for the other groups of variables preventing that factors maximum being feasible, before the flexible section of the weights have been optimised. In other words, for a particular factor; 100% less all other minima may leave less than the defined maximum, making it impossible for that maximum to be reached. Hence the 'actual' maximum would be less in such circumstances than that which was 'implied'.

Figure 5.13 is, then, an example of the 'DEAPMAS Variable Weight Limit Combiner' spreadsheet in use, and illustrates the above points. The example utilises 'Australian University Engineering School data' which was used in an undeveloped DEA application by Cameron (1988). This example featured three inputs and eight outputs and the spreadsheet considers the factors which the variables represent. The limits used were derived with little formal process, purely for the purpose of illustration.

There are several occasions in this representation of the spreadsheet which demonstrate 'actual' maxima being less than that which is 'implied'. The 'staff' inputs (I_1 and I_2) have a maximum by addition of 120%, naturally only 100% is feasible, but the actual maximum in effect is 80%; 100% less the minimum for I_3 (20%).

Similarly, 'teaching' is represented by the outputs O_1 to O_5, the implied maximum for 'teaching' would be 125%. Taking the other outputs minima (O_6 to O_8), however, yields an actual maxima for 'teaching' of 70% (The feasible 100% less 10% for each of O_6, O_7 and O_8).

Within the DEAPMAS program, the actual maxima for all defined variable groups, as opposed to those implied by simple addition, is calculated by the subroutine 'GROUPMINMAX'. As already referred to, the Subroutine 'PRNGROUP' then outputs the performance profile set for the individual variables. It then also defines each factor and displays the actual limits in effect on these. This is repeated whenever changes have occurred to the performance profile. Further information on both these subroutines can be found in Appendix B.

The variables applied in both undeveloped DEA and the DEAPMAS process are, then, merely points of measurement, whether specifically collected or simply utilised after being collated for other purposes. Hence it is the actual factors on which concentration should focus, naturally any individual variable may or may not be a factor in itself.

As will be seen in the following section which covers specialisation, when weight limits are being adjusted, an understanding of these factors as opposed to the individual variables applied becomes essential. This is why definition of variable groups is only mandatory when specialisation amongst variables is involved, although clearly such definition will improve the analysis whichever options are involved. As with all analytical techniques the significance of the results being highly dependent on the quality of the input data utilised.

5.4. Incomplete Data Sets; Specialisation Amongst Variables.

From a cursory examination of the various sources of UK university statistics, there are clearly many missing values in the various data sets. In some cases a 'zero' may be the appropriate method by which the data can be completed. In most cases this will not be acceptable, however, the missing value being simply unavailable or that statistic being inappropriate for the particular DMU.

Use of 'zeros' in such circumstances will affect the rating in different ways depending on a number of factors. If it is an input statistic, then a zero would imply no use of that resource and hence unfairly advantage the DMU in question. Similarly, if it is an output variable; the implication would be that the DMU had failed to achieve any output whatsoever, and hence would be disadvantaged.

The disadvantage suffered where the missing value is an output could be significantly increased where a performance profile is in place and a non-zero minimum variable weight limit has been defined. Naturally, the higher this minimum, the more difficult it will be for the DMU to achieve pareto efficiency. Very low ratings can be recorded in such circumstances, this will be dramatically illustrated in Section 7.4 of the results chapter, Chapter Seven.

In many cases, then, the lack of a method by which specialisation amongst variables can be handled within DEA will lead to some sub-set of DMU being disadvantaged, possibly severely, in other cases it may actually make the use of DEA completely impractical. For these reasons a methodology by which specialisation amongst variables can be handled has been developed within the DEAPMAS process.

The procedures for handling variable specialisation adopted within the DEAPMAS process are designed to eradicate any disadvantage that a DMU would suffer as a result of specialisation; where the specialisation itself is acceptable to those governing the analysis or where such 'specialisation' is actually due to problems of statistical availability. It is equally important, however, that the theory is implemented in such a way as to give the specialised

DMU no direct advantage from its specialisation beyond the elimination of any disadvantage.

The following sub-sections will look more closely at what specialisation entails; the transfer of minimum and maximum weight restrictions and the limits to which specialisation can be allowed to reach before the significance of the results is reduced.

All of the manipulations operate on data read into the DEAPMAS program subroutine 'SPECINPUT'. The subroutine 'SPECIALISE' carries out the alterations required to the weight limits of the performance profile; 'PERPROF' then forms the specialised set of performance profile constraints of the DEA LP problem. Summaries of the alterations and their effect are produced, with the aid of calls to the subroutines 'GROUPMINMAX' and 'PRNGROUP'.

The calls to these subroutines, necessary to effect the specialisation are called by the subroutine 'NEXTDMU' which additionally makes other required adjustments to the DEA LP problem. Further details of all these subroutines can be found by referring to the DEAPMAS program listing and program documentation in Appendix B.

5.4.1. The Rationale of DEAPMAS Variable Specialisation.

'Specialisation' as used here, is defined as the compensation of a DMU which is disadvantaged by a performance profile which demands a weight application on, or considers in the calculation of other restrictions, a variable in which that particular DMU does not participate, and as a result of which its deletion from the calculation of that DMU's pareto efficiency rating is not unacceptable to those governing the analysis.

The circumstances where participation would not be deemed necessary are either as a result of acceptable specialisation amongst activities or by restricted data collection/availability factors.

The 'compensation' is by means of calculation of a performance profile specific to that DMU, which is derived from the 'standard' or 'base' performance profile for the group of DMU under analysis. The purpose of this is to eliminate the source of relative disadvantage to the particular DMU, and hence to ensure the most appropriate and fair profile is used for each of the DMU. Equally, however, this form of compensation must be designed to ensure that no direct advantage is gained by a DMU as a result of such specialisation imparting a more 'generous' performance profile.

Specialisation within the DEAPMAS process involves the elimination of one or more variables in the analysis for a particular DMU or set of DMU and the recalculation of the performance profile pertaining to those DMU, usually including the transfer of each eliminated variable's weight restrictions.

5.4.2. Transfer of Variable Weight Restriction after a DMU Specialises Out of a Variable.

The eliminated variable's minimum weight limit, as defined in the standard performance profile, is 'transferred', by simple addition, in order to maintain the total level of minimum restriction, the proportion of fixed to flexible weighting. This is carried out pro-rata either to all others in the class (outputs or inputs) of variables, or to particular factors.

As already discussed (Section 5.3.2), the 'actual' maximum for a particular variable group may be less than that which is 'implied' by the addition of the maxima of its component variables, as a result of the arithmetic effect of the 'fixed' portion of the weighting. The elimination of a variable without transfer of its minimum weight application would therefore affect this 'actual', calculated maxima in such cases.

Transfer of an eliminated variable's weighting restriction within the DEAPMAS process is carried out directly to factors of the performance profile. This is always possible as definition of variable groups is mandatory in applications where specialisation amongst variables has been signalled as present (See Section 5.6). This form of transfer includes the ability to 'maintain' the previous level of total minimum weighting for a factor which the eliminated variable was a constituent of, simply by transferring the minimum restriction figure directly to that defined variable group.

Just as it is the insistence of minimum weight application on variables which together form the 'fixed' element in a performance profile, the setting of maximum weight restrictions define the limits to the way that the flexible portion of weighting can be applied.

The maximum weight restriction on a variable, or consequently on a factor, in effect defines the amount of the 'flexible' portion of the weighting which that variable, or factor, can receive. As such, the maxima figures set for variables are entirely independent and in isolation from each other. Where a single variable is eliminated, without any transfer of the set maximum weight limit for that variable, therefore, distribution of this 'flexible' element would be unaffected. For this reason, one option within the DEAPMAS program, is not to 'transfer' the maximum weight restriction at all.

Some 'maintenance' of the maximum weight effectively placed on a factor rather than a variable will usually be desirable, however, as the variable group maximum may have been defined, independently of the actual number of variables composing that factor. The option provided within the DEAPMAS program, therefore, is to 'transfer' the maximum weight restriction of the eliminated variable pro-rata to a particular factor.

Which of the above options is taken in a particular application would require examination of the complex inter-relationship of minima and maxima between both factors, and individual variables. In such analysis the spreadsheet supplement to DEAPMAS process 'DEAPMAS Variable Weight Limit

Combiner' provides necessary insight, as in the establishment of the standard performance profile (see Section 5.3.2), into the effects of changes resulting from the elimination of variables.

The possible permutations of transfers covering the exact response to variable deletion and the subsequent building of a specialised performance profile are clearly numerous. To demonstrate the principle of 'pro-rata transfer', however, one of the examples used in the previous section (Figure 5.13) is reproduced as Figure 5.14, with just variable codes, rather than the cumbersome variable names.

Figure 5.14. Example of DEAPMAS Variable Weight Limit Combiner Spreadsheet, Reproduced from Figure 5.13.

	I1	*I2*	*I3*	*O1*	*O2*	*O3*	*O4*	*O5*	*O6*	*O7*	*O8*
MINIMUM	20	20	20	10	0	5	5	5	10	10	10
MAXIMUM	60	60	60	40	10	25	25	25	40	40	40
	STAFF		*I3*	*O1*	*O2*	*GRADUATES*			*RESEARCH*		
MINIMUM	40		20	10	0	15			20		10
MAXIMUM	80		60	40	10	60			65		40
	STAFF		*I3*	*TEACHING*					*RESEARCH & CONSULTANCY*		
MINIMUM	40		20	25					30		
MAXIMUM	80		60	70					75		
	INPUTS			*OUTPUTS*							
MINIMUM	60			55							
MAXIMUM	100			100							

If, for a particular DMU, output O_5 was not participated in, and this was deemed acceptable, then the decision could be made that the appropriate course of action was to maintain the 'Graduates' factor, 'transferring' both the minimum and maximum weight limits, pro-rata between the remaining variables representing the factor. In this simple case this would simply be the addition of half of the values for that variable between outputs O_3 and O_4. The resulting specialised performance profile is shown in Figure 5.15.

Figure 5.15 Specialised Performance Profile After Deletion of Output O_5 from Spreadsheet of Figure 5.14.

Higher Degree Graduates Avg (O5)
Graduate Diploma Graduates Avg (O4)
Bachelor Degree Graduates Avg (O3)

	I1	I2	I3	O1	O2	O3	O4	O5	O6	O7	O8
MINIMUM	20	20	20	10	0	7.5	7.5	-	10	10	10
MAXIMUM	60	60	60	40	10	37.5	37.5	-	40	40	40

	STAFF	*I3*	*O1*	*O2*	*GRADUATES*	*RESEARCH*	
MINIMUM	40	20	10	0	15	20	10
MAXIMUM	80	60	40	10	60	65	40

	STAFF	*I3*	*TEACHING*	*RESEARCH & CONSULTANCY*
MINIMUM	40	20	25	30
MAXIMUM	80	60	70	75

	INPUTS	*OUTPUTS*
MINIMUM	60	55
MAXIMUM	100	100

Note that in the above figure the weight limits in effect on 'Graduates' have remain unaltered, as stipulated. Without transfer this factor would have been restricted to a minimum of 10% and a maximum of 50% of the total virtual outputs and furthermore; the maximum virtual output that could be applied to 'Research' would have increased to 70%. There would also, naturally, be similar consequences at the next level up.

Suppose that additionally this DMU, or group of DMU, also failed to participate in O_8, and that again this was deemed acceptable. It may be decided that in this case the minimum should be transferred to O_6 and O_7 in order to maintain the balance between teaching and non-teaching activities in the fixed element of virtual outputs. 'Research and Consultancy' would in effect no longer exist, and it may also be decided not to increase the maximum virtual weighting that can be applied to the individual variables of the factor 'research', and hence not to transfer the maximum. The effect of this is shown in Figure 5.16.

This confirms that despite not transferring the maximum weight restriction on O_8, the balance between teaching and non-teaching is maintained. Although there can statistically be exceptions, this demonstrates the general case. This norm is that the transfer of the minima of deleted variables is crucial to the performance profile at all levels, but that, generally, the transfer of variable maxima only has an affect at the individual variable level.

Figure 5.16. Specialised Performance Profile After Deletion of Outputs O_5 and O_8 from Spreadsheet of Figure 5.14.

Relative Consultancy Rate (O8)
Relative Publication Rate (O7)
Research Expenditure Avg. (O6)

	I1	I2	I3	O1	O2	O3	O4	O5	O6	O7	O8
MINIMUM	20	20	20	10	0	7.5	7.5	-	15	15	-
MAXIMUM	60	60	60	40	10	37.5	37.5	-	40	40	-

	STAFF	I3	O1	O2	GRADUATES	RESEARCH
MINIMUM	40	20	10	0	15	30
MAXIMUM	80	60	40	10	60	75

	STAFF	I3	TEACHING	RESEARCH
MINIMUM	40	20	25	30
MAXIMUM	80	60	70	75

	INPUTS	OUTPUTS
MINIMUM	60	55
MAXIMUM	100	100

As already stated, the type of transfers in the event of specialisation amongst variables being present used will vary according to preferences when a particular application is being analysed.

Finally, the option has also been provided of supplying, as part of the input data, a full set of minima or maxima for the group of DMU which have a particular variable or variables eliminated. This data would perhaps originate from consideration of the spreadsheet supplement, direct input being, in some cases, easier than arranging input data for a transfer to be effected during the data run.

5.4.3. The Limits of Specialisation; Questions of Significance.

It has been shown in the preceding section that for any DMU, regardless of the number of variables present, a specific specialised performance profile can be developed from the standard performance profile. This does not, unfortunately, entirely solve the problem which gives rise to the need for specialisation procedures; that of non-homogeneity of relevant or available variables.

Once a specialised performance profile has been developed for a DMU, or group of DMU, which does not participate in one or more variables, the pareto efficiency rating for these specialised DMU can be established. These specialised DMU, however, can play no significant role in the calculation of the pareto efficiency for the remaining DMU. To explain this point, take an application with numerous DMU in which DMU 'P' participates in all variables and DMU 'S' participates in all bar one; an output which has a lower weight limit in the standard performance profile of 20%.

A pareto efficiency could be established for DMU 'S' after the creation of a specialised performance profile in which the 20% fixed weighting on the output which it did not participate in was transferred to the other variables of the factor to which the 'missing' variable belonged. In the optimisation, there would be constraint lines for all DMU with the same 'missing' variable (and no others), and all the non-specialised DMU. There would, therefore, be a satisfactory level of 'competition' created as all DMU were involved in the calculation of the pareto efficiency rating for the specialised DMU.

In the calculation of the rating for DMU 'P', however, the standard performance profile would be applied. Hence DMU 'P' would face 'competition' via the constraint lines of the DEA LP matrix, from the other non-specialised DMU, but not of any significance from the group of specialised, and hence in terms of the standard performance profile 'disadvantaged', DMU.

Taking DMU 'S' as the example, in the constraint lines for the optimisation leading to DMU 'P's rating, the 'competition' which it provides will be insignificant as 20% of its virtual output must be created by applying a massive weighting to a variable in which it registers no output and is hence set by the DEAPMAS program at epsilon. Therefore, unless the eliminated variable has a lower weight limit of zero, in the optimisations for all other DMU the constraint line for any specialised DMU will have little effect on the rating achieved. As explained, this being due to the fact that some portion of the fixed weighting will be allocated against a variable in which that DMU does not participate.

Whether or not this lack of competition is of significance depends on whether the group of non-specialised DMU gains direct advantage, that is, gain higher ratings as a direct result of the presence of specialisation in the data for other DMU.

Clearly where a large number of DMU are involved and a very small percentage of DMU require a specialised performance profile, the calculation of the pareto efficiency of the non-specialised DMU will be satisfactory. There will clearly be a point beyond which the percentage of DMU involving specialisation begins to affect the calculation of ratings for the remaining DMU. Equally as this ratio rises a point will be reached where the pareto efficiencies calculated for the relatively small set of DMU using the standard performance profile are in reality of little or no significance.

No firm 'rule' can be stated regarding the precise point, in all applications, at which the proportion of specialised DMU first adversely influences the significance of the ratings of the other DMU or the point at which it severely affects this significance, as there are a number of contributory factors.

The proportion of DMU conforming to the standard performance profile is the vital consideration, but other factors will have an influence including; the size of the variable set, the proportion of the weight restrictions which are fixed rather than flexible, other details of the performance profile, and the complex relationship between the statistics of the different DMU in the particular application.

Initially, this appears to be a problem suffered within the DEAPMAS process, which is not present in the undeveloped DEA theory, however, it must be questioned if the ability to combine any DMU, regardless of the variables involved is actually an advantage in terms of the significance of the results.

Two DMU could in fact have no variables in common, but be combined and compared in an application of undeveloped DEA without any problem beyond that of attempting to interpret the results.

In fact, this discrepancy between the two approaches only highlights further, the impracticality of the undeveloped technique, and the way in which the developments within the DEAPMAS process yield an important increase in the practicality of this form of analysis.

It would seem, then, that the key issue surrounding the presence of specialised DMU is whether these DMU are a variant sub-set of a larger set of Decision-Making Units, or whether they constitute an incomparable separate set.

Separate sets of DMU could be indicated either in terms of there being a large proportion of specialised DMU, or when there are many variables which one or more of the specialised DMU does not participate in. The variable group structure developed for a particular application will aid determination of whether too great a degree of non-homogeneity exists.

With regard to the number of variables in which a particular DMU does not participate, clearly the importance of those variables, as defined in the performance profile, will be of paramount significance. A large number of relatively trivial variables could be excluded therefore, with less significance than a small number of key variables.

The solution to this problem would seem to be to monitor the proportion of the fixed element of the weighting which requires transferring in the building of a specialised performance profile for a particular DMU. Clearly, each individual application will differ on this, depending on the acceptability of the transfers, but confidence in the results would surely be affected once variables representing over half the fixed element of weighting, on either the input or output variables in the standard performance profile, were excluded.

In the case of the number of specialised DMU; the key issue is the ratio of DMU utilising the standard performance profile (those that are non-specialised) to those for which specialised performance profiles are developed. The variety and extent of specialisation by individual DMU is not relevant to this, just the total numbers of DMU involved.

As no firm generality has been put forward, a degree of caution has been exercised in order to attempt to minimise the risk of the specialised DMU gaining relative advantage from the lack of effective constraint on other DMU. Due to the number of different factors involved; the setting of an upper bound on the extent to which specialisation can be permitted in terms of the proportion of specialised DMU will be essentially arbitrary, but clearly a line must be drawn at some point.

A number of data runs were made to determine the area in which the proportion of non-specialised DMU becomes small enough to significantly affect the results. From the results of these a sufficiently cautious figure could then be adopted. Table 5.17 reports the results of these data runs. The test data was designed such that the degree of 'competition' between the DMU would be sufficient to intuitively suggest that any DMU would benefit significantly from a reduction in the total number of 'competitors'.

A 30 variable, 45 DMU fictional data set was utilised with a performance profile containing 60% fixed weights on both inputs and outputs, which as will be seen in Chapter Seven is typical of the largest of the actual data sets that will be considered within the thesis.

The calculations for the 'Specialised' DMU are irrelevant for the current purposes, the desired information can be gleaned by progressively reducing the number of DMU in the data set to simulate differing proportions of DMU adhering to the standard performance profile, and examining the results for DMU which are retained in all the data runs.

For academic interest this process was continued to a point where only five DMU remained, were figures more seriously required for the small proportion which these represent, the data runs could be repeated with a far larger data set in order that a larger number of DMU could be 'tracked' through the process of progressive reduction in the number of DMU.

Table 5.17. Results of Data Runs to Examine the Consequence of Differing Proportions of Non-Specialised DMU in a Data Set.

(%PE)	Number of total DMU in Data Run								
	45	40	35	30	25	20	15	10	5
DMU									
1	77	77	77	77	**78**	78	78	78	**100**
2	100	100	100	100	100	100	100	100	100
3	90	90	90	90	90	90	90	90	**100**
4	100	100	100	100	100	100	100	100	100
5	28	28	28	28	28	28	**38**	38	**55**
6	90	90	90	**91**	**94**	**99**	**100**	100	-
7	100	100	100	100	100	100	100	100	-
8	100	100	100	100	100	100	100	100	-
9	80	80	80	80	80	80	**86**	86	-
10	95	95	95	95	**100**	100	100	100	-
11	61	61	61	61	61	61	**100**	-	-
12	33	33	33	33	33	33	33	-	-
13	100	100	100	100	100	100	100	-	-
14	99	99	99	99	99	99	99	-	-
15	100	100	100	100	100	100	100	-	-
16	100	100	100	100	100	100	-	-	-
17	100	100	100	100	100	100	-	-	-
18	100	100	100	100	100	100	-	-	-
19	81	81	81	81	81	**82**	-	-	-
20	100	100	100	100	100	100	-	-	-
21	77	77	77	77	**82**				
22	100	100	100	100	100				
23	90	90	90	90	**100**				
24	100	100	100	100	100				
25	100	100	100	100	100				

Examining Table 5.17, it is suggested that the percentage of DMU utilising the standard performance profile should be in a majority, but by the mathematics of DEA, the effect of the absence of the specialised DMU in the optimisations for non-specialised DMU will become negligible where the non-specialised DMU constitute in excess of 80-90%.

In the absence of a more precise rationale, the figure used as a pass/fail measure within the DEAPMAS process errs on the side of caution at two-thirds (67%) of DMU utilising the standard performance profile. The DEAPMAS program displays a warning message questioning the significance of the results obtained where this test is failed, and a stronger warning advising of severely reduced significance where specialised DMU form a majority.

In the case of the university data prepared in the following chapter, the results of which are reported in Chapter Seven, wherever the two-thirds figure is breached, the DMU will be split to more comparable, distinct sets of DMU.

The following example is used to demonstrate these principles in practice, again drawing on the Australian University Engineering Schools data first introduced in Figure 5.13. Table 5.18 contains the variables used in the original application of undeveloped DEA, and shows which of the 22 DMU of that study were, in terms of the DEAPMAS process, specialised.

It is worth noting that in this application of the undeveloped theory only seven of the DMU were not revealed as 100% pareto efficient despite only five of the

Table 5.18. Extent of Specialisation Present for Each DMU in Australian University Engineering School Data.

	Academic Staff	Technical Support Staff	Minimum Entry Centile Rank	Avg. Apparent Completion Rates	Total EFTSU	Bachelor Degree Graduates Avg.	Graduate Diploma Graduates Avg.	Higher Degree Graduates Avg.	Research Expenditure Avg.	Relative Publication Rate	Relative Consultancy Rate
	I1	*I2*	*I3*	*O1*	*O2*	*O3*	*O4*	*O5*	*O6*	*O7*	*O8*
UNSW	.	.	.	.	.	.	.	.	.	.	.
RMIT	.	.	.	.	.	.	.	.	X	.	.
SYD	.	.	.	.	.	.	.	.	.	.	.
MON	.	.	.	.	.	.	.	.	.	.	.
UTS	.	.	.	.	.	.	.	.	X	.	.
QLD	.	.	.	.	.	.	X	.	.	.	.
MELB	.	.	.	.	.	.	X	.	.	.	.
CURT	.	.	.	.	.	.	.	.	X	.	.
QIT	.	.	.	.	.	.	.	.	X	.	.
SWIN	.	.	.	.	.	.	.	.	X	.	.
ADEL	.	.	.	.	.	.	X	.	.	.	.
UWA	.	.	.	.	.	.	X	.	.	.	.
SAIT	.	.	.	.	.	.	.	.	X	.	.
CHIS	.	.	.	.	.	.	.	X	X	.	.
WOLL	.	.	.	.	.	.	.	.	.	.	.
NEWC	.	.	.	.	.	.	.	.	.	.	.
FOOT	.	.	.	.	.	.	.	X	X	.	.
TAS	.	.	.	.	.	.	X	.	.	.	.
BALL	.	.	.	.	.	.	.	X	X	.	.
DDI	.	.	.	.	.	.	X	X	X	.	.
JCU	.	.	.	.	.	.	X	.	.	.	.
CIAE	.	.	.	.	.	.	.	.	X	.	.

22 participating in all variables. None of these five DMU were, not surprisingly, pareto inefficient.

In the tables and figures of this sub-section; an 'X' denotes a variable which is not participated in, and a dash (-) one which has been specialised out of.

There are, as already stated, only five DMU from the 22 present which are non-specialised; clearly failing the '2/3' rule adopted. It is, therefore, necessary to sub-divide the DMU into more comparable groups.

The most obvious course of action to achieve this sub-division is to separate the research and non-research Engineering Schools. This, extracting those DMU with zero research expenditure (O_6), creates two separate sets of DMU as shown in Tables 5.19 and 5.20.

Table 5.19. Extent of Specialisation Present for Each DMU in Table 5.18 Participating in Research.

	I1	I2	I3	O1	O2	O3	O4	O5	O6	O7	O8
UNSW	.	.	.	.	.	.	.	.	.	.	.
SYD	.	.	.	.	.	.	.	.	.	.	.
MON	.	.	.	.	.	.	.	.	.	.	.
QLD	.	.	.	.	.	.	X	.	.	.	.
MELB	.	.	.	.	.	.	X	.	.	.	.
ADEL	.	.	.	.	.	.	X	.	.	.	.
UWA	.	.	.	.	.	.	X	.	.	.	.
WOLL	.	.	.	.	.	.	.	.	.	.	.
NEWC	.	.	.	.	.	.	.	.	.	.	.
TAS	.	.	.	.	.	.	X	.	.	.	.
JCU	.	.	.	.	.	.	X	.	.	.	.

Table 5.20. Extent of Specialisation Present for Each DMU

in Table 5.18 Not Participating in Research.

	I1	I2	I3	O1	O2	O3	O4	O5	(O6)	O7	O8
RMIT	.	.	.	.	.	.	.	.	-	.	.
UTS	.	.	.	.	.	.	.	.	-	.	.
CURT	.	.	.	.	.	.	.	.	-	.	.
QIT	.	.	.	.	.	.	.	.	-	.	.
SWIN	.	.	.	.	.	.	.	.	-	.	.
SAIT	.	.	.	.	.	.	.	.	-	.	.
CHIS	.	.	.	.	.	.	.	X	-	.	.
FOOT	.	.	.	.	.	.	.	X	-	.	.
BALL	.	.	.	.	.	.	.	X	-	.	.
DDI	.	.	.	.	.	.	X	X	-	.	.
CIAE	.	.	.	.	.	.	.	.	-	.	.

The split between research and non-research Engineering Schools is, hence, 50/50. Of the Eleven DMU participating in research, there are, of course, still the same five participating in all variables, a figure well below the necessary two/thirds. This indicates a further split is necessary, from Table 5.19 it will obviously be the separation of those DMU which do not produce Graduate Diploma Graduates (O_4).

In the case of the DMU which do not participate in research, seven of the eleven would use the standard performance profile for this group. This is narrowly less than two-thirds of the total, and therefore as for the Engineering Schools which do participate in research; a further split is necessary. Table 5.20 clearly indicates that this separation will be of the non-research DMU which do, and those which do not, produce Higher Degree Graduates (O_5).

Table 5.21 shows the four separate groupings which would result. Ratings for all of which could then be satisfactorily established. There would, in fact, finally be only the one specialised DMU in the group of non-research, non-higher degree schools; the Engineering School 'DDI' not participating in Output O_4, that is, not producing Graduate Diploma Graduates.

Hence only one DMU in this example actually makes use of specialisation, the DEAPMAS process having determined that the data cannot be considered as a whole, but in fact represents four distinct sets of DMU. Each of which can then be internally compared, with confidence in the relevance of the results obtained.

Table 5.21. Four Distinct Groupings of Australian University Engineering Schools Indicated by the DEAPMAS Process.

GROUP 1. (DMU participating in all variables).

	I1	I2	I3	O1	O2	O3	O4	O5	O6	O7	O8
UNSW	•	•	•	•	•	•	•	•	•	•	•
SYD	•	•	•	•	•	•	•	•	•	•	•
MON	•	•	•	•	•	•	•	•	•	•	•
WOLL	•	•	•	•	•	•	•	•	•	•	•
NEWC	•	•	•	•	•	•	•	•	•	•	•

GROUP 2. (DMU participating in research (O_6), but not Graduate Diplomas (O_4)).

	I1	I2	I3	O1	O2	O3	(O4)	O5	O6	O7	O8
QLD	.	.	.	.	.	.	-	.	.	.	.
MELB	.	.	.	.	.	.	-	.	.	.	.
ADEL	.	.	.	.	.	.	-	.	.	.	.
UWA	.	.	.	.	.	.	-	.	.	.	.
TAS	.	.	.	.	.	.	-	.	.	.	.
JCU	.	.	.	.	.	.	-	.	.	.	.

GROUP 3. (DMU not participating in research (O_6), but participating in Higher Degrees (O_5)).

	I1	I2	I3	O1	O2	O3	O4	O5	(O6)	O7	O8
RMIT	.	.	.	.	.	.	.	.	-	.	.
UTS	.	.	.	.	.	.	.	.	-	.	.
CURT	.	.	.	.	.	.	.	.	-	.	.
QIT	.	.	.	.	.	.	.	.	-	.	.
SWIN	.	.	.	.	.	.	.	.	-	.	.
SAIT	.	.	.	.	.	.	.	.	-	.	.
CIAE	.	.	.	.	.	.	.	.	-	.	.

GROUP 4. (DMU neither participating in research (O_6), nor Higher Degrees (O_5)).

	I1	I2	I3	O1	O2	O3	O4	(O5)	(O6)	O7	O8
CHIS	.	.	.	.	.	.	.	-	-	.	.
FOOT	.	.	.	.	.	.	.	-	-	.	.
BALL	.	.	.	.	.	.	.	-	-	.	.
DDI	.	.	.	.	.	.	X	-	-	.	.

5.4.4. The DEA LP Matrix After Specialisation.

It has been shown so far in section 5.4 that the DEAPMAS process effects specialisation amongst variables by introducing a specialised performance profile for DMU which, acceptably, do not participate in certain variables. This section illustrates that although the main difference in the preparation of the DEA LP matrix for rating these DMU is a series of adjustments to the standard performance profile, a number of other important differences do exist.

These differences are adjustments to the first lines of the LP matrix, those constraining the outputs of the subject DMU to unity, and all the DMU constraint lines which follow. Adjustments which are necessary in order to ensure correct adoption of the specialised performance profile (which by definition leads to an optimisation with one or more variables completely absent from the matrix), and that other incompatible specialised DMU are not involved in the optimisation.

This sub-section, therefore, reveals the way in which the DEA LP matrix is altered to adopt these changes. Further details of this can be found by reference to the responsible subroutines in Appendix B, namely 'SPECINPUT', 'ANALYSE', 'NEXTDMU', and 'SPECIALISE'.

The primary loop within the DEAPMAS program adjusts the DEA LP matrix and objective function ready for the calculation of each DMU's pareto efficiency; as detailed in Section 5.2. This process begins after the initial input information has been read in, including most of the information necessary to carry out specialisation amongst variables. In fact, the only program input which does not take place prior to this loop is the direct input of lower or upper weight limits for a particular group of specialised DMU, where that option has been selected, as introduced in Section 5.4.3.

For all DMU, whether they utilise the standard performance profile, or a specifically created specialised performance profile, the performance profile constraint lines are built by the same subroutine, without any difference, ready for optimisation by the DEAPMAS linear program subroutines. There are a number of extra alterations which take place elsewhere in the primary loop, however, when the set of DMU includes some which do not participate in all variables.

Where specialisation is present in a particular application, for any DMU, after the LP matrix has had the first two lines (the 'unity' constraints of Section 5.2) set and the performance profile constraints added after all the DMU constraint lines, a number of other adjustments are made. The 'master' matrix is always safeguarded as it is a copy which is adjusted before being submitted for optimisation.

If the current, subject, DMU is specialised then each eliminated variable is set at zero for all the DMU constraint lines, and the two unity lines. The objective function needs no alteration as the specialised performance profile also sets both the lower and upper limit for eliminated variables to zero.

Finally, where the subject DMU is specialised, all the specialised DMU constraint lines except those belonging to the group in which the subject DMU belongs are completely set at zero, that is, eliminated from the analysis.

Full details of these additional alterations can be found by referring to the program documentation and listing for the subroutine 'ANALYSE' in Appendix B.

5.5. Environmental Factor Consideration; Affected Variable Adjustment.

Recalling the Section 4.4 in the fourth chapter; an environmental factor was defined as an influence external to a DMU, but which affects its operation and associated statistics, thus complicating comparison with other DMU. These environmental factors are often the effect simply of geographic or demographic variations.

When undeveloped DEA has been applied with environmental factors identified, the most common method of including them has been to treat them as 'Contextual Input Variables'; and include them alongside the inputs identified for the application. It was argued that this approach was inappropriate as, rather than taking into account such information, it could lead to assessment of a DMU being affected by or possibly dominated by, statistics which are entirely independent of the DMU and which it has no control over.

Conceptually, the problem with this approach is that it is the 'system' in which the DMU operates, and which includes the DMU, which is assessed rather than solely the activities of the DMU itself.

The pareto efficiency of a DMU could conceivably alter over time as a result of changes in an environmental factor, and regardless of the activities of the DMU, and in particular; regardless of its reaction to that very change in environmental influence.

It was concluded in Section 4.4 that a different approach should be taken to including the influence of environmental factors, that of Affected Variable Adjustment (AVA). It is this principle which is adopted within the DEAPMAS process, adding or subtracting a percentage from existing variables.

The primary advantage of this method is that percentage adjustments are made to actual statistics, in a compensatory manner. This both avoids the inclusion of 'fabricated' separate variables and targets the adjustment directly on the relevant variables. Separate inclusion under an application of the undeveloped theory would endow the environmental factor with equal status to that of the other inputs; there being no distinction between any of the input set. Within an application of the DEAPMAS process, separate inclusion would require the setting of limits within the performance profile for the environmental factor; for which there would be no apparent rationale. This somewhat contradictory concept only serves to further highlight the shortcomings of the 'contextual input' approach.

One or more variables, which could consist of inputs, outputs, or both, can be adjusted for all DMU, for each environmental factor identified. It could be, of course, that an environmental factor only affects a subset of the DMU, or possibly is relevant to just a single DMU. Naturally, such circumstances are not a problem with a pre-adjustment technique such as AVA, were the 'contextual input' approach used, however, this would clearly not be the case.

With the undeveloped technique, an environmental factor which does not affect all the DMU could not be utilised, as a zero for the DMU which are not involved would unfairly advantage these DMU, zero, of course, being the 'perfect' input. Equally, within the DEAPMAS process, the 'contextual input' approach could lead to reductions in the significance of the results due to the need to build specialised performance profile for all DMU which are not involved in each environmental factor (as discussed in Section 5.4.3).

Affected Variable Adjustment is, then, a pre-adjustment of the data which takes place prior to any of the optimisations for individual DMU, that is, before the primary program loop, rather than as part of the data preparation preceding each calculation of a pareto efficiency.

The environmental factors themselves must be clearly established, identifying which variables are affected and whether the influence is advantageous or disadvantageous, from which the opposite, compensatory direction is identified.

Full details of the way in which Affected Variable Adjustment is carried out can be found by referring to the program documentation and listing for the Subroutine AVA in Appendix B. This section of the DEAPMAS program is designed to carry out manipulation of the environmental factor data itself from its raw form, thus preventing the need for calculations outwith the program.

These calculations depend on the form in which the environmental factor data originates. The effect of the environmental factor (advantageous or disadvantageous) taken in connection with whether the data is progressive or regressive, will determine whether the DEAPMAS program should be instructed to invert the data or not and whether it should then be added or subtracted; Figure 5.22 displays the possible permutations.

The only other data necessary is a scaling factor for each environmental factor, to keep the statistics manageable by compensating for the magnitude of the original environmental factor data.

Figure 5.22 shows all the possibilities for adjusting a variable by a percentage represented by an environmental factor, where the variable is an output. Where an input is to be adjusted, then the same rules can be applied, the only difference being that it will, of course, be necessary to multiply the adjustment statistic by -1 in order to create the correct compensatory direction. This step is carried out automatically within the DEAPMAS program.

Figure 5.22. Forms of Affected Variable Adjustment.

		FORM OF DATA	
		PROGRESSIVE	REGRESSIVE
COMPENSATORY DIRECTION REQUIRED	+	ADD NO INVERSION	ADD INVERTED
	-	SUBTRACT NO INVERSION	SUBTRACT INVERTED

5.6. Summary of Options Within DEAPMAS Process.

For the purposes of comparison, the various aspects of the DEAPMAS process formalised in this chapter will be introduced consecutively in Chapter Seven to the data that will be selected in Chapter Six.

This will begin with running the data through undeveloped DEA, and then introducing weight restriction, specialisation amongst variables, and finally environmental factor consideration into the analysis.

Naturally, any subsequent use of the DEAPMAS program would not require the many data runs which are produced; the aspects of the process which are required for a particular application could be selected in a single data run. Figure 5.23 shows the principal options available, subsidiary options allow the inclusion of both DMU and variable names. Additionally, the provision of variable group data is also optional, except where specialisation amongst variables is included, in which case it becomes mandatory to allow clear operation of the specialisation procedures.

Figure 5.23. Principal Options Within the DEAPMAS Program.

	OPTIONS					
DATA ENVELOPMENT ANALYSIS	*	*	*	*	*	*
WEIGHT RESTRICTION BY PERFORMANCE PROFILE		*	*	*	*	
SPECIALISATION AMONGST VARIABLES			*	*		
ENVIRONMENTAL FACTOR CONSIDERATION (AVA)				*	*	*

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6. DATA SELECTION AND ANALYSIS.

In Chapters Three, Four and Five the choice of analytical model was made and the somewhat unsatisfactory Data Envelopment Analysis was developed to a considerable extent. The resultant process is both more practical and more flexible than that from which it is derived and is, hence, suitable for use in a wide range of applications including the measurement of university performance.

Drawing on the findings of Chapters One and Two, the purpose of this chapter is to obtain, from existing sources, appropriate university performance indicators and determine the range of 'DMU' over which these can be applied; noting all caveats that are encountered or created during the process of data selection and manipulation.

6.1. Scope of Data Analysis.

The analysis for universities was not carried out for the institutions as a whole, but at a level more close to Academic Departments, though this term was applied fairly loosely, conforming primarily to the Universities Funding Council's (UFC) administrative practices rather than academic considerations.

Comparison of universities at institutional level appeared unrealistic as the differing subject mixes make any attempt at practical analysis somewhat tenuous as a result of the widely differing nature of resource use and activities across different subjects.

Comparison at levels where the academic decision making over activities and to a limited extent over resource use is carried out is most appropriate to the analysis, and maximises the opportunity to compare like with like.

The first example used was Business and Management, or more accurately, data corresponding to the UFC's cost centre 32; "Business and Management Studies". This comprises of 27 universities or DMU, the variables which will be discussed at length later amounted to eight inputs and nine outputs. Whilst this is modest compared to the second example, it would have been considered large scale had the data been input to a program effecting undeveloped, or basic, DEA.

The second example is more ambitious combining data representing several cost centres, all of which are contained within one of the UFC's Academic Subject Groups, namely Subject Group Five; "Physical Sciences". Data is used which refers to the subject group wherever possible, otherwise the following cost centre data is utilised; 14: Chemistry, 15: Physics, and 16: Other Physical Sciences. A total of 46 universities are involved, with no less than 33 variables (twenty inputs/thirteen outputs), making this example larger than the previous one in all respects.

There are important caveats pertaining to both of the above subject/departmental definitions in addition to those regarding the individual items of data, and these can be found in Section 6.6.

Caveats regarding the data used are an integral part of any discussion of data analysis and results, whenever they exist for a particular example and they have been included within the main text in order to stress this importance rather than, as more commonly when such statistics are presented, hidden in the Appendices.

6.2. Choice of Variables for University Departments.

When considering variables for use in analysis, it should be remembered that it is required and desirable outputs which are of relevance, and not merely the products of a system, similarly it is the use of all scarce resources, or resources that could have been fed to an alternative university that need to be included as inputs.

First the ideal measures will be discussed, followed by a conversion of these to conform to available data with as little alteration as possible. As with any application of an analytical model, including the DEAPMAS process, the significance of the results obtained will be determined directly by the extent of this difference, taken together with the quality of the data used.

6.2.1. Inputs to University Departments.

At the broadest level, as would be the norm for the input side, inputs to university departments fall into two categories, financial and other resources. Ideally we would like the income of a university split to the two main functions; teaching and research, with a residual category covering expenditure which does not fall under either of these headings. Administrative expenditure would all be split appropriately between teaching and research.

Non-monetary resources for our example are those which by their deployment in one university could be viewed as depriving other universities of a scarce resource. Thus, for example, catering employees or security staff would be adequately reflected as an input through their inclusion within the overall budget of the university. Their services at one university could not be considered as depriving other universities of a resource which is in scarce supply. The appropriate measures which do reflect the use of scarce resources are those pertaining to academic staff and to students.

Ideally some form of weighting would be utilised to develop a statistic which reflects the composition of staff rather than simply the number within the department. Equally rather than simply looking at student numbers, the entry qualifications would also be an important indicator, for both undergraduates and postgraduates. It would also be vital to distinguish between research and taught postgraduates.

The presence of student input statistics together with the output statistics relating to graduates which are discussed in Section 6.2.2, initially causes some conceptual concern as in effect the same statistic can be interpreted as being present as both an input and an output.

It would seldom be argued that the number of graduates produced is not relevant, but it could be suggested that because of its inclusion as an output, there should not be a corresponding input connected to student numbers. There would appear to be two levels of reasoning, however, which point to inclusion in this manner.

Firstly, it could be argued that the same statistic is not in fact being used, that the inputs of students and other resources combine to produce various outputs collectively known as graduates, and that there is hence no 'double-counting' any more than if the input 'sand' to concrete production could not be considered because of the output 'quantity of concrete'.

Secondly, however, in a dynamic situation where assessment was repeated at regular intervals, the presence of student input statistics ensures that an institution cannot appear relatively efficient by taking in excessive numbers of students, having very high wastage rates and producing only high quality graduates. Without available wastage rate statistics only inclusion of student data as an input can avoid this problem.

It should be noted that it is a somewhat different development that leads to research income appearing as both an input and an output, surrogating in one time period for resource use (input) and in a later one the figure representing turnover (output). Here the, not entirely satisfactory, situation arises purely because figures more closely related to the ideal measures sought are simply not available.

Figure 6.1 summarises these measures, showing that ideally there would be a total of eight separate input variables. The availability of data, however, will inevitably alter this list.

Unfortunately it is not possible under current accounting practices to split a department's income cleanly into teaching and research. It is generally accepted, however, that a department's recurrent expenditure is split by a ratio of approximately 60:40 between teaching and research respectively, for example see Turney (1987), and this is used as the closest approximation available. To the 40% attributable to research can be added the departmental recurrent specific expenditure from research grants and contracts.

Information on the breakdown of academic staff in individual departments could not be obtained and a choice had to be made between either using salaries of academic and academic related staff or using academic staff numbers. Full-time wholly university-financed academic staff was chosen as this ignored all academic staff financed from other sources.

Figure 6.1. Ideal Input Measures for University Departments.

1. DEPARTMENTAL INCOME.

A. ATTRIBUTED TO RESEARCH.

B. ATTRIBUTED TO TEACHING.

2. ACADEMIC STAFF WITHIN DEPARTMENT.

A. STATISTIC CREATED BY WEIGHTING OF:

(i) PROFESSORS.
(ii) READERS / SENIOR LECTURERS.
(iii) LECTURERS.
(iv) PART-TIME AND OTHERS (Full-Time Equivalent).

3. STUDENT ENTRY TO DEPARTMENT.

A. UNDERGRADUATE NUMBERS.

B. STATISTIC REFLECTING UNDERGRADUATE ENTRY QUALIFICATIONS.

C. RESEARCH POSTGRADUATE NUMBERS.

D. TAUGHT POSTGRADUATE NUMBERS.

E. STATISTIC REFLECTING POSTGRADUATE ENTRY QUALIFICATIONS.

The advantage of omitting academic staff financed from other sources becomes clear when it is remembered that, as with undeveloped DEA, DEAPMAS is not designed only to assess units at a single point in time. As the process can be used at regular intervals, to assess the changes that occur over time, the choice of variables must therefore take into account the reaction that units may make to assessment. University departments are therefore strongly encouraged to finance staff from sources other than the university itself through its omission from the analysis. Such staff are, hence, 'free' inputs in this sense, departments being encouraged to generate additional income without being penalised in analysis as a result.

Statistics for the use of the resource of students were available as above with the exception that there is no available statistic reflecting postgraduate entry qualifications and this had to be omitted. The undergraduate entry qualification is, however, somewhat of a surrogate as it deals only with a 'mean score' based solely on the principal entry qualification, and hence ignores students with other entry qualifications. it is important therefore that variables for total numbers be retained as above.

The revised list of inputs is hence as given in Figure 6.2 which results, coincidentally, in eight actual input measures.

6.2.2. Outputs from University Departments.

As with the inputs, ideally outputs should fall into two main categories; teaching and research. Additionally an acceptable and desirable output would be the benefit derived from a university by the local business and social community.

Figure 6.2. Actual Input Measures Utilised for University Department Application.

1. DEPARTMENTAL EXPENDITURE.

A. TOTAL RECURRENT FROM GENERAL INCOME ATTRIBUTABLE TO RESEARCH.

B. RECURRENT SPECIFIC ON RESEARCH GRANTS AND CONTRACTS.

C. TOTAL RECURRENT FROM GENERAL INCOME ATTRIBUTABLE TO TEACHING.

2. ACADEMIC STAFF WITHIN DEPARTMENT.

A. FULL-TIME WHOLLY UNIVERSITY FINANCED.

3. STUDENT ENTRY TO DEPARTMENT.

A. UNDERGRADUATE NUMBERS.

B. MEAN SCORE OF MAIN UNDERGRADUATE ENTRY QUALIFICATIONS.

C. RESEARCH POSTGRADUATE NUMBERS.

D. TAUGHT POSTGRADUATE NUMBERS.

On the teaching side ideally we would use measures which reflect both the suitability of former students, and in the longer term former student achievement. There are two aspects to note here: Firstly, we are dealing with all former students and not just those who graduate; and secondly, analysis is focused on the use made of former students by society, their success after leaving university. By merely focusing on degrees, we are looking simply at the product at the factory gates and not its suitability or success in the marketplace. As argued in the second chapter, degrees and other qualifications are in reality only intermediate outputs, or final processes.

It is widely believed that one acceptable measure of research quality is research income, as the vast majority of research work is won under competition and reflects the reputation that a department has earned. But monetary assessment is not sufficient in itself and ideally a statistic which reflects cumulative research importance and achievement in individual projects would be compiled.

The statistic would finally comprise only a relatively small percentage of all projects which would be chosen by the department itself, which would not only make assessment more practical but more importantly would not dissuade the undertaking of projects with a low chance of a successful outcome.

Such projects could gain much merit if deemed successful therefore, but could otherwise be overlooked in favour of other more successful projects.

These areas of output measures are summarised in Figure 6.3. This figure and the preceding discussion indicate at least six separate output measures that would ideally be used.

Figure 6.3. Ideal Output Measures for University Departments.

1. TEACHING QUALITY.

A. FORMER STUDENT SUITABILITY.

WEIGHTED STATISTIC CALCULATED FROM FORMER STUDENTS IN:
- (i) Permanent employment.
- (ii) Temporary/short term employment.
- (iii) Research.
- (iv) Education/training excluding research.

B. FORMER STUDENT ACHIEVEMENT.

MEASUREMENT BY PROGRESS IN TERMS OF BOTH:
- (i) SALARY.
- (ii) ATTAINMENT OF POSITIONS OF DISTINCTION.

2. RESEARCH QUALITY.

A. EARNED RESEARCH INCOME.

B. RESEARCH PROJECT IMPORTANCE/ACHIEVEMENT.

3. COMMUNITY/LOCAL BUSINESS INVOLVEMENT.

A. STATISTIC REFLECTING BENEFIT GAINED FROM PRESENCE OF DEPARTMENT.

A lack of empirical information on nearly all these areas prevails, however, and the discrepancy between the ideal and actual measures for outputs will be far greater than that for inputs in this example.

Figures are simply not available for former students as a whole and deal only with graduates. Likewise there is no reliable, comprehensive measures of former student or graduate achievement. We can use statistics from first destination surveys, however, to represent the initial occupations of graduates. As such surveys are not comprehensive, there is no alternative but to also include the number of graduates as an indicator and in the case of higher degrees this is the sole measure as no first destination figures are available.

The research measures follow the ideal measures more closely. Earned research income is represented by recurrent specific expenditure on research grants and contracts, and although no assessment of research exists in the terms couched, the Universities Funding Council's Research Selectivity Exercise rated research quality on a scale of five down to one. These ratings were by somewhat subjective means, the standards against which they were awarded are listed in Appendix C.

In reality it would be very difficult to assess the benefits accrued to local business and the community as the result of the presence of a university department. Continuing education is, however, an important aspect of this, and figures for this area are readily available. Student-hours would be a more relevant measure, but course numbers is the only available category for the statistic at the required level.

The revised list of output measures is hence as given in table 6.4. Section 6.3 deals with the sources of data from which these actual input and output

Figure 6.4. Actual Output Measures Utilised for University Department Application.

1. TEACHING QUALITY.

A. FIRST DESTINATIONS OF GRADUATES.

(i) TOTAL NUMBER OF KNOWN DESTINATION.
(ii) NUMBER IN PERMANENT EMPLOYMENT.
(iii) NUMBER IN SHORT-TERM EMPLOYMENT.
(iv) NUMBER IN FURTHER EDUCATION, RESEARCH OR TRAINING.

B. NUMBER OF FIRST DEGREE GRADUATES.

C. NUMBER OF HIGHER DEGREE GRADUATES.

2. RESEARCH QUALITY.

A. RECURRENT SPECIFIC EXPENDITURE ON RESEARCH GRANTS AND CONTRACTS.

B. RESEARCH SELECTIVITY EXERCISE RATING.

3. CONTINUING EDUCATION.

A. TOTAL COURSES.

measures are drawn for the two examples. Later sections also examine the choice of timescales, the actual data tabulation including the Decision-Making Units involved, and relevant caveats on these.

6.3. Data Sources for University Department Application.

As explained in Section 6.2, the difference between the 'ideal' inputs and outputs and the actual variables listed is entirely due to the availability of data. The lists of actual variables used was therefore, compiled after the sources of data had been established. Many of the statistics are taken directly from these sources, others required some manipulation or estimate. The data sources for all the variables are covered in this section. The tabulation of the data is covered in Section 6.6, with additional detail given in Appendix C.

In addition to establishing the data sources, there are two other issues which must be dealt with prior to the data tabulation. Section 6.4 covers the universities involved in each example and Section 6.5 explains the logic of the various time periods which different statistics refer to.

A total of nine statistical publications were used as data sources, seven of these being different editions and volumes of the same series published jointly by the University Grants Committee (UGC) and Universities' Statistical Record (USR). One of the other publications was produced jointly by the UGC and the Committee of Vice-Chancellors and Principals (CVCP), and the remaining source was published by the Universities' Funding Council (UFC).

The full titles of these publications are given below in Table 6.5 together with codes used for reference later in this Chapter.

Table 6.5. Data Sources for University Performance Indicators.

SOURCE	TITLE	CODE
UGC/USR	UNIVERSITY STATISTICS VOLUME 1 "STUDENTS AND STAFF". 1985-86 & 1987-88 EDITIONS	(V1S)
UGC/USR	UNIVERSITY STATISTICS VOLUME 2 "FIRST DESTINATIONS OF UNIVERSITY GRADUATES". 1987-88 EDITION	(V2D)
UGC/USR	UNIVERSITY STATISTICS VOLUME 3 "FINANCE". 1984-85, 1985-86, 1986-87 & 1987-88 EDITIONS	(V3F)
CVCP/UGC	UNIVERSITY MANAGEMENT STATISTICS AND PERFORMANCE INDICATORS IN THE UK. 1988 EDITION	(MST)
UFC	RESEARCH SELECTIVITY EXERCISE 1989: THE OUTCOME.	(RSE)

6.4. University Departments; The Decision Making Units.

The universities included in both examples were primarily determined by the presence of statistics within the sources of data. If a university had no entries in any of the three editions referenced of Volume Three of the UGC/USR publication (specifically table Nine), then it was deemed for the purposes of the study as not being involved in that academic area.

Additionally, data for a number of universities was substantially incomplete for various reasons over the time period involved, and these universities were also excluded from analysis. The universities involved in the two examples are shown in Table 6.6. At this point the abbreviated codes for the DMU are introduced, these four-letter codes are input and used within the DEAPMAS program.

To aid clarity the first example, Business and Management Studies (Cost Centre 32), will be referred to as 'Example A'. The second and larger example involving the Physical Sciences (Subject Group Five) and specifically Physics, Chemistry and Other Physical Sciences (Cost Centres 14, 15 and 16 respectively) will therefore be referred to as 'Example B'.

'Example A' therefore involves a total of 27 universities or DMU and the larger 'Example B' contains 46 DMU.

6.5. Variable Time Period Selection.

All data used refers to time periods of one year, with the exception of the research quality statistic, which refers to reputation established over a number of years (see definition in Appendix C). In the majority of cases this 'year' is the academic year, but in some it refers to the calendar year.

The latest available data for all output measures published by the end of 1989 was utilised. At this point the majority of the latest data refers to the academic

Table 6.6. The Decision Making Units of Examples 'A' and 'B'.

	EXAMPLE A	EXAMPLE B	ABBREV. CODE
Aston	*	-	ASTN
Bath	*	*	BATH
Birmingham	-	*	BHAM
Bradford	*	*	BRAD
Bristol	-	*	BRIS
Brunel	-	*	BRUN
Cambridge	-	*	CAMB
City	*	-	CITY
Durham	-	*	DHAM
East Anglia	-	*	EANG
Essex	-	*	ESSX
Exeter	-	*	EXTR
Hull	*	*	HULL
Keele	-	*	KEEL
Kent	*	*	KENT
Lancaster	*	*	LANC
Leeds	*	*	LEED
Leicester	-	*	LEIC
Liverpool	-	*	LIVR
London Business School	*	-	LBUS
London	*	*	LOND
Loughborough	*	*	LBRO
Manchester Business School	*	-	MBUS
Manchester	-	*	MANU
Manchester Inst. of Sci. and Tech.	*	*	MIST
Newcastle	*	*	NEWC
Nottingham	-	*	NOTT
Oxford	-	*	OXFD
Reading	-	*	READ
Salford	-	*	SALF
Sheffield	*	*	SHEF
Southampton	*	*	SOTN
Surrey	*	*	SURY
Sussex	-	*	SUSX
Warwick	*	*	WARW
York	-	*	YORK
Aberystwyth	-	*	ABWY
Bangor	-	*	BNGR
Cardiff	*	*	CARD
St. Davids Lampeter	-	-	
Swansea	-	*	SWAN
Univ. Wales College of Medicine	-	-	
Univ. Wales Inst. of Sci. and Tech.	*	*	UWST
Aberdeen	-	*	ABDN
Dundee	-	*	DUND
Edinburgh	*	*	EDIN
Glasgow	*	*	GLAS
Heriot-Watt	*	*	HWAT
St. Andrews	-	*	ANDW
Stirling	*	*	STIR
Strathclyde	*	*	CLYD
Queen's Belfast	*	*	BELF
Ulster	*	-	ULST

year 1987-1988. There are exceptions to this, however, referring for example to the Calendar year 1987.

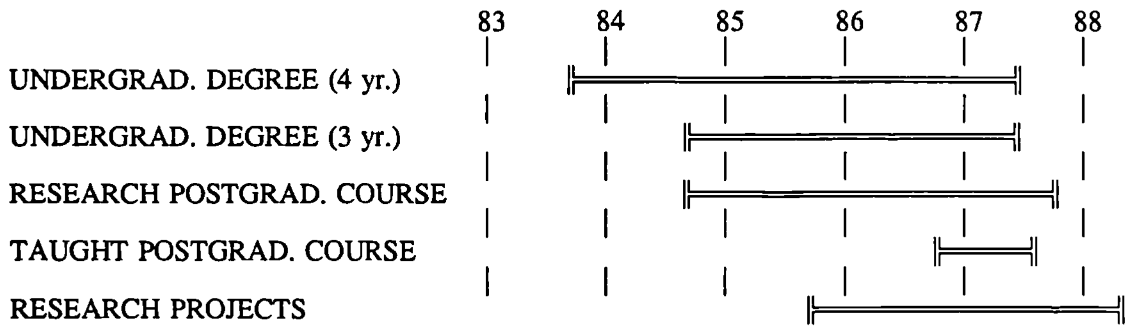
The quality and breadth of data collection and presentation has increased year by year since the early 1980's to an extent that would have made the use of many of the performance indicators examined impossible just a few years earlier.

In practice data is utilised which refers to 1987-1988 and to Calendar years 1987 and 1989 (The 1989 data being the research quality statistics which actually refer to an undisclosed period of years up to 1989), with in one case the latest available data being that referring to 1986-87.

The identification of the appropriate time periods for the input measures is naturally more complex, the need being to relate relevant inputs to the subsequent outputs as accurately as possible, in terms of appropriate time lag. Figure 6.7 details the principles used in choosing these time periods. These generalities are used in selecting the time periods, naturally such assumptions do not cover all possibilities, but are nevertheless sufficiently significant to allow satisfactory selection.

The mix of both three/four year and ordinary/honours programmes for undergraduate degrees requires a single time period to be chosen relating to input statistics. This is due to the fact that there is no discrepancy made

Figure 6.7. Assumptions Used in Variable Time Period Selection.



between any of these in the corresponding output statistics in the sources of data.

Reflecting the student load within a department over the period of an undergraduate study rather than attempting to isolate the input data referring solely to those students within the particular time period of the undergraduate output statistic was felt to be more relevant. The shortest possibility, three years prior to the 1987 point of measurement of the output statistics, was therefore selected for the input figures, and hence the time period 1984-1985 was utilised for the undergraduate numbers variable.

By the same principle as referred to above. The *financial and staff input* measures relating to teaching are taken from the year 1985-86 to reflect the resources in use at a mid-point of study rather than at the beginning, and hence minimise the effect of a change in scale of a department across the period.

Unfortunately, the earliest entry qualification data available relates to the 1985-1986 undergraduate intake a year later than we would ideally seek data for. The effect of this inconsistency, although clearly a relevant caveat, is minimised by the fact that the data for this statistic deals with a mean-score which would not normally differ greatly from that of the year before and can hence be used as a surrogate measure, actual student numbers not being involved.

To determine time periods for the research input statistics it is necessary to make generalities concerning the duration of activities associated with research. It is assumed that Research Postgraduates study for a three year period (the relevant input period therefore being 1984-1985), and that Taught Postgraduates study for a single academic year (the input period therefore being 1986-87). Finally, it is assumed that research projects are carried out over a two to three year period, and the input period chosen based on this generality is 1986-1987.

Table 6.8 cross-references each of the input and output measures to the originating data source and the time period from which it is taken, using the reference codes provided for the data sources as listed in Table 6.5.

In addition, at this point the abbreviations and reference codes used within the program for the variables are introduced. The references from the full-title listings of the variables in Figures 6.2 (inputs) and 6.4 (outputs) have been retained for this table only to ensure clarity in interpretation of the abbreviated names.

<u>Table 6.8. Source and Time Period of all Variables.</u>

Table 6.2/6.4 refer.	DEAPMAS abbreviated var. description	DEAPMAS identity code	V1S	V2D	V3F	MST	RSE
1A	GEN-INCOME-RESEARCH	I1	-	-	86-87	-	-
1B	GRANTS-RESEARCH	I2	-	-	86-87	-	-
1C	GEN-INCOME-TEACHING	I3	-	-	85-86	-	-
2A	ACADEMIC-STAFF	I4	-	-	85-86	-	-
3A	UNDERGRAD-NUMBERS	I5	84-85 (EG. B only)	-	84-85 (EG. A only)	-	-
3B	UNDERGRAD-ENTR-QUAL	I6	-	-	-	85-86	-
3C	POSTGRAD-RESEARCH	I7	-	-	84-85	-	-
3D	POSTGRAD-TAUGHT	I8	-	-	86-87	-	-
4A(i)	GRADS-KNOWN-DEST	O1	-	87-88	-	-	-
4A(ii)	GRADS-LONGTRM-EMPL	O2	-	87-88	-	-	-
4A(iii)	GRADS-SHORT-EMPLOY	O3	-	87-88	-	-	-
4A(iv)	GRADS-EDUC-TRAIN	O4	-	87-88	-	-	-
4B	FIRST-DEG-GRADS	O5	1987	-	-	-	-
4C	HIGHER-DEG-GRADS	O6	1987	-	-	-	-
5A	RESEARCH-QUALITY	O7	-	-	-	-	1989
5B	RESEARCH-TURNOVER	O8	-	-	87-88	-	-
6A	CONT-EDUC-PROVSN	O9	86-87	-	-	-	-

6.6. Data Tabulation, Assumptions and Caveats.

Recalling Section 6.3, much of the data was taken directly from the data sources and fed to the DEAPMAS program. Some of the statistics, however, required a degree of manipulation or estimate to equate them to the required measure and hence become suitable for input to the program.

Table 6.9 reveals the extent to which the different variables required adjustment from the form in which they were published. Those listed under 'DIRECT' in the table were utilised exactly as they were published without the need for any adaptation, and hence perfectly match the desired statistic. Those which did not happen to have been published exactly in the form that would be desired are shown in two categories; 'ARITHMETIC' and 'ESTIMATE'.

Those variables which required simple arithmetic manipulation are listed under 'ARITHMETIC', this includes those involving arithmetic calculation made possible only by means of a general assumption. The remaining variables involved a large degree of subjectivity by way of major assumptions or estimates in their calculation from published figures, and these are shown under 'ESTIMATE'.

Additionally, this table displays the original collection basis used for each of the statistics in the data sources. These are divided into three categories, Cost Centre based (CCT), Subject Group based (SGR), and Quasi-Subject Group based (QSG). The latter category covers a number of other groupings of

Table 6.9. Extent of Calculation Used in Preparation of Data.

		DIRECT	ARITHMETIC	ESTIMATE			DIRECT	ARITHMETIC	ESTIMATE
GEN-INCOME-RESEARCH CCT	I1	-	-	A/B	GRADS-KNOWN-DEST QSG	O1	-	A/B	A
GRANTS-RESEARCH CCT	I2	A/B	-	-	GRADS-LONGTRM-EMPL QSG	O2	-	A/B	A
GEN-INCOME-TEACHING CCT	I3	-	-	A/B	GRADS-SHORT-EMPLOY QSG	O3	-	A/B	A
ACADEMIC-STAFF CCT	I4	A/B	-	-	GRADS-EDUC-TRAIN QSG	O4	-	A/B	A
UNDERGRAD-NUMBERS CCT/SGR	I5	A/B	-	-	FIRST-DEG-GRADS SGR	O5	B	A	A
UNDERGRAD-ENTR-QUAL SGR	I6	A/B	-	-	HIGHER-DEG-GRADS SGR	O6	B	A	A
POSTGRAD-RESEARCH CCT	I7	A/B	-	-	RESEARCH-QUALITY CCT	O7	A/B	-	-
POSTGRAD-TAUGHT CCT	I8	A/B	-	-	RESEARCH-TURNOVER CCT	O8	A/B	-	-
					CONT-EDUC-PROVSN QSG	O9	A/B	-	-

subjects, all at least as broad-based as subject groups. These are discussed in the sub-sections of this chapter dealing with the variables derived from them (Sections 6.6.9, and 6.6.13).

The information is shown for both example 'A' and example 'B' as there are some differences in the attainment of the final data from its original form between the two examples.

It should be remembered that the degree of accuracy in these statistics is not simply linked to the degree of manipulation required before they are applied, more often the method of division of data used in their original calculation, the headings under which the statistics are compiled, is more relevant.

The majority of the limitations of the study that are linked to Data collection were covered in Section 6.2 in establishing the actual input and output measures to be used. The following sections state caveats general to each of the two examples (Sections 6.6.1. and 6.6.2), and then particular to each of the variables used (Section 6.6.3 to Section 6.6.13).

Whilst these notes and assumptions concentrate on the appropriateness of the actual figures used there is inevitably an overlap with the information of Section 6.2. This has not been avoided as it serves to clearly emphasize the extent of significance that can be taken from the results of the data runs documented in Chapter Seven.

6.6.1. Notes on Data Used in Both Example 'A' and Example 'B'.

The Universities' Statistical Record has a subject classification which includes the subject of 'Business and management studies' (62). This classification has not been used, however, as its use is restricted mainly to student statistics and no financial information is available in this form. Use was made, therefore, of the USR Cost Centre classification system under which financial and other information is grouped.

Cost Centres are groupings of academic departments designed to reflect "both academic similarities and comparable resource requirements" (UGC/USR 1989). It should be noted, therefore, that Cost Centre 32 'Business and Management Studies' includes but is not entirely equal to the subject definition of the same name.

Single time periods are used exclusively in both examples to represent the inputs to the process. In reality, clearly a proportion of each of several years inputs are used to produce the outputs of a particular time period.

The single input is used therefore as an estimate which makes the assumption that a Cost Centre is not undergoing rapid expansion or decline during the related period. In a dynamic phase in higher education, this will not always be the case. A mid-point is used in each case rather than the first related year in order to attempt to minimise the effect of changes in scale on the statistic. Major changes, however, in the scale of operation would still significantly affect the results.

6.6.2. Notes on Data Used Throughout Example 'B'.

The points made in Section 6.6.1 equally applies to the three Cost Centres used in example 'B', Cost Centres 14, 15 and 16, (Chemistry, Physics, and Other Physical Sciences) do not equate directly to subject classifications.

This larger example is based on an area of subjects, represented (with the above Caveat) by the three Cost Centres listed above. Data for these is used individually for some variables and collectively for others. The collective data used represents a group of subjects, and is referred to by the USR as subject group five 'Physical Sciences'. Subject group five, naturally, does not perfectly equate to the combination of the three Cost Centres for the reason already given, and particularly as it includes another major subject.

Subject group five includes 'Geography' (subject 28) which is also listed as a Cost Centre (29 'Geography'). This obviously introduces a major inaccuracy with regard to the variables which use Subject Group based data.

Example 'A' attempts to provide an indication of relative quality for a particular subject/cost centre and every effort is made to provide the most significant results possible. The purpose of example 'B' differs in that it is a deliberate attempt to use a complex example in order to investigate the problems created by the increased complexity which a wider comparison entails. It will also serve as a more rigorous test of the DEAPMAS process. Were this not the case, data referring to the three Cost Centres would be used wherever possible for consistency.

Data has been used referring to the Subject Group when it is available and thus the results for this example are perhaps not the most significant that could have been produced.

6.6.3. Notes and Assumptions Relating to the Variables Used.

There is no direct link between the input figures and the output variables used, the inputs are used purely as an estimate. Referring back to Table 6.7, part of these inputs will relate to outputs of other time periods from that which we are using, and equally the inputs from other time periods will also clearly have affected our inputs. The relationship is assumed to be fairly static year to year, however, and therefore a mid-point is adopted.

The remaining sub-sections of Section 6.6 contain notes and assumptions on the individual variables.

6.6.4. Total Recurrent Departmental Expenditure from General Income Attributable to Teaching and to Research.

<GEN-INCOME-RESEARCH..I1>

<GEN-INCOME-TEACHING..I3>

The data for these variables is taken directly from the source as single figures, the midpoints used being 1985-86 for Teaching and 1986-87 for Research. The figures for each Cost Centre are then split to form the two variables relating to teaching and research. Note that it is not literally the same statistic which is split into the two variable figures as the time period used differs. The arithmetic split uses the assumption that 60% of General Income is allocated to teaching with the remainder attributed to research. It should be noted that this resource allocation is not a formal requirement laid down, and therefore the assumption is effectively creating an estimate for the two variables.

6.6.5. Recurrent Specific Departmental Expenditure on Research Grants and Contracts.

<GRANTS-RESEARCH......I2>

Recurrent specific departmental expenditure is defined as that incurred in order to render a specific service to or for an outside body. This includes, inter alia, research grant and contract expenditure.

The data is divided in the source into 'Research Grants and Contracts' and 'Other'. The latter category includes special and short courses and other undefined items. Only that presented as being in connection with Research grants and contracts has been used, though some items under 'Other' may in fact be attributable to research.

6.6.6. Full-Time Wholly University Financed Academic Staff Within Department.

<ACADEMIC-STAFF.......I4>

Data for Academic staff numbers is available in the form of Full-time-equivalents (FTE's), the most appropriate form for our purposes. Full-time wholly University financed academic staff numbers has been used instead, due to the 'free input' reasoning discussed in section 6.2.1.

Analysis of part-time staff is effectively excluded as a result of not using FTE's, although examination of the data reveals an extremely low occurency of staff of this category during the period of analysis. Rather than introduce a somewhat spurious additional input to represent part-time staff, a maximum ratio of part-time to full-time staff could be set beyond which an adjustment is made to the full-time figure for the purposes of analysis.

Were analysis by this means to be carried out at regular intervals, it is assumed that in reality an FTE figure would be compiled for wholly university financed staff.

6.6.7. Undergraduate Numbers and Research and Taught Postgraduate Numbers.

<UNDERGRAD-NUMBERS....I5>
<POSTGRAD-RESEARCH....I7>
<POSTGRAD-TAUGHT......I8>

As shown in Table 6.9, the source for example 'A' and 'B' differs for the undergraduate numbers variable, being Cost Centre and Subject Group based for examples 'A' and 'B' respectively.

These figures represent total FTE student load for each of these three variables and, as explained in sections 6.6.3 and 6.6.5, are not an attempt to perfectly isolate the graduates in the output statistics and connect them to input statistics which show only these people at the point of their entry to the system.

Mid-points of courses were estimated for the Undergraduate and Research Postgraduate variables, on the principle contained in Section 6.6.3, but for an assumed one-year Taught Postgraduate course there would only be one set of students per year and hence, under this assumption, the link between input and output would be achieved.

6.6.8. Mean Score of Main Undergraduate Entry Qualifications.

<UNDERGRAD-ENTR-QUAL..I6>

Data used for this statistic uses the predominant main qualification for each University only, hence three or more 'A' levels in English and Welsh Universities, and five or more Higher grades in Scottish Universities. All other qualifications, academic and otherwise are hence overlooked.

Because of the differences in the education systems leading to 'A' levels and Scottish 'Highers', direct comparison between the two systems is not possible.

The system of 'point-scoring' used in the data source to calculate a mean entry score is as follows; GCE 'A' levels A=5, B=4,...E=1; SCE 'H' grade A=3, B=2, C=1. For the two categories we are concerned with, very similar averages are found when comparing the Scottish average with the English average under their respective points systems.

Despite the above caveat, therefore, the mean score of the main entry qualification was felt to be the most suitable statistic available.

The data is calculated on a Subject Group basis and cannot be readily manipulated. This is therefore a source of inaccuracy in example 'A', as Subject Group ten data is used which includes in its calculation five other subject definitions.

The first data published refers to 1985-86, and this time period is therefore used as a surrogate for 1984-85, though as explained in Section 6.5, this should not greatly reduce its significance.

6.6.9. First Destinations of First Degree Graduates.

<GRADS-KNOWN-DEST.....O1>

<GRADS-LONGTRM-EMPL...O2>

<GRADS-SHORT-EMPLOY...O3>

<GRADS-EDUC-TRAIN.....O4>

As the only available data representing student success beyond graduation it was clearly necessary that First destination data be included in analysis. Unfortunately, however, it is only available at individual University level divided to just six academic categories. Example 'A' falls within the three Subject Groups under 'Social studies' and example 'B' is one of four Subject Groups collectively termed 'Pure science'.

Clearly these statistics are too broad-based to be of any significance if included directly in analysis. Only by making the major and highly questionable assumption that first destinations are homogenous across the subjects within these categories can the data be used.

The variable representing the number of First Degree graduates, which has caveats of its own (Section 6.6.10), is used to find the proportion which it, theoretically, represents amongst the total graduates. This proportion is then multiplied by the totals within each of the four categories chosen as variables, and data hence obtained for examples 'A' and 'B'.

The data created in this way is very much surrogate data, and should be viewed with this in mind. The data only represents former undergraduates, similar figures are not available for postgraduates.

6.6.10. Number of First Degree and Higher Degree Graduates.

<FIRST-DEG-GRADS......O5>

<HIGHER-DEG-GRADS.....O6>

The data from which these variables originate is presented as Subject Groups and therefore for example 'B' the data is used directly, its suitability being restricted only by the points noted in Section 6.6.2.

The data source being at this level is a severe drawback when considering example 'A', however, Subject Group 10 'Business and Financial Studies', covering six different subject headings.

As the data is in the form of totals, unlike the mean score data referred to in Section 6.6.8, the data can be split after making certain assumptions. Although no exact comparison is possible, Subject Group 10 appears to be broadly equivalent to just two Cost Centres; Business and management studies (32) (example 'A'), and Accountancy (33). Accepting this assumption allows manipulation of the data to form statistics relating solely to the Cost Centre of example 'A'.

If a University has no Accountancy Cost Centre activities, then the data for Subject Group 10 is assumed to relate solely to example 'A'. Where Accountancy is present, the original Subject group data is multiplied by the proportion which the Business and management studies student load represents when totalled with the Accountancy student load. The surrogate figure is clearly a source of inaccuracy.

The same procedure is applied to obtain data for both First degree and Higher degree graduates.

6.6.11. Research Selectivity Exercise Rating.

<RESEARCH-QUALITY.....O7>

The figures for this variable are taken from the Universities Funding Council's research selectivity exercise. These were used to 'inform calculations of grants' (UFC 1989) for both the academic year 1990-91 and the funding period 1991-1995. Individual Cost Centres were allocated ratings on their research activities on a scale of five down to one. The standards for which the different ratings were awarded are given in Appendix C.

The obvious drawback with the use of the UFC research selectivity exercise is that its ratings are based on subjective assessment of research activities within a Cost Centre. Inclusion of this variable, unfortunately, in itself prevents the analysis as a whole from being free from subjectivity.

There is clear justification for its inclusion amongst the output variables, however, as Cost Centre expenditure on research, indicating research turnover, is the only other comprehensive output measure relating to (non-student) research available.

6.6.12. Recurrent Specific Departmental Expenditure On Research Grants and Contracts.

<RESEARCH-TURNOVER....O8>

This output variable is precisely the same as the input variable <GRANTS-RESEARCH......I2>, the only difference being the time period from which it is taken. The reasoning behind this is contained in Section 6.2.2.

The notes in Section 6.6.5, which dealt with this statistic when used as an input measure, equally apply when it is used as an output measure. Additionally, it should be remembered that this output variable indicates the quantity of research carried out rather than its quality. The former, as explained in Section 6.2.2, being used as a surrogate for the latter.

6.6.13. Continuing Education Courses.

<CONT-EDUC-PROVSN.....O9>

The number of continuing education courses offered was chosen as a variable as it was the only available data which in anyway gives an indication to the benefit derived by the local community and its businesses from the presence of a particular department, as discussed in Section 6.2. Obviously it represents only one aspect of such benefits.

The data is available for individual universities only grouped into categories no longer used for any other statistics. Example 'A' falls within 'Old subject classification group VI' (Administrative, business and social studies), and example 'B' within 'group V' (Biological and Physical Sciences). There is no practical way of splitting this data to more relevant categories.

Student hours or student numbers would both have been more appropriate measures, but only total course numbers were available with any subject analysis. The latest time period available is the least recent of all the output measures, relating to the academic year 1986-87.

6.7. The Performance Profile for the University Applications.

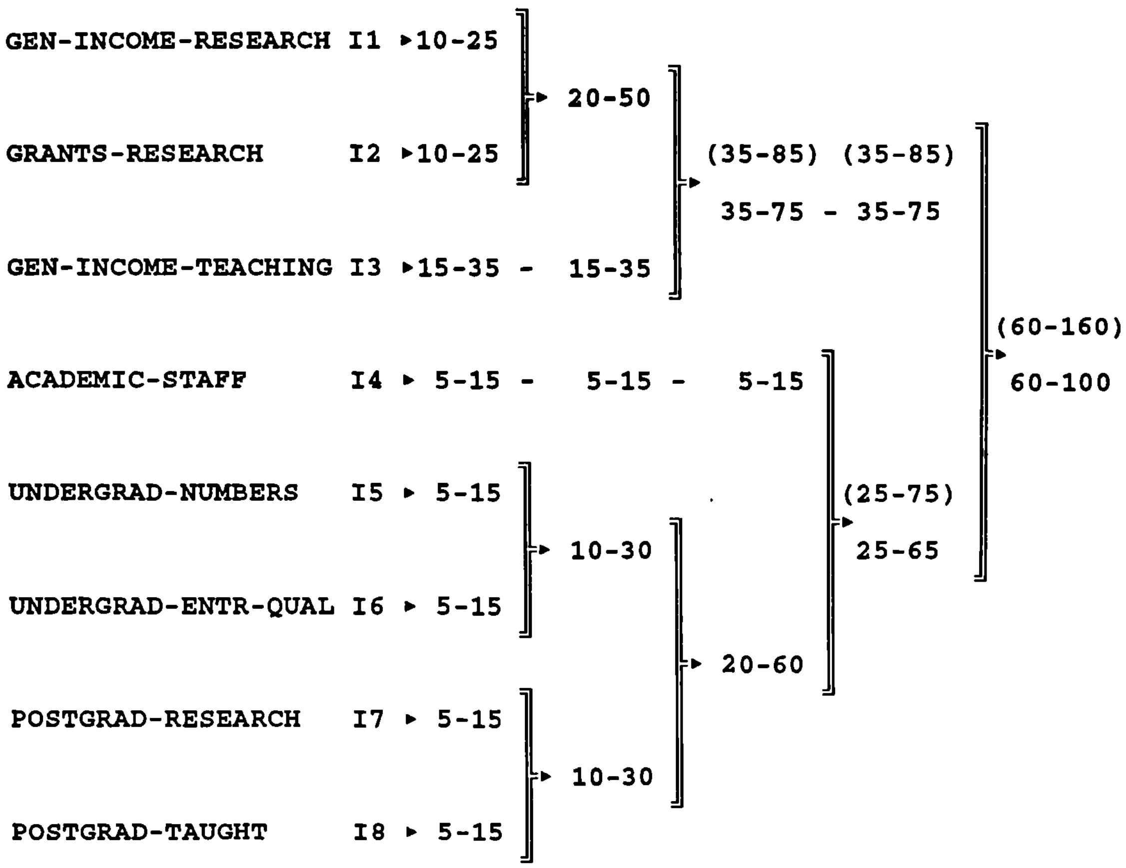
Setting a performance profile for the variables selected, inevitably introduces an element of subjectivity into the analysis. Such subjectivity can be justified, however, if it is reasonably exercised, given that the alternative is complete weight flexibility which clearly cannot be justified (See Section 4.2).

The figures within the performance profile were discussed at length with a number of lecturers at the University of Stirling, and a clear consensus towards a 'balancing' of a majority of the variables, particularly those within the categories of teaching and research was identified as being the most rational approach to specifying the relative importance of the variables. This rationale is now summarised.

The input variables used (Figure 6.10) could largely be divided into two categories; monetary and non-monetary. It was felt that the monetary variables should not outweigh the non-monetary inputs by more than a ratio of 3:1, nor should the non-monetary inputs ever be allowed to outweigh the monetary inputs by more than 2:1.

Taking this as a starting point, monetary measures could be broken down into those relating to teaching and those to research. A balance was sought between these, however, it was noted that 'GRANTS-RESEARCH' was the only non-government income statistic, and therefore a range of 20-50% was set for research measures as opposed to 15-35% for teaching measures. There were two

Figure 6.10. Performance Profile; Input Side for Example 'A'.



statistics for research and these were treated equally with a range of 10-25% each.

The non-monetary measures can be sub-divided into staff and student statistics. The student statistics in turn into Undergraduate and postgraduate figures. A balance was sought between the two student categories, both being set at 10-30%. The 'ACADEMIC-STAFF' variable is somewhat far from the ideal measure sought in Chapter Four and was therefore set at 5-15%.

The undergraduate figures composed of two measures, numbers and entry qualifications, little consensus exists about the relative significance of these and they were therefore set equally at 5-15%. Finally postgraduates were represented by two statistics; research and taught, these were also allocated half of the postgraduate limits each at, again 5-15%.

The output variables are broadly split into three groups; teaching, research and continuing education. A small degree of specialisation was allowed between teaching and research; roughly 60:40 ratio in either direction. This was slightly complicated to administer, however, as 'HIGHER-DEG-GRADS' can be viewed as both a teaching and a research output. Figure 6.11 has it grouped as teaching, but by examining the weight limits it can be noted that by including it in either group a minimum is prescribed in the range 39-42%.

A balance was sought between undergraduate and postgraduate teaching (21-45%/48% each). The two distinct research statistics were treated equally (9-36%). Continuing education is a poor substitute for the original ideal measure it replaces and therefore a range of 0-10% was set, thus DMU need not apply any weight to it at all.

Undergraduate teaching sub-divides into first destination figures and number of graduates. With scepticism over the former, numbers were given slight preference, set at 12-25% as opposed to 9-23% for First Destination figures. The First Destination figures comprise of four statistics. the first simply rewards universities for keeping track of their graduates (a long term view) and is therefore restricted between 1% and 4%. The measures for long-term employed and those in further education or training were set equally at 4-8% and the relatively trivial short-term employed set at 0-3%.

Figure 6.11. Performance Profile; Output Side for Example 'A'.

```
GRADS-KNOWN-DEST     O1 ► 1- 4 ┐
                               │
GRADS-LONGTRM-EMPL   O2 ► 4- 8 │
                               ├► 9-23  ┐
GRADS-SHORT-EMPLOY   O3 ► 0- 3 │        │
                               │        ├► 21-48 ┐
GRADS-EDUC-TRAIN     O4 ► 4- 8 ┘        │        │
                                        │        │
FIRST-DEG-GRADS      O5 ►12-25 -  12-25 ┘        ├► 42-93 ┐
                                                 │        │
HIGHER-DEG-GRADS     O6 ►21-45 -  21-45  -  21-45 ┘       │
                                                          │(60-165)
RESEARCH-QUALITY     O7 ► 9-36 ┐                          ├►
                               ├► 18-72  -  18-72 -  18-72│ 60-100
RESEARCH-TURNOVER    O8 ► 9-36 ┘                          │
                                                          │
CONT-EDUC-PROVSN     O9 ► 0-10 -   0-10  -   0-10 -   0-10┘
```

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7. RESULTS OF THE APPLICATION OF THE DEAPMAS PROCESS TO THE TWO SETS OF UNIVERSITY DATA.

In the previous chapter, data for two UK university examples was developed, the Decision-Making Units for each were set and the appropriate variables for inclusion were established. The following sections cover the application of these data sets to the undeveloped Data Envelopment Analysis technique, and then, in stages, the application of the same (plus necessary supplementary) statistics, to the 'DEAPMAS' process.

7.1. Introduction to discussion of results.

In all the following data runs, results for the two examples are discussed concurrently. Recalling the discussion of Chapter Six, 'Example A' refers to 'Business and Management Studies' (Cost Centre 32), and 'Example B' to the larger example involving 'Physical Sciences' (Subject Group 5); specifically 'Physics', 'Chemistry' and 'Other Physical Sciences' (Cost Centres 14, 15 and 16).

The Decision-Making Units in these examples were discussed in Section 6.4, with a list of the 27 DMU of Example A and 46 of Example B, and their associated four-letter codes given in Table 6.6. The full data sets used for these two groups of DMU can be found in Appendix D.

Much of Chapter Six was concerned with the development of the variables to be used in the two examples. In particular, however, Section 6.6 and its sub-sections cover Data Tabulation, Assumptions and Caveat. Naturally, as discussed in Section 6.1, results drawn from the data should not be analysed without consideration of the content of those sections having been made.

Section 7.2 contains the results of processing the statistics through the undeveloped Data Envelopment Analysis. This, as with all the other data runs, was carried out using the DEAPMAS program, an option of which emulates the basic theory to provide such results. These results have been derived for comparison and theoretical discussion only, however, it having been firmly established in Chapter Four that they hold little or no practical significance.

The performance profile for this application was developed in Section 6.7, in Section 7.3.1 further development of this is carried out for 'Example B'. These performance profile are then utilised to provide the results reported in subsequent sections, which include data runs using the concepts of both variable specialisation, (by creation of Specialised Performance Profiles) and environmental factor consideration (by Affected Variable Adjustment (AVA)).

In the discussion of results which follows, it should be noted that, as with any Linear Program, the calculation ends when the optimisation has been achieved. It should be born in mind therefore, that the weight combinations used by 100% pareto efficient Decision-Making Units, may not be unique, and for some, there may be a large number of permutations which would have yielded the same result, the actual result depending simply on the particular linear program algorithm used and the order in which the variables have been arranged. In cases where pareto efficiency ratings below 100% are recorded, however, the weight combination will almost always be unique.

Recalling the linear program problem for DEA discussed in Chapter Five (Figure 5.8); the problem states that the virtual inputs must equal or exceed the virtual outputs for all DMU including that which is the subject of the particular optimization, with the virtual outputs for that DMU fixed at unity. The Virtual inputs of the subject DMU are then minimised.

For pareto efficient DMU, the virtual inputs can be minimised as far as is ever permissible, the 'tight' constraint being that they must not be exceeded by the DMU's virtual outputs, which were fixed at unity. This may be possible with more than one, and possibly many, combinations of values for the variable weights.

For the pareto inefficient DMU, however, as the virtual inputs are reduced other constraints become 'tight', those relating to other DMU who are hence more efficient with the same weight combinations. The LP solution algorithm will search using progressively more intricate weight combinations to reduce the objective value, under which different sets of the other DMU constraints become 'tight', this process ends when the solution search algorithm is satisfied, and hence the optimal value found. It will be very unlikely, therefore, that the solution is not unique.

7.2. Basic Data Envelopment Analysis.

Authors advocating the use of DEA point out the importance of limiting the number of variables included to a few key measures in order to yield discriminatory results. This issue is fully discussed in Chapter four, but it is necessary to summarize the conclusions here before results of such runs are presented.

These authors suggest that a low number of variables be utilised in order to create sufficient 'competition' between the DMU to prevent a disappointingly high number of the DMU being 100% relatively efficient. Furthermore, including only the most important few variables is the only means by which these variables can be emphasised, given that there exists absolutely no facility to take account of the comparative importance of different statistics.

The consequences of this are two-fold. Firstly, if the number of important, relevant variables is extremely low, then less important, though relevant, variables are likely to be included, with equal ranking, thus potentially severely distorting results. Equally if the number of key variables is high then variables which have a direct, and potentially crucial, influence on the efficiency or effectiveness of one or more DMU are likely to be excluded from the analysis.

It should be remembered, of course, that in a particular application it may be extremely difficult to define a small number of key variables. Unfortunately the likelihood of this is particularly high where DEA is in use, as, ironically, it may form part of the reasoning by which the technique was selected for a particular application, being one which requires no definition of the relationship between the inputs and outputs.

Secondly, there is clearly a desire to have few 100% efficient DMU, with discrimination to produce a highly acceptable 'league table' of results with varying percentages. Ideally this would be the natural consequence of using the technique, but clearly from the previous paragraphs this will not necessarily be the case for any particular data run without careful prior consideration of the number of variables included. This discrimination clearly can become the primary consideration in selecting the number of variables, the acceptability of such an approach to assessing performance is certainly brought into question.

As concluded in Chapter Four, all relevant variables must be included, from the crucial to the relatively trivial. If this leads to a large number of 100% results, then this is simply the answer to the question as defined. With undeveloped DEA, many of these 100% figures will have been achieved without any weighting being attached to the majority of variables.

The extreme case would a pairing of just one input and one output, having been found to be sufficiently superior for the particular DMU. These two variables may well be wholly unrelated. In the case of Universities this could lead to, for example, an efficiency ratio consisting of solely research grants over undergraduate entry qualifications.

The conclusion should be that the model needs considerable development, before it can be considered of any practical use, and not that the technique be used again with the number of variables systematically reduced until the desired distribution of ratings is achieved.

7.2.1. Results of Data Run 1 of Example A.

The results of data run 1, for Example A, are given in Figure 7.1, 25 of the 27 DMU have achieved 100% pareto efficiency (PE), with only 'Heriot-Watt' and 'Belfast' recordings lower results. With 17 variables there was inevitably going to be such a high number of 100% PE results, in fact, six of the DMU achieved this with more than 95% of the weighting on a single output and 16 applied weights to three or less inputs or outputs.

There were no 'one-to-one' relationships between inputs and outputs, 'London Business School', however, achieved 100% PE using just two inputs (I2.GRANTS-RESEARCH 73.2%, I3.GEN-INCOME-TEACHING 26.8%) and a single output (O8.RESEARCH-TURNOVER), 'Manchester Business School' used the same combination, but with a 51.8%/48.2% split respectively between the inputs, and 'Surrey' linked Continuing Education Provision almost exclusively to two Undergraduate statistics, this DMU was chosen as the example for Figure 7.2, demonstrating the output for each DMU produced by the DEAPMAS program.

Figure 7.1. Results for Data Run 1 of Example A.

```
*****************************************************************

 PARETO EFFICIENT UNITS

*****************************************************************


        DMU   1    ASTN      100%
        DMU   2    BATH      100%
        DMU   3    BRAD      100%
        DMU   4    CITY      100%
        DMU   5    HULL      100%
        DMU   6    KENT      100%
        DMU   7    LANC      100%
        DMU   8    LEED      100%
        DMU   9    LBUS      100%
        DMU  10    LOND      100%
        DMU  11    LBRO      100%
        DMU  12    MBUS      100%
        DMU  13    UMST      100%
        DMU  14    NEWC      100%
        DMU  15    SHEF      100%
        DMU  16    SOTN      100%
        DMU  17    SURY      100%
        DMU  18    WARW      100%
        DMU  19    CARD      100%
        DMU  20    UWST      100%
        DMU  21    EDIN      100%
        DMU  22    GLAS      100%
        DMU  24    STIR      100%
        DMU  25    CLYD      100%
        DMU  27    ULST      100%

*****************************************************************
*****************************************************************

 PARETO INEFFICIENT UNITS

*****************************************************************


        DMU  23    HWAT       91%
        DMU  26    BELF       70%

*****************************************************************
*****************************************************************
*****************************************************************
```

Figure 7.2. Output from Data Run 1 of Example A Specific to Surrey.

```
*****************************************************************

       DMU  17      SURY          PARETO EFFICIENCY:  100%

*****************************************************************
   ID       DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.
*****************************************************************
 I1)GEN-INCOME-RESEARCH
             -308.0     .000000       .000000         .000
 I2)GRANTS-RESEARCH
              -51.0     .000000       .000000         .000
 I3)GEN-INCOME-TEACHING
             -415.0     .000000       .000000         .000
 I4)ACADEMIC-STAFF
              -21.0     .000000       .000000         .000
 I5)UNDERGRAD-NUMBERS
             -259.0     .002935      -.760097       76.010
 I6)UNDERGRAD-ENTR-QUAL
              -10.9     .017404      -.189699       18.970
 I7)POSTGRAD-RESEARCH
               -7.0     .007172      -.050204        5.020
 I8)POSTGRAD-TAUGHT
              -59.0     .000000       .000000         .000
*****************************************************************
                             TOTAL VIRTUAL INPUTS  -1.000000

*****************************************************************
   ID       DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.
*****************************************************************
 O1)GRADS-KNOWN-DEST
               52.0     .000000       .000000         .000
 O2)GRADS-LONGTRM-EMPL
               37.0     .000000       .000000         .000
 O3)GRADS-SHORT-EMPLOY
                3.0     .000000       .000000         .000
 O4)GRADS-EDUC-TRAINING
               10.0     .000000       .000000         .000
 O5)FIRST-DEG-GRADUATES
               64.0     .000000       .000000         .000
 O6)HIGHER-DEGREE-GRADS
               32.0     .000000       .000000         .000
 O7)RESEARCH-QUALITY
                3.0     .000000       .000000         .000
 O8)RESEARCH-TURNOVER
               87.0     .000060       .005244         .524
 O9)CONT-EDUC-PROVISION
              279.0     .003565       .994756       99.476
*****************************************************************
                             TOTAL VIRTUAL OUTPUTS   1.000000

*****************************************************************
```

It has been suggested (See Section 4.5) that although the actual relative efficiency of the 100% pareto efficient DMU' can be questioned, clearly any DMU which cannot achieve a rating of 100% given weight combination flexibility such as that permitted as a result of the number of variables in this example, must be unarguably inefficient.

This is not necessarily true, however, as argued in the fourth chapter (Section 4.5); DMU which are above average in many ratios between outputs and inputs, but inferior to other DMU when considering any individual ratio, will show a considerable increase in their rating if weights had to be placed on all variables and a large number of the other DMU only achieved 100% PE by being permitted to concentrate on a small sub-set of the variables in the original data run.

7.2.2. Results of Data Run 1 of Example B.

Recalling Chapter Six, 'example B' attempts to assess data at subject group level rather than a single cost centre, using the same set of factors or variables.

Some variables could only be included by utilising figures for the three cost centres broadly equivalent to the subject group. Hence this resulted in some factors being sub-divided to three collectively equivalent variables (See Section 6.6).

As a result of the sub-division, this example not only contains a larger number of DMU, but additionally 20 inputs and 13 outputs. It is of little surprise therefore, that all 46 DMU achieved 100% PE when applied to undeveloped DEA.

Six DMU applied 95% or greater weighting to a single variable. It is intuitively curious that this number is not higher, the explanation may partly lie in the linear program algorithm used in DEAPMAS, but more likely it indicates that a relatively small sub-set of the total DMU are dominant in nearly all ratios involving just one input or output, hence forcing the LP solution search algorithm when other DMU are the subject, to continue optimization by introducing further variables.

As with example 'A', there are no one-to-one relationships, however, 'East Anglia' links undergraduate numbers (100%) to two sub-divisions of Research Turnover, with 99% on one of them (O8P.RESEARCH-TURNOVER 1%, O8S.RESEARCH-TURNOVER 99%). 'Swansea', interestingly, links Undergraduate Numbers (I5.UNDERGRAD-NUMBERS 99%, I7S.POSTGRAD-RESEARCH 1%) solely to research turnover in Other Physical Sciences and the number of First Degrees awarded! (O5.FIRST-DEG-GRADUATES 51.8%, O8S.RESEARCH-TURNOVER 48.2%).

While, at best, barely more than half of the variables were utilised to provide the ratings for particular DMU, many of which were at very small percentages, the spread of weights was greater than might have been anticipated, probably due to the sub-set dominance mentioned above.

Over a quarter of the DMU applied weights in over a dozen variables to achieve 100% PE, many applying no more than around 35% to 40% to any one input or output, 'Hull' and 'Aberystwyth' utilised a total of 18 variables, 'Aberystwyth's weightings are the example output of Figure 7.3.

7.2.3. The Elimination of Zero Input Variables.

In the first data run of both examples as reported in the previous sections, a number of DMU had no figures available for one or more inputs. The inclusion of these DMU is unacceptable both in undeveloped DEA and when a performance profile is being used (Section 7.3 onwards).

Naturally a DMU cannot 'use' a zero variable as there would be no contribution to the total virtual inputs, anything multiplied by zero is still zero. The lower the inputs the better (with fixed outputs) the rating for the DMU will be, but in the extreme case, zero, the result of the calculation of the total virtual inputs will be completely unaffected by the size of the weight applied. It is not, therefore, immediately apparent why a DMU must be eliminated from the set.

The DEA model searches for the highest possible relative rating that can be achieved when any particular set of weights is applied to both the DMU under assessment and to all other DMU in the set. Substantial unfair advantage can

Figure 7.3. Output from Data Run 1 of Example 'B'

Specific to 'Aberystwyth'.

```
*****************************************************************

     DMU  33      ABWY          PARETO EFFICIENCY:  100%

*****************************************************************
  ID      DATA VALUE  OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.
*****************************************************************
 I1C)GEN-INCOME-RESEARCH
            -148.0       .000526      -.077785        7.778
 I1P)GEN-INCOME-RESEARCH
            -178.0       .000000       .000000         .000
 I1S)GEN-INCOME-RESEARCH
            -186.0       .000487      -.090514        9.051
 I2C)GRANTS-RESEARCH
            -102.0       .002227      -.227152       22.715
 I2P)GRANTS-RESEARCH
            -265.0       .000000       .000000         .000
 I2S)GRANTS-RESEARCH
             -35.0       .000000       .000000         .000
 I3C)GEN-INCOME-TEACHING
            -232.0       .000156      -.036267        3.627
 I3P)GEN-INCOME-TEACHING
            -245.0       .000301      -.073773        7.377
 I3S)GEN-INCOME-TEACHING
            -274.0       .000000       .000000         .000
 I4C)ACADEMIC-STAFF
             -10.0       .000000       .000000         .000
 I4P)ACADEMIC-STAFF
             -10.0       .000000       .000000         .000
 I4S)ACADEMIC-STAFF
             -14.0       .000000       .000000         .000
 I5)UNDERGRAD-NUMBERS
            -697.0       .000000       .000000         .000
 I6)UNDERGRAD-ENTR-QUAL
              -8.5       .040211      -.341796       34.180
 I7C)POSTGRAD-RESEARCH
              -7.0       .008493      -.059453        5.945
 I7P)POSTGRAD-RESEARCH
             -10.0       .000000       .000000         .000
 I7S)POSTGRAD-RESEARCH
             -14.0       .000451      -.006316         .632
 I8C)POSTGRAD-TAUGHT
              -1.0       .000000       .000000         .000
 I8P)POSTGRAD-TAUGHT
              -2.0       .005529      -.011058        1.106
 I8S)POSTGRAD-TAUGHT
              -9.0       .008432      -.075886        7.589
*****************************************************************
                              TOTAL VIRTUAL INPUTS  -1.000000
```

```
*****************************************************************
  ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.
*****************************************************************
 O1)GRADS-KNOWN-DEST
             79.0      .000000        .000000          .000
 O2)GRADS-LONGTRM-EMPL
             32.0      .000000        .000000          .000
 O3)GRADS-SHORT-EMPLOY
              5.0      .036311        .181554        18.155
 O4)GRADS-EDUC-TRAINING
             31.0      .012179        .377537        37.754
 O5)FIRST-DEG-GRADUATES
             92.0      .000000        .000000          .000
 O6)HIGHER-DEGREE-GRADS
              8.0      .016229        .129835        12.983
 O7C)RESEARCH-QUALITY
               .1      .000000        .000000          .000
 O7P)RESEARCH-QUALITY
              2.0      .000000        .000000          .000
 O7S)RESEARCH-QUALITY
              3.0      .000211        .000634          .063
 O8C)RESEARCH-TURNOVER
            147.0      .001293        .190123        19.012
 O8P)RESEARCH-TURNOVER
            176.0      .000127        .022409         2.241
 O8S)RESEARCH-TURNOVER
             51.0      .000329        .016785         1.678
 O9)CONT-EDUC-PROVISION
             17.0      .004772        .081124         8.112

*****************************************************************
                             TOTAL VIRTUAL OUTPUTS   1.000000

*****************************************************************
```

therefore be achieved when a DMU's optimum set contains a relatively large weight coupled to a zero input. Its own virtual input is zero while the weight could be set sufficiently large to ensure an 'uncompetitive' virtual input for all other DMU which results in a 100% rating for the DMU under assessment.

In example 'A', 'Hull' and 'Newcastle' have a single zero input, 'London Business School' and 'Manchester Business School' have two. Only

'Newcastle' does not apply some weight to its zero input, the two business schools apply weight to both their zero input variables. 'Manchester Business School', for example, applies its weights as shown in Figure 7.4, with almost two-thirds of its weights applied to its two zero inputs.

38 of the 46 DMU in example 'B' have one or more zero inputs, of these no less than 27 had weights applied to zero inputs. Two examples are 'Cambridge' and 'Swansea'. 'Cambridge' applied .011412 to I6.UNDERGRAD-ENTRY-QUAL for which it has no statistic, from a weights total of just .012059. 'Swansea', recalling section 7.2.2, created over 99% of its virtual input from just one variable. The weight that it applied to that variable, however, only constituted around 5% of its total input weights (.000915 from a total of .0017960).

As stated already, however, such analysis demonstrates the general problem but it should be born in mind that both the proportion of DMU involved and detailed results for particular DMU affected; result from the LP algorithm and chance ordering of the variables and therefore examples used are no more than just chance examples used to demonstrate the general case.

In later sections, specialisation amongst variables is introduced to overcome this and other related problems. The DMU eliminated prior to Data Run two, remain eliminated after introduction of the performance profile in Section 7.3 (until specialisation is introduced), however, as it would be impossible to set a

Figure 7.4. Output from Data Run 1 Specific to

Manchester Business School.

```
*****************************************************************

     DMU  12      MBUS          PARETO EFFICIENCY:  100%

*****************************************************************
  ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.    PERC. TOT.
*****************************************************************
 I1)GEN-INCOME-RESEARCH
             -373.0      .000000        .000000          .000
 I2)GRANTS-RESEARCH
             -463.0      .001120      -.518354         51.835
 I3)GEN-INCOME-TEACHING
             -574.0      .000839      -.481646         48.165
 I4)ACADEMIC-STAFF
              -40.0      .000000        .000000          .000
 I5)UNDERGRAD-NUMBERS
                 .0      .000759        .000000          .000
 I6)UNDERGRAD-ENTR-QUAL
                 .0      .002979        .000000          .000
 I7)POSTGRAD-RESEARCH
              -30.0      .000000        .000000          .000
 I8)POSTGRAD-TAUGHT
             -242.0      .000000        .000000          .000

*****************************************************************
                             TOTAL VIRTUAL INPUTS   -1.000000

*****************************************************************
  ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.    PERC. TOT.
*****************************************************************
 O1)GRADS-KNOWN-DEST
                 .0      .000000        .000000          .000
 O2)GRADS-LONGTRM-EMPL
                 .0      .000000        .000000          .000
 O3)GRADS-SHORT-EMPLOY
                 .0      .000000        .000000          .000
 O4)GRADS-EDUC-TRAINING
                 .0      .000000        .000000          .000
 O5)FIRST-DEG-GRADUATES
                 .0      .000000        .000000          .000
 O6)HIGHER-DEGREE-GRADS
              109.0      .000000        .000000          .000
 O7)RESEARCH-QUALITY
                3.0      .000000        .000000          .000
 O8)RESEARCH-TURNOVER
              612.0      .001634       1.000000       100.000
 O9)CONT-EDUC-PROVISION
               50.0      .000000        .000000          .000
*****************************************************************
                             TOTAL VIRTUAL OUTPUTS   1.000000

*****************************************************************
```

minimum virtual input level where the statistic is zero. A different procedure exists in the case of outputs as discussed in Section 7.4.

7.2.4. Results of Data Run Two.

As indicated in the preceding section; the second data run for both examples is another run involving undeveloped DEA. The difference being simply that all Decision-Making Units with one or more zero inputs are eliminated from the set of DMU for analysis. This eliminates four of the DMU in example 'A' ('Hull', 'London Business School', 'Manchester Business School' and 'Newcastle') leaving twenty-three for analysis.

The results revealed, as with Data Run one, all but two of the DMU as relatively efficient. With a reduced number of DMU a general increase would be expected due to the reduction in 'competition' over relative ratios that occurs, the two relatively inefficient DMU both show an increase; 'Heriot-Watt' moves from 91% PE (Data Run 1) to 97% PE (Data Run 2) and 'Belfast' moves slightly from 70% PE to 71% PE.

In example 'B', the elimination of DMU with any zero inputs has a dramatic effect, with only eight of the original 46 surviving. This quite dramatically demonstrates the need for a procedure which can deal with specialisation if fragmented data sets such as that in example 'B' are to be within the scope of any development of Data Envelopment Analysis.

Obviously if all 46 DMU were pareto efficient then any sub-set of the DMU'S with the variables unaltered will also be entirely 100% PE, the results are shown in Figure 7.5, primarily to indicate the eight Decision Making Units involved.

Figure 7.5. Results of Data Run Two for Example 'B'.

```
*************************************************************
*************************************************************

             SUMMARY OF RESULTS

*************************************************************
*************************************************************


*************************************************************
*************************************************************

 PARETO EFFICIENT UNITS

*************************************************************

      DMU   1    BHAM     100%
      DMU   2    LANC     100%
      DMU   3    LOND     100%
      DMU   4    READ     100%
      DMU   5    SOTN     100%
      DMU   6    SUSX     100%
      DMU   7    ABWY     100%
      DMU   8    ABDN     100%

*************************************************************
*************************************************************

 PARETO INEFFICIENT UNITS

*************************************************************

      (NONE)

*************************************************************
*************************************************************
```

Examination of the results pertaining to the two relatively inefficient DMU in both runs of example 'A' reveals that the variables to which weights were attached remained the same for 'Belfast', though in slightly different proportions. The results for 'Heriot-Watt' over the two runs of the undeveloped technique are contrasted in Figure 7.6, the six percentage point increase was achieved through being able to concentrate more on one each of its utilised inputs and outputs, and by switching from I6.UNDERGRAD-ENTR-QUAL to I7.POSTGRAD-RESEARCH.

Figure 7.6. Results of Data Runs One and Two
Specific to Heriot-Watt.

```
******************************************************************
      DATA RUN ONE     HWAT          PARETO EFFICIENCY:    91%
******************************************************************
  ID       DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.    PERC. TOT.
******************************************************************
 I1)GEN-INCOME-RESEARCH
            -185.0      .000000       .000000          .000
 I2)GRANTS-RESEARCH
            -130.0      .000000       .000000          .000
 I3)GEN-INCOME-TEACHING
            -241.0      .000000       .000000          .000
 I4)ACADEMIC-STAFF
             -16.0      .000000       .000000          .000
 I5)UNDERGRAD-NUMBERS
            -197.0      .002031     -.400153         36.554
 I6)UNDERGRAD-ENTR-QUAL
             -10.9      .014626     -.159421         14.563
 I7)POSTGRAD-RESEARCH
              -6.0      .000000       .000000          .000
 I8)POSTGRAD-TAUGHT
             -33.0      .016216     -.535123         48.883
******************************************************************
                                   TOTAL VIRTUAL INPUTS  -1.094697
```

ID	DATA VALUE	OPTIMUM VAL.	VIRTUAL CONT.	PERC. TOT.
O1)GRADS-KNOWN-DEST	53.0	.000000	.000000	.000
O2)GRADS-LONGTRM-EMPL	39.0	.020673	.806234	80.623
O3)GRADS-SHORT-EMPLOY	1.0	.000000	.000000	.000
O4)GRADS-EDUC-TRAINING	9.0	.000000	.000000	.000
O5)FIRST-DEG-GRADUATES	68.0	.000000	.000000	.000
O6)HIGHER-DEGREE-GRADS	11.0	.000000	.000000	.000
O7)RESEARCH-QUALITY	1.0	.000000	.000000	.000
O8)RESEARCH-TURNOVER	132.0	.001468	.193766	19.377
O9)CONT-EDUC-PROVISION	22.0	.000000	.000000	.000
		TOTAL VIRTUAL OUTPUTS		1.000000

DATA RUN TWO HWAT PARETO EFFICIENCY: 97%

ID	DATA VALUE	OPTIMUM VAL.	VIRTUAL CONT.	PERC. TOT.
I1)GEN-INCOME-RESEARCH	-185.0	.000000	.000000	.000
I2)GRANTS-RESEARCH	-130.0	.000000	.000000	.000
I3)GEN-INCOME-TEACHING	-241.0	.000000	.000000	.000
I4)ACADEMIC-STAFF	-16.0	.000000	.000000	.000
I5)UNDERGRAD-NUMBERS	-197.0	.003868	-.761999	74.149
I6)UNDERGRAD-ENTR-QUAL	-10.9	.000000	.000000	.000
I7)POSTGRAD-RESEARCH	-6.0	.036887	-.221320	21.536
I8)POSTGRAD-TAUGHT	-33.0	.001344	-.044343	4.315
		TOTAL VIRTUAL INPUTS		-1.027662

ID	DATA VALUE	OPTIMUM VAL.	VIRTUAL CONT.	PERC. TOT.
01)GRADS-KNOWN-DEST	53.0	.000000	.000000	.000
02)GRADS-LONGTRM-EMPL	39.0	.023513	.916989	91.699
03)GRADS-SHORT-EMPLOY	1.0	.000000	.000000	.000
04)GRADS-EDUC-TRAINING	9.0	.000000	.000000	.000
05)FIRST-DEG-GRADUATES	68.0	.000000	.000000	.000
06)HIGHER-DEGREE-GRADS	11.0	.000000	.000000	.000
07)RESEARCH-QUALITY	1.0	.000000	.000000	.000
08)RESEARCH-TURNOVER	132.0	.000629	.083011	8.301
09)CONT-EDUC-PROVISION	22.0	.000000	.000000	.000
			TOTAL VIRTUAL OUTPUTS	1.000000

7.3. Performance Profiles.

Problems inherent in undeveloped Data Envelopment Analysis such as the complete absence of any facility for variable ranking and the inappropriate application of zero weighting to a large number of variables place a severe practical limitation on the use of this technique.

These problems were overcome by the development of the DEAPMAS process in Chapter Five in response to the analysis of Chapter Four. Full details of the theory underpinning the use of the 'Performance Profile' can be found in Section 5.3.

In summary, undeveloped DEA can be considered as allowing the available variable weights to be applied in any proportion in order to maximise the pareto efficiency. Effectively this allows each variable to have a weighting attached which creates a virtual input or output in the range 0-100%. By setting a lower and upper limit for each virtual input and output at any point within this range, a model of performance can be created, designed to specifically reflect the objectives of the DMU under assessment.

This restriction on the weight allocation adds effectiveness to what has been previously, at best, an efficiency model. Additionally, the use of a performance profile compensates for the level of the point of measurement of the data.

In setting the limits for the variables in examples 'A' and 'B', the objectives and scarce resource requirements were the primary consideration. In addition, it was taken into consideration how far each actual measure used varied from the original derived in Chapter Six.

The Performance Profile for the university application was developed in Section 6.7 of the previous chapter. Figure 7.7 shows this performance profile, reproduced from Figures 6.10 and 6.11. These weight restrictions can be applied directly for example 'A'; Section 7.3.1 contains further development which is necessary for example 'B'.

Figure 7.7. Performance Profile for University Departments.

INPUTS.

```
GEN-INCOME-RESEARCH I1  10-25 ┐
                              ├─▶ 20-50 ┐
GRANTS-RESEARCH     I2  10-25 ┘         ├─▶(35-85) (35-85)┐
                                        │   35-75 - 35-75 │
GEN-INCOME-TEACHING I3  15-35 -   15-35 ┘                 │(60-160)
                                                          ├─▶
ACADEMIC-STAFF      I4   5-15 -    5-15 -    5-15 ┐       │ 60-100
                                                  │(25-75)│
UNDERGRAD-NUMBERS   I5   5-15 ┐                   ├─▶     │
                              ├─▶ 10-30 ┐         │ 25-65 ┘
UNDERGRAD-ENTR-QUAL I6   5-15 ┘         │         │
                                        ├─▶ 20-60 ┘
POSTGRAD-RESEARCH   I7   5-15 ┐         │
                              ├─▶ 10-30 ┘
POSTGRAD-TAUGHT     I8   5-15 ┘
```

OUTPUTS.

```
GRADS-KNOWN-DEST    O1   1- 4 ┐
                              │
GRADS-LONGTRM-EMPL  O2   4- 8 │
                              ├─▶  9-23 ┐
GRADS-SHORT-EMPLOY  O3   0- 3 │         │
                              │         ├─▶ 21-48 ┐
GRADS-EDUC-TRAIN    O4   4- 8 ┘         │         │
                                        │         ├─▶42-93 ┐
FIRST-DEG-GRADS     O5  12-25 -   12-25 ┘         │        │
                                                  │        │
HIGHER-DEG-GRADS    O6  21-45 -   21-45 -   21-45 ┘        │
                                                           │(60-165)
RESEARCH-QUALITY    O7   9-36 ┐                            ├─▶60-100
                              ├─▶ 18-72 -   18-72 - 18-72  │
RESEARCH-TURNOVER   O8   9-36 ┘                            │
                                                           │
CONT-EDUC-PROVSN    O9   0-10 -    0-10 -    0-10 -  0-10  ┘
```

7.3.1. Variable Sub-Division, The Performance Profile of Example 'B'.

All the input statistics for example 'B' except the two relating to undergraduate entry are included at cost centre level. This is due to the fact that the cost centre is the primary accounting unit in use in universities.

It would have been feasible to simply add the three constituent figures, in order that the initial 'point of measurement' appeared to be approximate to the subject group. This was not the option taken, however, to demonstrate by means of the performance profile that minor variations in the point of measurement are effectively irrelevant. Additionally, it should be remembered, as discussed in the previous chapter, Subject Group 5 (Physical Sciences) cannot be directly equated to the three cost centres 14, 15, and 16 (Chemistry, Physics, and 'Other Physical sciences').

As there is no ranking between the three cost centres for these purposes, the weight limits that would have applied were the statistic presented at subject group level are split evenly between the three cost centre creating equal sub-divisions of those variables.

In this way, for example, I1.GEN-INCOME-RESEARCH in example 'A' has weight limits of 10% and 25% of the virtual inputs. In example 'B', three variables I1C/I1P/I1S.GEN-INCOME-RESEARCH have limits of 3.3%-8.3% each, these are grouped together at level one in the group definition data at limits of 9.9%-24.9% for the group, thus the variables relating to general income from research are broadly equivalent between the two examples.

As can be seen in Figure 7.8, the total fixed input weights total 60.1%, varying by just 0.1% from that of example 'A', naturally this 'rounding error' could have been reduced but such action was unnecessary remembering that we are dealing with two independent examples.

Notice that as more and more variables are combined in the different levels of group definition, the combined maxima soon surpass 100% and equally the combined minima set a limit on the possible maximum figures for other groups. Both the effective and arithmetical combinations are stated with the latter given in brackets. Fuller discussion of these points is contained in Chapter Five. The output from the DEAPMAS program summarising the performance profile always quotes these effective weight limits rather than simply the arithmetical combination of the limits of the constituent variables.

Figure 7.9 reveals the output side of the performance profile, this is very similar to that for example 'A', with only two outputs presented at Cost Centre level; the variables pertaining to research quality and research turnover. As for the

Figure 7.8. Performance Profile, Input Side, for Example 'B'.

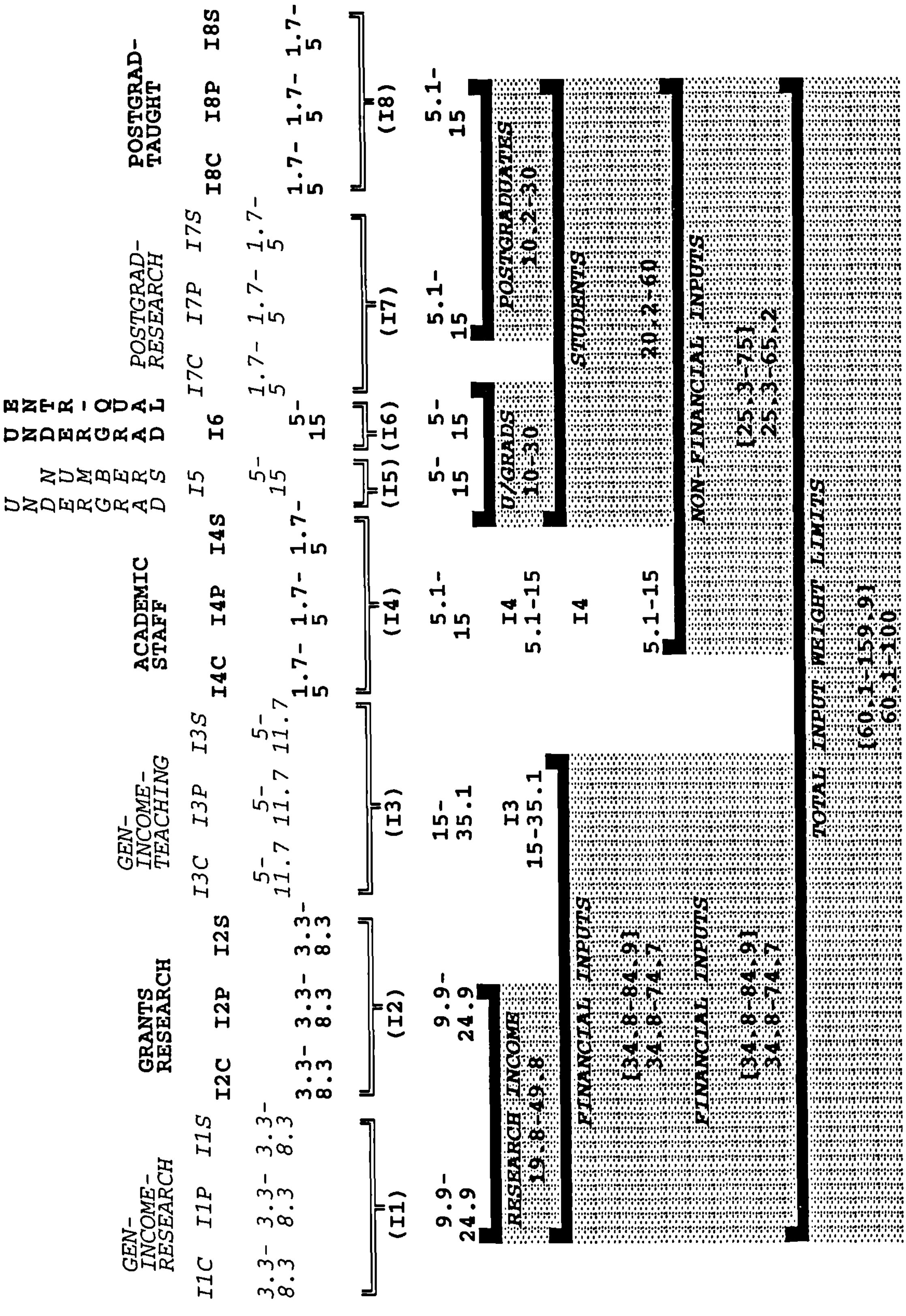
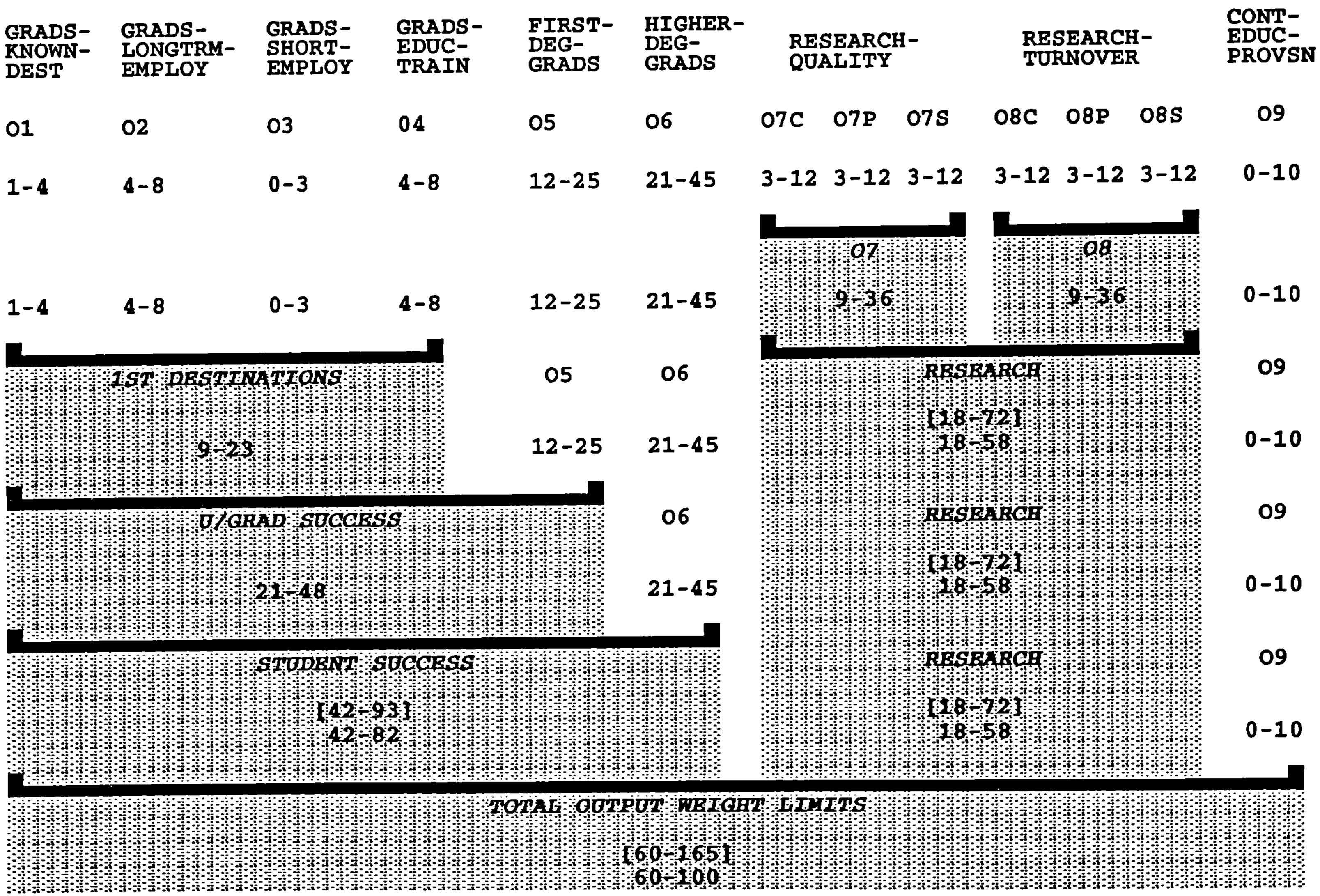


Figure 7.9. Performance Profile, Output Side, for Example 'B'.



input side of the performance profile, these each take an equal proportion of the weights attributed to their equivalent statistic in example 'A'. Hence O7C/O7P/O7S.RESEARCH-QUALITY each have limits of 3%-12% combining at level one in the group data to 9%-36% which is the limits set in example 'A' for O7.RSEARCH-QUALITY.

7.4. The Introduction of Variable Weight Restriction.

The third and fourth data runs of the two examples involved the use of the performance profile detailed in Figure 7.7 (example 'A') and its extension detailed in Figures 7.8/7.9 (example 'B').

A performance profile is achieved by the input of two additional sets of data, the upper and lower weight limits for all virtual inputs and outputs, and data defining the variable groups. Definition of variable groups does not affect the results and is not mandatory with the particular option of the DEAPMAS program used for this data run, but its inclusion effects the production of information which is highly desirable when large numbers of variables are present. An example of this information, a summary of variable groups and their effective weight limits at every defined level can be found also be found in Appendix E.

7.4.1. Data Run Three of Example 'A'.

The twenty-three DMU present in the second data run of example 'A' were applied with the performance profile introduced for the third data run, producing the results shown in Figure 7.10.

Seven of the DMU achieved 100% pareto efficiency with a further seven recording ratings of over 90% PE, but the most interesting results are the three lowest; 21% PE ('Belfast'), 15% PE ('University of Wales Institute of Science and Technology') and just 2% PE for 'Sheffield'.

It is also worth noting that the two inefficient Decision-Making Units of the first two data runs ('Heriot-Watt' and 'Belfast'), although recording reduced percentage scores, and hence having moved to a worse position relative to the pareto efficient units; in terms of ranking have improved somewhat as a result of poorer ratings achieved by other DMU. 'Belfast' moves above the two other DMU listed above and 'Heriot-Watt' (61% PE) also now rates substantially above 'London' (42% PE).

There is a common link between the three decision making units with the lowest ratings, and these units ('Belfast', 'University of Wales Institute of Science and technology' and 'Sheffield') are discussed further in Section 7.4.3.

Figure 7.10. Results of Data Run Three of Example 'A'.

```
*************************************************************
*************************************************************

 PARETO EFFICIENT UNITS

*************************************************************


     DMU   4    CITY     100%
     DMU   9    LBRO     100%
     DMU  17    EDIN     100%
     DMU  18    GLAS     100%
     DMU  20    STIR     100%
     DMU  21    CLYD     100%
     DMU  23    ULST     100%

*************************************************************
*************************************************************

 PARETO INEFFICIENT UNITS

*************************************************************


     DMU  10    MIST      97%
     DMU   5    KENT      96%
     DMU  12    SOTN      96%
     DMU  13    SURY      95%
     DMU   6    LANC      93%
     DMU   7    LEED      92%
     DMU  15    CARD      91%
     DMU   1    ASTN      85%
     DMU   3    BRAD      83%
     DMU   2    BATH      81%
     DMU  14    WARW      74%
     DMU  19    HWAT      61%
     DMU   8    LOND      42%
     DMU  22    BELF      21%
     DMU  16    UWST      15%
     DMU  11    SHEF       2%

*************************************************************
*************************************************************
*************************************************************
```

With the exception of these three units, the introduction of restrictions on the placing of variable weights by means of the performance profile has had the most marked effect on 'London', dropping from Pareto Efficiency to 42% PE.

The detailed results specific to 'London' are shown as an example output for this data run, details of the optimal weights and subsequent virtual inputs and outputs which it adopted are shown in Figure 7.11 alongside a template indicating the minimum and maximum percentage virtual input/output permitted by the performance profile.

Recalling Chapter Five (Section 5.2), the version of the DEA model utilised in the DEAPMAS program is that which minimises the total inputs having set the outputs to a fixed total, subject to those total inputs never being exceeded by the total outputs. Note therefore, that in all figures portraying the optimal weights for a particular DMU, the outputs will always total exactly one, with the greater the totalled inputs, the lower the pareto efficiency rating.

7.4.2. Data Run Three of Example 'B'.

The eight decision making units of data run two of example 'B' were again input to the third data run, together with the performance profile data detailed in Figures 7.8/7.9. In contrast to the previous runs, all DMU must now place some weight on all variables (with the possible exception of O3.GRADS-SHORT-EMPLOY and O9.CONT-EDUC-PROVISION, on which the minimum permissible application of weights is zero).

Figure 7.11. Output from Data Run Three of Example 'A', Specific to London (with Template of Variable Weight Limits).

DMU 8 LOND PARETO EFFICIENCY: 42%

ID	DATA VALUE	OPTIMUM VAL.	VIRTUAL CONT.	PERC. TOT.	MIN.	MAX.
I1) GEN-INCOME-RESEARCH	-504.0	.000476	-.239910	10.000	10	25
I2) GRANTS-RESEARCH	-275.0	.000872	-.239910	10.000	10	25
I3) GEN-INCOME-TEACHING	-698.0	.000859	-.599775	25.000	15	35
I4) ACADEMIC-STAFF	-45.0	.007997	-.359865	15.000	5	15
I5) UNDERGRAD-NUMBERS	-175.0	.002056	-.359865	15.000	5	15
I6) UNDERGRAD-ENTR-QUAL	-12.1	.029741	-.359865	15.000	5	15
I7) POSTGRAD-RESEARCH	-57.0	.002104	-.119955	5.000	5	15
I8) POSTGRAD-TAUGHT	-187.0	.000641	-.119955	5.000	5	15

TOTAL VIRTUAL INPUTS -2.399101

ID	DATA VALUE	OPTIMUM VAL.	VIRTUAL CONT.	PERC. TOT.	MIN.	MAX.
O1) GRADS-KNOWN-DEST	15.0	.000667	.010000	1.000	1	4
O2) GRADS-LONGTRM-EMPL	9.0	.004444	.040000	4.000	4	8
O3) GRADS-SHORT-EMPLOY	.1	.000000	.000000	.000	0	3
O4) GRADS-EDUC-TRAINING	3.0	.013333	.040000	4.000	4	8
O5) FIRST-DEG-GRADUATES	22.0	.005455	.120000	12.000	12	25
O6) HIGHER-DEGREE-GRADS	210.0	.002143	.450000	45.000	21	45
O7) RESEARCH-QUALITY	3.0	.030000	.090000	9.000	9	36
O8) RESEARCH-TURNOVER	341.0	.000733	.250000	25.000	9	36
O9) CONT-EDUC-PROVISION	312.0	.000000	.000000	.000	0	10

TOTAL VIRTUAL OUTPUTS 1.000000

As can be seen from the results in Figure 7.12; despite the restrictions on the application of weights now imposed seven of the eight maintained pareto efficiency, with the eighth, 'Aberystwyth' recording a rating of 86% PE.

Figure 7.12. Results of Data Run Three of Example 'B'.

```
*******************************************************************
*******************************************************************

 PARETO EFFICIENT UNITS

*******************************************************************


       DMU    1     BHAM       100%
       DMU    2     LANC       100%
       DMU    3     LOND       100%
       DMU    4     READ       100%
       DMU    5     SOTN       100%
       DMU    6     SUSX       100%
       DMU    8     ABDN       100%


*******************************************************************
*******************************************************************

 PARETO INEFFICIENT UNITS

*******************************************************************


       DMU    7     ABWY        86%


*******************************************************************
*******************************************************************
*******************************************************************
*******************************************************************
```

7.4.3. Removal of DMU Disadvantaged By Mandatory Application of Weights to Zero Outputs.

In Section 7.4.1, discussion of the results of the three very low rated decision making units in data run three of example 'A' was deferred to this section. These DMU together with a further three of example 'A' and the only pareto inefficient DMU of the third run of Example 'B' would appear to have been significantly disadvantaged as a result of the introduction of the performance profile.

As can be seen in Table 7.13, the common link between these decision making units is that they all have one or more 'zero' outputs. Were these to have been input to the DEAPMAS program as zero's then the program could not function, as a non-zero virtual input/output could never be created as a result of multiplication by zero. In fact, as explained in Chapter Five, any number less than 0.001 is converted to 0.1 by the DEAPMAS program as a practical surrogate for zero to allow the program to produce results in such circumstances.

From Table 7.13 it can also be seen that these DMU fall into two distinct categories; those which are forced to create a virtual output using a variable for which they have a 'zero' figure, and those for which the minimum level set in the performance profile for that variable is 0% of total virtual outputs. Note that 'Belfast' (example 'A') has two zero variables, one of each type.

Table 7.13. DMU of Examples A and B with Zero Outputs.

Example	DMU	Zero Output	Minimum Virtual Output Level
A	Kent	O3.GRADS-SHORT-EMPLOY	0%
A	Leeds	O3.GRADS-SHORT-EMPLOY	0%
A	London	O3.GRADS-SHORT-EMPLOY	0%
A	Sheffield	O8.RESEARCH-TURNOVER	9%
A	U. Wales Inst. Sci./Tec.	O7.RESEARCH-QUALITY	9%
A	Belfast	O3.GRADS-SHORT-EMPLOY	0%
		O7.RESEARCH-QUALITY	9%
B	Aberystwyth	O7C.RESEARCH-QUALITY	3%

The latter group are unaffected by the presence of a nil value in their data set, these four DMU all have zero figures for O3.GRADS-SHORT-EMPLOY, these are genuine zero values for a variable which the performance profile, by setting a minimum of 0%, does not enforce inclusion of in the calculation of the total virtual outputs.

Examination of the results for these DMU confirms that no weighting has been applied to O3.GRADS-SHORT-EMPLOY, and as a result the virtual output associated with that variable is precisely 0% of the total. There is no reason, therefore, to remove the DMU 'Kent', 'Leeds', or 'London' from the analysis.

'Belfast' was the fourth DMU with no graduates in short-term employment, it also, however, has a 'zero' value for the research quality variable (O7.RESEARCH-QUALITY), the effect of which is significant. 'Belfast' must use a weight of 0.9, or 90% of its total output weights, to achieve a virtual output equal to 9% of the total.

During the optimization for 'Belfast', under the DEA model, it is the pareto efficiency of 'Belfast' in comparison with all other DMU with these same weights applied to all DMU which is calculated. This explains the extremely poor pareto efficiency rating achieved.

The same is true for the 'University of Wales Institute of Science and Technology' which also has no research quality rating. Similar problems arise for 'Sheffield', no research turnover figure (O8.RESEARCH-TURNOVER), and in example 'B' for 'Aberystwyth'.

Clearly, these four DMU are set at an unfair disadvantage, and hence, until Specialisation amongst variables is introduced in Section 7.6, the DMU 'Belfast', 'University of Wales Institute of Science and Technology', and 'Sheffield' of example 'A' and 'Aberystwyth' of example 'B' are excluded from the analysis. Sub-section 7.4.4 details the fourth data runs of both examples, which are simply the third data runs repeated with the data for the withdrawn DMU deleted.

7.4.4. Results of Data Run Four of Examples 'A' and 'B'.

As would be intuitively expected, the data runs after deletion of the 'inefficient' DMU identified in Section 7.4.3, result in pareto efficiency ratings for the remaining DMU in the fourth data runs which are almost identical to those obtained in the third data runs.

The only variation in example 'A' between the two data runs is that 'Kent' rises from 96% PE to 98%, rising above 'University of Manchester Institute of Science and Technology' to become the highest rated pareto inefficient DMU. Figure 7.14 contrasts the virtual inputs and outputs used to achieve the pareto efficiency ratings of 'Kent' in the third and fourth data runs.

Figure 7.14 reveals that the slight increase in pareto efficiency has been achieved by switching weights to undergraduate and teaching statistics from taught postgraduates in the inputs and to undergraduate teaching variables from research and 'community' variables in the outputs.

One or more of the DMU excluded from the fourth data run, despite their own low rating, must have nevertheless had a significant competitive effect on 'Kent'. This 'competition' was sufficient to prevent 'Kent' utilising the pattern of weights it adopted in the fourth data run to achieve a higher rating than 96% PE in the third data run.

Recalling Sub-section 7.4.2, all the DMU in the third data run of example 'B' were pareto efficient except 'Aberystwyth'. As 'Aberystwyth' was the DMU excluded from the analysis in Sub-section 7.4.3, naturally all the remaining seven DMU recorded pareto efficiency ratings in the fourth data run of 100%.

Figure 7.14. Output of Data Runs Three and Four

of Example 'A' Specific to 'Kent'.

```
*****************************************************************

      DATA RUN 3     KENT          PARETO EFFICIENCY:    96%

*****************************************************************
  ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.    PERC. TOT.
*****************************************************************
 I1)GEN-INCOME-RESEARCH
               -81.0      .001287      -.104242        10.000
 I2)GRANTS-RESEARCH
                -2.0      .130303      -.260606        25.000
 I3)GEN-INCOME-TEACHING
               -92.0      .003506      -.322569        30.944
 I4)ACADEMIC-STAFF
                -6.0      .008687      -.052121         5.000
 I5)UNDERGRAD-NUMBERS
               -65.0      .000802      -.052121         5.000
 I6)UNDERGRAD-ENTR-QUAL
               -11.3      .004612      -.052121         5.000
 I7)POSTGRAD-RESEARCH
                -2.0      .026061      -.052121         5.000
 I8)POSTGRAD-TAUGHT
               -21.0      .006977      -.146521        14.056
*****************************************************************
                                 TOTAL VIRTUAL INPUTS  -1.042423

*****************************************************************
  ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.    PERC. TOT.
*****************************************************************
 O1)GRADS-KNOWN-DEST
                19.0      .000526       .010000         1.000
 O2)GRADS-LONGTRM-EMPL
                12.0      .003333       .040000         4.000
 O3)GRADS-SHORT-EMPLOY
                  .1      .000000       .000000          .000
 O4)GRADS-EDUC-TRAINING
                 5.0      .008000       .040000         4.000
 O5)FIRST-DEG-GRADUATES
                26.0      .004615       .120000        12.000
 O6)HIGHER-DEGREE-GRADS
                31.0      .014516       .450000        45.000
 O7)RESEARCH-QUALITY
                 1.0      .150000       .150000        15.000
 O8)RESEARCH-TURNOVER
                 1.0      .090000       .090000         9.000
 O9)CONT-EDUC-PROVISION
               107.0      .000935       .100000        10.000
*****************************************************************
                                 TOTAL VIRTUAL OUTPUTS   1.000000

*****************************************************************
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DATA RUN 4 KENT PARETO EFFICIENCY: 98%

ID	DATA VALUE	OPTIMUM VAL.	VIRTUAL CONT.	PERC. TOT.
I1) GEN-INCOME-RESEARCH	-81.0	.001261	-.102101	10.000
I2) GRANTS-RESEARCH	-2.0	.127626	-.255252	25.000
I3) GEN-INCOME-TEACHING	-92.0	.003884	-.357353	35.000
I4) ACADEMIC-STAFF	-6.0	.008508	-.051050	5.000
I5) UNDERGRAD-NUMBERS	-65.0	.001571	-.102101	10.000
I6) UNDERGRAD-ENTR-QUAL	-11.3	.004518	-.051050	5.000
I7) POSTGRAD-RESEARCH	-2.0	.025525	-.051050	5.000
I8) POSTGRAD-TAUGHT	-21.0	.002431	-.051050	5.000

TOTAL VIRTUAL INPUTS -1.021008

ID	DATA VALUE	OPTIMUM VAL.	VIRTUAL CONT.	PERC. TOT.
O1) GRADS-KNOWN-DEST	19.0	.000526	.010000	1.000
O2) GRADS-LONGTRM-EMPL	12.0	.003333	.040000	4.000
O3) GRADS-SHORT-EMPLOY	.1	.000000	.000000	.000
O4) GRADS-EDUC-TRAINING	5.0	.016000	.080000	8.000
O5) FIRST-DEG-GRADUATES	26.0	.009231	.240000	24.000
O6) HIGHER-DEGREE-GRADS	31.0	.014516	.450000	45.000
O7) RESEARCH-QUALITY	1.0	.090000	.090000	9.000
O8) RESEARCH-TURNOVER	1.0	.090000	.090000	9.000
O9) CONT-EDUC-PROVISION	107.0	.000000	.000000	.000

TOTAL VIRTUAL OUTPUTS 1.000000

7.5. Examination of the Results After Data Runs Introducing Variable Weight Restriction into DEA.

With 38 of the original 46 DMU of example 'B' excluded from analysis, the introduction of a 'performance profile' would not appear particularly helpful at this stage; little can be drawn from the results of example 'B', therefore, prior to the introduction of 'Specialisation' in Section 7.6.

The pareto efficiency ratings for example 'A' at this stage, however, provide a 'desirable' pattern of results. Figure 7.15 shows the results for the fourth data run of example 'A', seven of the DMU are pareto efficient with a clear ranking amongst the remaining DMU with ratings very close to pareto efficiency down to one very poorly rated DMU.

It would be useful at this stage to compare the results of example 'A' with the results that might have been expected, given existing assessments of the merits of various Business and Management Departments. Analysis of teaching quality has always been controversial, Table 7.16, however, shows the DMU ranked by the 'subjective' research variable that is used in the analysis, taken from the Universities' Funding Councils's 1989 Research Selectivity Exercise.

Several points arise from the statistics of Table 7.16; firstly and most obviously, very few DMU applied any more weight to this variable than the minimum necessary to reach the minimum virtual output defined by the performance profile. Only three of the twenty DMU achieve their pareto efficiency rating by

Figure 7.15. Results of Data Run Four of Example 'A'.

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PARETO EFFICIENT UNITS

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DMU	4	CITY	100%
DMU	9	LBRO	100%
DMU	15	EDIN	100%
DMU	16	GLAS	100%
DMU	18	STIR	100%
DMU	19	CLYD	100%
DMU	20	ULST	100%

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PARETO INEFFICIENT UNITS

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DMU	5	KENT	98%
DMU	10	MIST	97%
DMU	11	SOTN	96%
DMU	12	SURY	95%
DMU	6	LANC	93%
DMU	7	LEED	92%
DMU	14	CARD	91%
DMU	1	ASTN	85%
DMU	3	BRAD	83%
DMU	2	BATH	81%
DMU	13	WARW	74%
DMU	17	HWAT	61%
DMU	8	LOND	42%

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Table 7.16. DMU Present in Data Run Four of Example 'A', Ranked By the Variable 'O7.RESEARCH-QUALITY'.

DMU	RESEARCH RATING	VIRTUAL OUTPUT	PARETO EFFICIENCY
WARW	5	12%	74%
MIST	4	9%	97%
BATH	3	9%	81%
BRAD	3	9%	83%
CITY	3	9%	100%
LANC	3	9%	93%
LOND	3	9%	42%
LBRO	3	9%	100%
SOTN	3	36%	96%
SURY	3	9%	95%
CLYD	3	9%	100%
ASTN	2	9%	85%
CARD	2	29%	91%
EDIN	2	9%	100%
GLAS	2	9%	100%
STIR	2	9%	100%
KENT	1	9%	98%
LEED	1	9%	92%
HWAT	1	9%	61%
ULST	1	9%	100%

creating a higher virtual output than the 9% minimum level, of these just one applies the maximum permitted weighting, 'Southampton' alone creating a virtual output equal to 36% of total virtual outputs. The fact that seventeen out of the twenty DMU place the minimum permissible weighting onto this variable suggests that the ratios created by one or more of the remaining three are dominant to such an extent that reduced pareto efficiencies would result if these other DMU were to place any larger weighting onto the variable.

Intuitively, this degree of dominance would suggest the presence of one or more 'easily' pareto efficient DMU, similar to 'LOTHIAN&BORDERS' in the example used in Chapter Four. The ratings for the three DMU concerned are, however, 96%, 91%, and 74% PE. With a performance profile in place and a large number of variables in use this is not, however, conceptually problematic, simply revealing that the 'dominance' is confined to one sub-part of the variables. The undeveloped theory would clearly rate these three DMU pareto efficient, this is confirmed by referring back to Figure 7.1.

What does pose conceptual problems in Table 7.16 is the fact that DMU with a value for O7.RESEARCH-QUALITY of three and two, place far higher weight onto the variable than not only all other DMU with a value of three, but also the DMU with values of four and five. Further information on some of these DMU would clearly be of help, this is presented in Table 7.17.

In can be seen immediately from Table 7.17 that the major difference between the two DMU with the highest value for O7.RESEARCH-QUALITY and the pair of DMU with the highest virtual output for the same variable is the scale of operation of the DMU. This is confirmed when similar consideration is made of the remaining variables.

Table 7.17. Selected Research Statistics From Fourth Data Run of Example 'A'.

Statistics for DMU shown in the format: VALUE/VIRTUAL CONTRIBUTION

INPUTS	I1	I2	I7	I8	*Total*
WARW	452/10%	944/10%	25/13%	135/15%	*1556/48%*
MIST	602/14%	494/25%	70/5%	105/15%	*1271/59%*
LIMITS (%)	*10-25*	*10-25*	*5-15*	*5-15*	*30-70*
SOTN	71/25%	22/10%	2/10%	12/15%	*107/60%*
CARD	70/25%	31/10%	5/5%	12/15%	*118/55%*

OUTPUTS	O6	O7	O8	*Total*
WARW	31/21%	5/12%	1096/36%	*1132/69%*
MIST	83/23%	4/9%	555/34%	*638/61%*
LIMITS (%)	*21-45*	*9-36*	*9-36*	*39-79*
SOTN	10/21%	3/36%	12/10%	*25/67%*
CARD	8/21%	2/29%	31/19%	*41/69%*

There are differences in the way that these DMU have applied weights to the research variables, but for variables such as I1.GEN-INCOME-RESEARCH and O8.RESEARCH-TURNOVER the differing virtual inputs/outputs created are entirely consistent with attempts to minimise inputs whilst maximising outputs under the DEA model. The virtual outputs for the two pairs of DMU for O7.RESEARCH-QUALITY, however, directly contradict this tendency.

One of the advantages of the technique of Data Envelopment Analysis is that it is not scale sensitive. Multiplication for all DMU of any variable by any value would have no effect on the results obtained. The observation that the scale of operation is affecting the use made of the research quality variable appears to conflict with this rule.

In Section 6.6.11 of Chapter Six, the subjective nature of the UFC's Research Selectivity Exercise statistic was noted, its inclusion was therefore not ideal, but necessary as there was no other variable for departmental research other than turnover.

O7.RESEARCH-QUALITY is unique in the application, in that it is based on ordinal values of one to five, and is, hence, a finite ordinal. It would appear that the DMU 'Southampton' and 'Cardiff' were able to gain relative advantage over, amongst others, the two DMU with the highest values for this variable, because the input required per unit of this particular output is far lower. The values for all inputs of the latter pair are at least ten times the equivalent values for the prior pair, whereas, a research rating of five is less than double a rating of three.

The conclusion would appear to be that the technique of DEA, being based upon concepts of productive efficiency, cannot readily include a strictly finite scale of values. Variables included must not, it would appear, stray far from being linearly productive, in a single input and single output situation, twice the input, given perfect efficiency, should produce twice the output.

For this particular application, the most practical course of action, is not to simply withdraw this variable, as the discussion of Chapter Six (Section 6.2) concluded that its contribution was necessary, but to combine it with the research turnover variable to create a combined research output variable.

For both examples 'A' and 'B', a 'composite research variable' was therefore created, by multiplying 'O7.RESEARCH-QUALITY' with 'O8.RESEARCH-TURNOVER' to create a new seventh output 'O7.RESEARCH-COMPOSITE'. In example 'B', this will, due to variable sub-division (see Section 7.3.1), create three new variables, one for each of the three cost centres, 'Physics', 'Chemistry' and 'Other Physical Sciences' from the six former variables.

The Performance Profile was adapted to accept the new variable, by simply adding together the values of the former variables. In example 'A', therefore, the limits set on O7.RESEARCH-COMPOSITE are a minimum of 18% and maximum of 58% of total virtual outputs. In example 'B' each of the three equivalent variables must be between 6% and 24% of total virtual outputs (the mathematics of the performance profile then restricts the composite research factor to being between 18% and 58% in example 'B').

Sub-section 7.5.1 detail the results of the data runs of examples 'A' and 'B', with the new outputs substituted in. These data runs are, then, equivalent to the fourth data runs, but with the altered set of output variables. In addition, in example 'A', two of the three DMU which were excluded from data run four can now be re-included, those which had no research quality rating variable ('University of Wales Institute of Science and Technology' and 'Belfast').

The reduction in the number of outputs from nine to eight (example 'A') or eleven to ten (example 'B') should have an effect which generally slightly decreases pareto efficiency ratings due to the reduction in combinations of weight placing which will now be possible.

This will in theory, for example 'A', be counteracted by the reduction of the 'dominance' of a sub-set of the DMU which were dominant in ratios involving the former variable O7.RESEARCH-QUALITY.

7.5.1. Results of Data Run Five of Examples 'A' and 'B'.

The fifth data run of example 'A' involving O7.RESEARCH-COMPOSITE, alters the number of variables to eight inputs and eight outputs. There are 22 DMU involved, with only 'Sheffield' from Data Run Three remaining excluded. The results are shown in Figure 7.18, with the pareto efficiencies achieved in Data Run Four added in Parenthesis.

Figure 7.18 shows that there have been substantial increases and large decreases in pareto efficiency ratings between the two data runs, and a number of DMU unaffected by the switch to the combined research output variable.

Figure 7.18. Results of Data Run Five of Example 'A'; the Introduction of the 'Composite' Research Variable.

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PARETO EFFICIENT UNITS

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DMU	4	CITY	100%	*(from 100%)*
DMU	9	LBRO	100%	*(from 100%)*
DMU	15	UWST	100%	*(no rating)*
DMU	16	EDIN	100%	*(from 100%)*
DMU	17	GLAS	100%	*(from 100%)*
DMU	19	STIR	100%	*(from 100%)*
DMU	20	CLYD	100%	*(from 100%)*
DMU	22	ULST	100%	*(from 100%)*

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PARETO INEFFICIENT UNITS

****

DMU	10	MIST	97%	*(from 97%)*
DMU	1	ASTN	95%	*(from 85%)*
DMU	12	SURY	94%	*(from 95%)*
DMU	6	LANC	93%	*(from 93%)*
DMU	7	LEED	90%	*(from 92%)*
DMU	2	BATH	87%	*(from 81%)*
DMU	3	BRAD	83%	*(from 83%)*
DMU	14	CARD	82%	*(from 91%)*
DMU	13	WARW	77%	*(from 74%)*
DMU	11	SOTN	69%	*(from 96%)*
DMU	18	HWAT	61%	*(from 61%)*
DMU	21	BELF	53%	*(no rating)*
DMU	5	KENT	46%	*(from 98%)*
DMU	8	LOND	45%	*(from 42%)*

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No DMU moved into or out of the pareto efficient set as compared with that of the fourth data run, but the set increased by one DMU, as the re-introduced 'University of Wales Institute of Science and Technology' moved directly to 100% PE, a rise of 85% PE from its rating in the third data run. The other re-introduced DMU 'Belfast' showed a 32% PE rise from its previous rating to one of 53%.

Four DMU gained from the change; 'Aston' (+10% PE), 'Bath' (+6% PE), 'Warwick' (+3% PE) and 'London' (+3% PE).

Four DMU received the same pareto efficiency ratings in both data runs. With two variables having been combined, this clearly merited further examination. In fact the ratings remained unaltered to the nearest percentage point, 'Bradford' and 'Heriot-Watt' achieved slightly better ratings, and 'Manchester Institute of Science and Technology' faired slightly worse, but not sufficient to alter their rating when rounded.

The fourth DMU in this group, 'Lancaster', altered 0.4% of its virtual input and over 20% of its virtual output allocation between variables, but achieved the same pareto efficiency rating to five decimal places!

The 'losers' amongst the DMU present in data runs four and five were more substantial than the gainers, it should be remembered of course that comparison cannot be more clearly made between those gaining and losing due to the presence of two re-introduced DMU, one of which enlarged the pareto efficient set from seven to eight members.

'Kent' drops dramatically from 98% PE to the second lowest ranking (-52% PE), 'Southampton' drops 27% PE, with the other 'losers' being 'Cardiff' (-9% PE), 'Leeds' (-2% PE) and 'Surrey' (-1% PE).

The performance profile defines a minimum value of 18% of virtual outputs for O7.RESEARCH-COMPOSITE, it is logically correct, therefore, that DMU with values of '1' ('Kent') and '15.6' ('Southampton') should receive poor pareto efficiency ratings. A figure of 18% defines the research composite variable as being 'highly desirable' and therefore the model is correctly penalising these DMU for their poor achievement. This, however, raises a further point about the application of data with the DEAPMAS process.

Were 'Kent' to have had a zero for this variable it would have been eliminated from the analysis until the introduction of specialisation amongst variables (Section 7.6), where it would have been deemed to have specialised out of this activity. This would undoubtedly place a better final rating on 'Kent' than it achieved with the variable included at a dreadfully small value.

Without the benefit of consultation that would normally exist in variable selection and creation of a performance profile, no alteration will be made in this application. This evidence suggests, however, that the point at which a

DMU is deemed 'not to participate' in a variable should not automatically be at a zero level but should be assessed for each variable individually.

In example 'B', the fifth data run sees the re-introduction of 'Aberystwyth' (total eight DMU), and transfer from three pairs of O7.RESEARCH-QUALITY and O8.RESEARCH-TURNOVER to three O7.RESEARCH-COMPOSITE variables (totalling 10 outputs).

Not unsurprisingly, 'Aberystwyth' joins the other seven DMU as pareto efficient. Clearly increased competition amongst the DMU is needed before anything can be significantly drawn from example 'B', and an attempt needs to be made at including the other 38 DMU. Specialisation amongst variables is introduced in Section 7.6.

7.6. The Introduction of Specialisation Amongst Variables.

In Section 7.2.3 all DMU with zero inputs were temporarily withdrawn from the analysis. This involved the loss of four of the original 27 DMU of example 'A' and 38 of the original 46 DMU of the larger example 'B'.

The discussion of Section 7.4.3 led to the further elimination of three DMU of example 'A' and one from example 'B'. These were DMU with zero outputs, though not all such DMU, as it was established that a zero value for O3.GRADS-SHORT-EMPLOY was an acceptable part of the data.

Section 7.5 examined the results of the first four data runs of both examples and observations made regarding the inclusion of finite ordinal values led to the rationalisation of two output variables to form O7.RESEARCH-COMPOSITE in example 'A', and its three sub-divided equivalents in example 'B'. One of the effects of this was the re-introduction in the fifth data runs of both two of the three DMU eliminated (Section 7.4.3) from example 'A', and the single DMU of example 'B' eliminated at the same stage.

The procedures developed in Section 5.4 for producing and governing the use of 'Specialised Performance Profiles' are applied in this and the subsequent section (Section 7.7), in order that an attempt can be made at assessing as large a number of the two sets of DMU of the University Department application as possible.

7.6.1. Specialisation Amongst Variables in Example 'A'.

Table 7.19 reveals diagrammatically the extent of specialisation in example 'A', denoting the variables which five of the 27 DMU are deemed to 'not participate in' for the purposes of invoking specialised performance profiles.

'London Business School' and 'Manchester Business School' also have nil values for O3.GRADS-SHORT-EMPLOY, but as already explained this need not be considered as part of the specialisation because of the 0% lower virtual output limit. The Business Schools, nevertheless, do show the most specialisation in terms of total percentage of virtual inputs or virtual outputs.

Table 7.19. Identification of Specialisation Amongst Variables in Example 'A'.

DMU	INPUT VARIABLES								OUTPUT VARIABLES							
	I1	I2	I3	I4	I5	I6	I7	I8	O1	O2	O3	O4	O5	O6	O7	O8
ASTN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BATH	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BRAD	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CITY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
HULL	-	X	-	-	-	-	-	-	-	-	-	-	-	-	X	-
KENT	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
LANC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
LEED	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
LBUS	-	-	-	-	X	X	-	-	X	X	-	X	X	-	-	-
LOND	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
LBRO	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
MBUS	-	-	-	-	X	X	-	-	X	X	-	X	X	-	-	-
MIST	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
NEWC	-	-	-	-	-	-	X	-	-	-	-	-	-	-	-	-
SHEF	-	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-
SOTN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SURY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
WARW	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CARD	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
UWST	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EDIN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
GLAS	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
HWAT	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
STIR	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CLYD	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BELF	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ULST	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

These variables represent levels of 10% (inputs) and 21% (outputs) of the total virtual inputs/outputs (TVI/TVO) and as such present no problems in terms of the significance of the results that are achieved by introducing a specialised performance profile.

There are no problems, either, with significance of results in terms of the number of DMU which do not adopt the 'Standard Performance Profile', as less than 15% of the DMU are specialised.

In Table 7.19 as with all similar tables in this section, a variable which has been 'specialised out of' is indicated with an 'X'. The four-letter abbreviated codes for the DMU names are used, these were originally introduced in Table 6.6 which has the full names for all DMU.

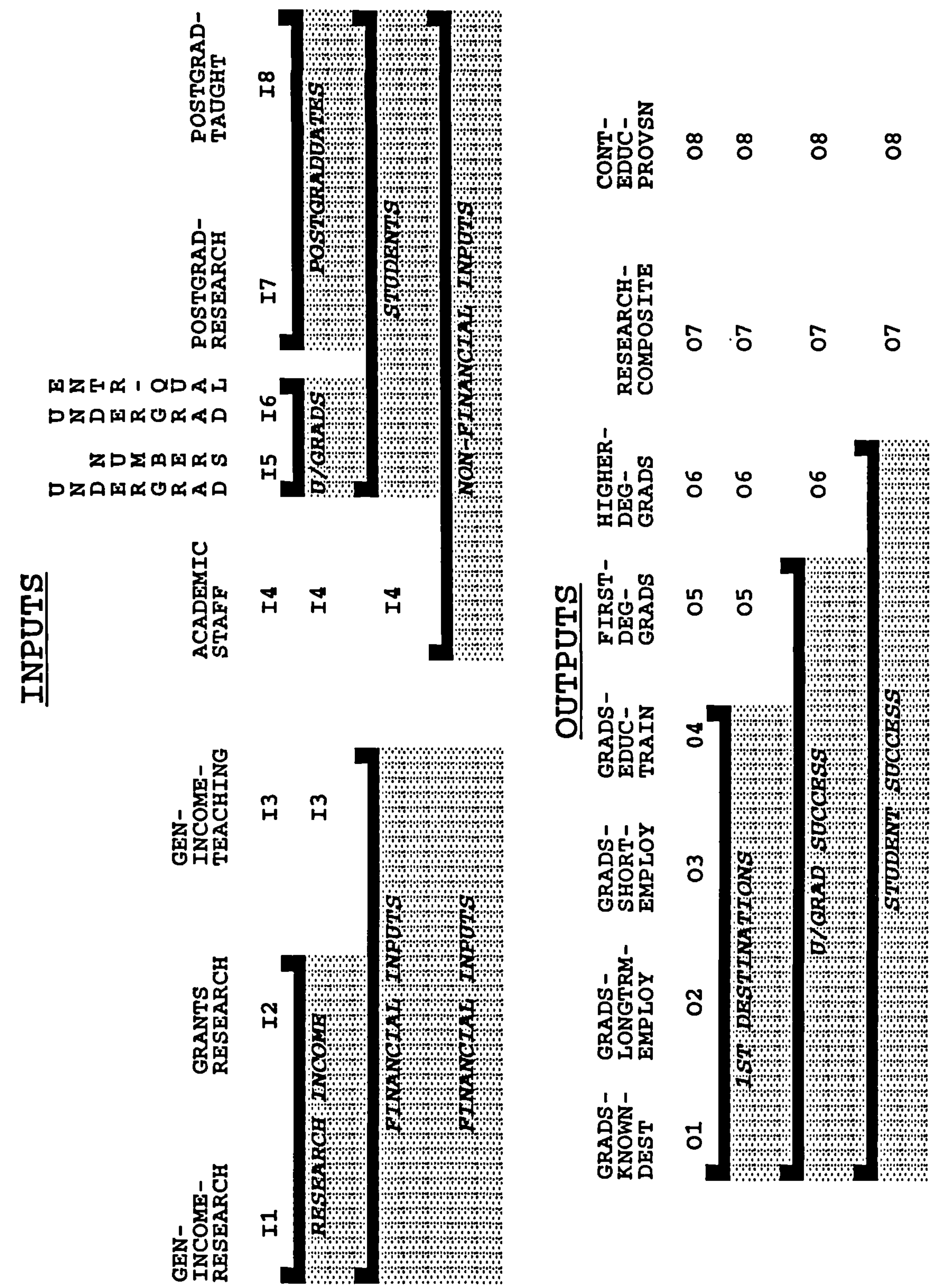
In most of the data runs involving specialisation, the type of specialisation carried out (see section 5.4) is the simplest; transfer of a deleted variables minimum and maximum weight restriction, pro rata, to the remainder of the factor to which it belongs. This type of transfer is possible as virtually all variables have been defined into factors, there being only two entirely 'independent' variables, one of which is not involved in specialisation for any of the DMU.

Figure 7.20 is derived from the performance profile of Figures 7.8 and 7.9, and identifies the variable groups which are used to identify the destination for weight restrictions to be transferred.

Using the structure identified in Figure 7.20, the weight limits in place on the variable which 'Newcastle' has specialised out of, I7.POSTGRAD-RESEARCH (restricted between 5%-15% TVI), are transferred to the other constituents of the 'POSTGRADUATES' factor, namely I8.POSTGRAD-TAUGHT (also restricted

Figure 7.20. Factor Identification in Performance Profile

for University Department Application.



to between 5%-15% TVI). In the specialised performance profile for 'Newcastle', therefore, I7.POSTGRAD-RESEARCH is not present and I8.POSTGRAD-TAUGHT has limits of 10%-30% of total virtual inputs.

The same specialised performance profile is used for both of the Business Schools; Table 7.19, in conjunction with Figure 7.20, reveals that for these DMU both the variables of the 'UNDERGRADUATES' factor are specialised out of, with the sum of their weight restrictions being transferred pro rata to the remaining two variables of the 'STUDENTS' factor, which are, in fact, the two variables representing 'POSTGRADUATES'.

Similarly, all 'UNDERGRADUATE SUCCESS' outputs are specialised out of by the Business Schools, their total weight restriction being transferred to the sole remaining member of the 'STUDENT SUCCESS' factor, namely O6.HIGHER-DEG-GRADS.

The specialised performance profile for 'London Business School' and 'Manchester Business School' is shown in Figure 7.21, revealing the weight restrictions in place in the calculation of pareto efficiency ratings for these DMU.

The specialised performance profile for the other two DMU identified in Table 7.19 ('Hull' and 'Sheffield'), require transfer of weight restriction of a different type from the other three specialised DMU. Both of these DMU are specialised out of O7.RESEARCH-COMPOSITE, which is at the 'top-level' in factor definition, that is, it is not identified as being part of a variable group. In these circumstances the lower and upper weight limits are transferred, pro-rata, to all other variables in its class (inputs or outputs).

Figure 7.21. Specialised Performance Profile for 'London Business School' and 'Manchester Business School'.

INPUTS.

```
GEN-INCOME-RESEARCH I1   10-25
                                20-50
GRANTS-RESEARCH     I2   10-25         (35-85)  (35-85)
                                        35-75    35-75
GEN-INCOME-TEACHING I3   15-35  15-35
                                                           (60-160)
ACADEMIC-STAFF      I4    5-15   5-15     5-15
                                                            60-100
(UNDERGRAD-NUMBERS   I5++NOT PRESENT++)         (25-75)

(UNDERGRAD-ENTR-QUAL I6++NOT PRESENT++)          25-65

POSTGRAD-RESEARCH   I7   10-30
                                20-60    20-60
POSTGRAD-TAUGHT     I8   10-30
```

OUTPUTS.

```
(GRADS-KNOWN-DEST     O1++NOT PRESENT++)

(GRADS-LONGTRM-EMPL   O2++NOT PRESENT++)

(GRADS-SHORT-EMPLOY   O3++NOT PRESENT++)

(GRADS-EDUC-TRAIN     O4++NOT PRESENT++)

(FIRST-DEG-GRADS      O5++NOT PRESENT++)

                          (42-93)      (42-93)
HIGHER-DEG-GRADS     O6    42-82        42-82
                                               (60-150)
RESEARCH-COMPOSITE   O7    18-58        18-58   60-100

CONT-EDUC-PROVSN     O8     0-10         0-10
```

Figure 7.22 contains an edited version of the DEAPMAS program output, reporting the figures for the output side of the specialised performance profile pertaining to these two DMU. The restrictions set on individual outputs are listed, followed by the effective limits on the defined variable groups. The full report also contains identical information on the inputs at each stage.

Figure 7.22. Edited Output from Data Run Six of Example 'A', Report Within the Data Run of Specialised Performance Profile (Output Side) for the DMU 'Hull' and 'Sheffield'.

```
***************************************************************
 PERFORMANCE PROFILE SPECIFIC TO:

                           DMU  5   HULL
                           DMU 15   SHEF

 AFTER DELETION OF VARIABLES:

                           O7)RESEARCH-COHORT
***************************************************************
 DETAILS OF PERFORMANCE PROFILE
***************************************************************
***************************************************************
   INDIVIDUAL VARIABLES:
   O1)GRADS-KNOWN-DEST
   RESTRICTED TO BETWEEN  1.43% AND  6.00%

   O2)GRADS-LONGTRM-EMPL
   RESTRICTED TO BETWEEN  5.71% AND 12.00%

   O3)GRADS-SHORT-EMPLOY
   RESTRICTED TO BETWEEN   .00% AND  5.00%

   O4)GRADS-EDUC-TRAINING
   RESTRICTED TO BETWEEN  5.71% AND 12.00%

   O5)FIRST-DEG-GRADUATES
   RESTRICTED TO BETWEEN 17.14% AND 39.00%
```

```
  06)HIGHER-DEGREE-GRADS
  RESTRICTED TO BETWEEN 30.00% AND 70.00%

  07)RESEARCH-COHORT
  NOT PRESENT IN SPECIALISED PERFORMANCE PROFILE.

  08)CONT-EDUC-PROVISION
  RESTRICTED TO BETWEEN   .00% AND 16.00%

**************************************************************
**************************************************************

  VARIABLE GROUPS:

**************************************************************
**************************************************************
 LEVEL  1
**************************************************************

 GROUP CONTAINING:

   01)GRADS-KNOWN-DEST
   02)GRADS-LONGTRM-EMPL
   03)GRADS-SHORT-EMPLOY
   04)GRADS-EDUC-TRAINING

 RESTRICTED TO BETWEEN 13% AND 35%


 GROUP CONTAINING:

   05)FIRST-DEG-GRADUATES

 RESTRICTED TO BETWEEN 17% AND 39%


 GROUP CONTAINING:

   06)HIGHER-DEGREE-GRADS

 RESTRICTED TO BETWEEN 30% AND 70%


 GROUP CONTAINING:

   08)CONT-EDUC-PROVISION

 RESTRICTED TO BETWEEN  0% AND 16%


**************************************************************
 LEVEL  2
**************************************************************

 GROUP CONTAINING:
```

```
  O1)GRADS-KNOWN-DEST
  O2)GRADS-LONGTRM-EMPL
  O3)GRADS-SHORT-EMPLOY
  O4)GRADS-EDUC-TRAINING
  O5)FIRST-DEG-GRADUATES

RESTRICTED TO BETWEEN 30% AND 70%


GROUP CONTAINING:

  O6)HIGHER-DEGREE-GRADS

RESTRICTED TO BETWEEN 30% AND 70%


GROUP CONTAINING:

  O8)CONT-EDUC-PROVISION

RESTRICTED TO BETWEEN  0% AND 16%

**************************************************************
 LEVEL  3
**************************************************************


GROUP CONTAINING:

  O1)GRADS-KNOWN-DEST
  O2)GRADS-LONGTRM-EMPL
  O3)GRADS-SHORT-EMPLOY
  O4)GRADS-EDUC-TRAINING
  O5)FIRST-DEG-GRADUATES
  O6)HIGHER-DEGREE-GRADS

RESTRICTED TO BETWEEN 84% AND 100%


GROUP CONTAINING:

  O8)CONT-EDUC-PROVISION

RESTRICTED TO BETWEEN  0% AND 16%

**************************************************************
**************************************************************

      TOTAL FIXED OUTPUT WEIGHTS: 60.00%; LEAVING 40.00%

      FREE FOR OPTIMISATION WITHIN PERFORMANCE PROFILE

**************************************************************
**************************************************************
**************************************************************
```

For example 'A', the sets of variables defining factors are at three levels. In Figure 7.22 there is clear demonstration of cases where the 'actual' restriction on the virtual outputs differs from that which is 'implied. At 'level two', by addition the maximum restriction on the undergraduate success factor (see Figure 7.20) would be 74% TVO, but the actual maximum is 70% TVO, as a result of the 30% TVO minimum restriction on O6.HIGHER-DEGREE-GRADS.

When these two factors are combined to produce the student success factor, their combined minimum weight restriction would be 60% TVO. The only variable outwith this group, however, is O8.CONT-EDUC-PROVISION, with a maximum limit of 16% TVO, the actual minimum restriction on the student success factor therefore being 84% of total virtual outputs.

The report on the specialised performance profile concludes with a statement of the magnitude of the total fixed proportion of output weights and the balance which this leaves free for optimization, the flexible portion.

'Hull' also specialises out of I2.GRANTS-RESEARCH (limited to between 10% and 25% TVI), again referring to Figure 7.20, this variable is one of the two variables which make up the factor 'RESEARCH INCOME' and as such I1.GEN-INCOME-RESEARCH moves from limits of 10%-25% of Total Virtual Inputs to 20%-50% TVI.

7.6.2. Results of Data Run Six of Example 'A'.

As discussed in the Chapter Five (section 5.4.4), DMU utilising a specialised performance profile face the 'competitive' influence, under the DEA model, of all the DMU which adhere to the Standard Performance Profile for that application. As explained, these specialised DMU, however, play no role in the calculation of the pareto efficiency ratings for any other DMU within the DEAPMAS program.

All results obtained for non-specialised DMU will remain constant, therefore, between data runs five and six. This is confirmed in the results from the sixth data run, the summary output of which is shown in Figure 7.23.

Two of the specialised DMU, 'London Business School' and 'Newcastle' join the pareto efficient set. The other three are considerably short of pareto efficiency, 'Manchester Business School' fairing best with 86% PE, while 'Hull' achieves 74% PE and ranks 21st of the 27 DMU and 'Sheffield' is rated 7% PE lower and 23rd.

The detailed output of the sixth data run specific to 'Hull' is shown in Figure 7.24, illustrating the way in which the weights have been placed within the restrictions of the DMU's specialised performance profile in order to maximise its pareto efficiency rating.

Figure 7.23. Results of Data Run Six of Example 'A'.

```
*****************************************************************

            SUMMARY OF RESULTS FOR
            EXAMPLE A    DATA RUN 6

*****************************************************************
*****************************************************************

 PARETO EFFICIENT UNITS

*****************************************************************


      DMU   4     CITY       100%
      DMU   9     LBUS       100%
      DMU  11     LBRO       100%
      DMU  14     NEWC       100%
      DMU  20     UWST       100%
      DMU  21     EDIN       100%
      DMU  22     GLAS       100%
      DMU  24     STIR       100%
      DMU  25     CLYD       100%
      DMU  27     ULST       100%


*****************************************************************
*****************************************************************

 PARETO INEFFICIENT UNITS

*****************************************************************


      DMU  13     MIST        97%
      DMU   1     ASTN        95%
      DMU  17     SURY        94%
      DMU   7     LANC        93%
      DMU   8     LEED        90%
      DMU   2     BATH        87%
      DMU  12     MBUS        86%
      DMU   3     BRAD        83%
      DMU  19     CARD        82%
      DMU  18     WARW        77%
      DMU   5     HULL        74%
      DMU  16     SOTN        69%
      DMU  15     SHEF        67%
      DMU  23     HWAT        61%
      DMU  26     BELF        53%
      DMU   6     KENT        46%
      DMU  10     LOND        45%


*****************************************************************
```

Figure 7.24. Output of Data Run Six of Example 'A',

Specific to the DMU 'Hull'.

```
*****************************************************************
*****************************************************************

     DMU    5       HULL          PARETO EFFICIENCY:    74%

*****************************************************************
  ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.
*****************************************************************
 I1)GEN-INCOME-RESEARCH
             -90.0      .006029      -.542598       40.000
 I2)GRANTS-RESEARCH
                .0      .000000       .000000         .000
 I3)GEN-INCOME-TEACHING
            -127.0      .001602      -.203474       15.000
 I4)ACADEMIC-STAFF
              -9.0      .007536      -.067825        5.000
 I5)UNDERGRAD-NUMBERS
             -76.0      .002677      -.203474       15.000
 I6)UNDERGRAD-ENTR-QUAL
             -10.4      .019565      -.203474       15.000
 I7)POSTGRAD-RESEARCH
              -8.0      .008478      -.067825        5.000
 I8)POSTGRAD-TAUGHT
             -22.0      .003083      -.067825        5.000
*****************************************************************
                              TOTAL VIRTUAL INPUTS  -1.356496

*****************************************************************
  ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.
*****************************************************************
 O1)GRADS-KNOWN-DEST
              26.0      .002308       .060000        6.000
 O2)GRADS-LONGTRM-EMPL
              16.0      .007500       .120000       12.000
 O3)GRADS-SHORT-EMPLOY
               1.0      .050000       .050000        5.000
 O4)GRADS-EDUC-TRAINING
               7.0      .008163       .057143        5.714
 O5)FIRST-DEG-GRADUATES
              29.0      .007893       .228897       22.890
 O6)HIGHER-DEGREE-GRADS
              17.0      .019056       .323960       32.396
 O7)RESEARCH-COHORT
                .1      .000000       .000000         .000
 O8)CONT-EDUC-PROVISION
              94.0      .001702       .160000       16.000
*****************************************************************
                              TOTAL VIRTUAL OUTPUTS   1.000000

*****************************************************************
```

In this section, DMU have been allowed to specialise amongst variables to a greater degree than otherwise would be permitted by the constraints of the 'base' performance profile in use, that is, to specialise out of one or more variables completely, adopting their own 'specialised' performance profile.

With 22 DMU adhering to the 'standard' performance profile, and five having specialised performance profiles created, hence, pareto efficiency ratings have been obtained for all the original 27 DMU of Example 'A'.

The larger Example 'B' involves very many 'missing values', and as a result applying the procedures for specialisation amongst variables will be more complex, with the significance of the results obtained more likely to be in question than for Example 'A'.

Only eight of the original 46 DMU of example 'B' were involved in the final run before specialisation amongst variables is introduced, leaving 36 which could not be assessed, with a performance profile in place, at this point. A separate section, section 7.7, is therefore devoted to attempts to re-introduce these 36 DMU into the analysis.

7.7. Specialisation Amongst Variables in Example 'B'.

In Section 7.6, the specialisation procedures of the DEAPMAS process were applied to Example 'A' in which a relatively small number of DMU required the ability to form specialised performance profiles. Pareto Efficiency ratings were readily achieved for all 27 DMU of the original set, with just five DMU utilising their own, specialised, performance profiles.

The larger example 'B' data has a significant number of missing values on the output side, but the input side is extremely incomplete with missing values across no less than fourteen of the twenty inputs. Table 7.25 shows the full extent of specialisation by the full 46 DMU, amongst the 30 variables.

As noted in Section 7.6.1; an 'X' denotes a variable which the particular DMU has 'specialised out of'. The table excludes both the six inputs and six outputs which are present for all DMU, and those for which the performance profile sets a minimum level of zero (03.GRADS-SHORT-EMPLOY and 08.CONT-EDUC-PROVISION).

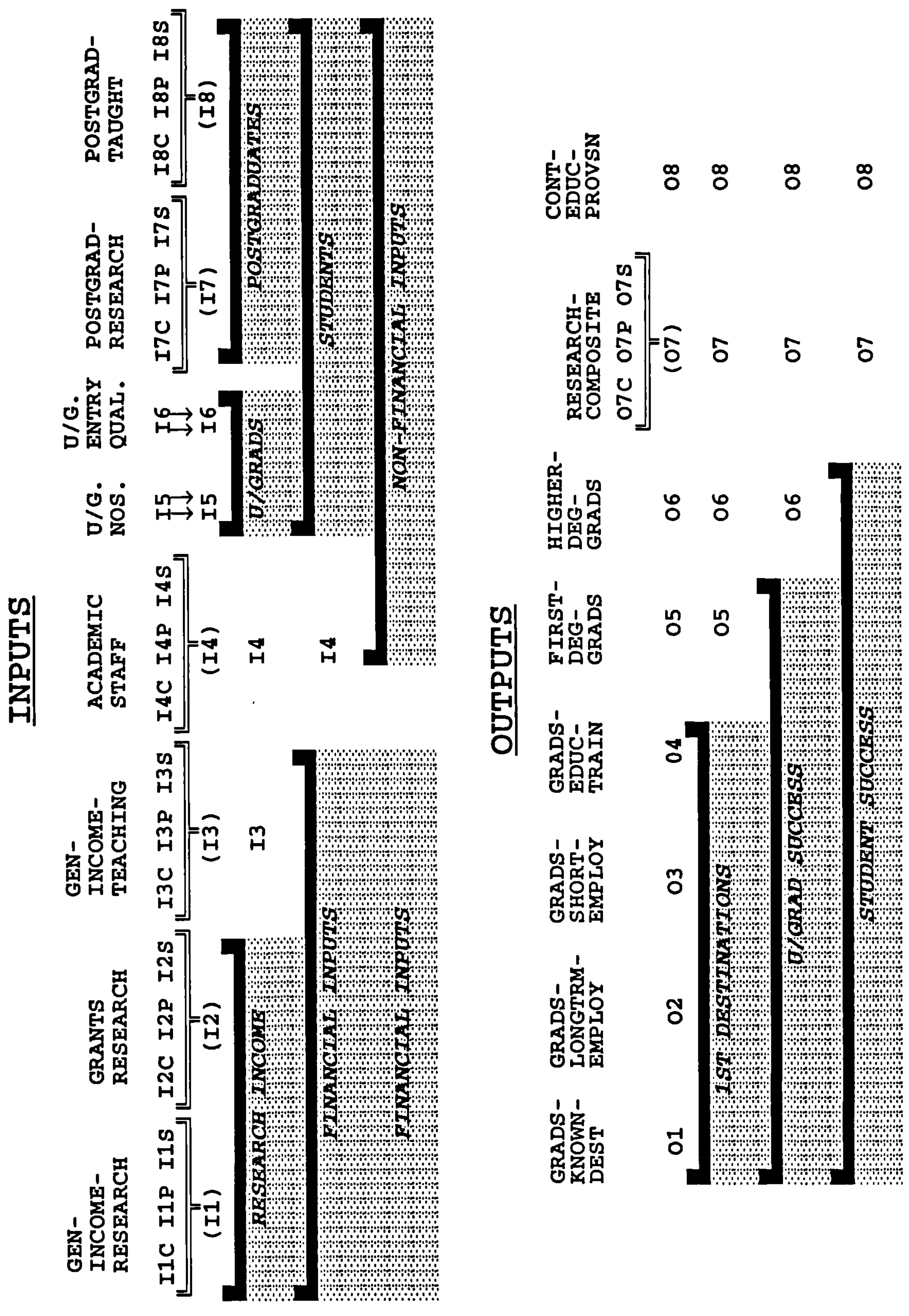
The table reveals a varied pattern of specialisation amongst the variables by the 46 DMU, from DMU with just one nil value to one particular DMU with no less than fifteen. Equally, some variables are present for all but one DMU, while 23 DMU lack I8C.POSTGRAD-TAUGHT.

Identification of the factors and their constituent variables for the University Department application was made in Figure 7.20. As many of these variables are sub-divided in example 'B' (see Section 7.3.1), Figure 7.20 is reproduced, adapted for example 'B', as Figure 7.26.

Table 7.25. Identification of Specialisation Amongst Variables in Example 'B'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	I8C	I8P	I8S	O7P	O7S
BATH	-	X	-	X	-	X	-	X	-	-	X	X	X	X	-	X
BHAM	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BRAD	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
BRIS	-	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-
BRUN	-	X	-	X	-	X	-	X	-	-	X	-	-	X	-	X
CAMB	-	-	-	-	-	-	-	-	X	-	-	X	-	-	-	-
DHAM	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
EANG	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
ESSX	-	X	-	X	-	X	-	X	-	-	X	-	-	X	-	X
EXTR	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
HULL	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
KEEL	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
KENT	-	X	-	X	-	X	-	X	-	-	X	X	X	X	-	X
LANC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
LEED	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
LEIC	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
LIVR	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
LOND	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
LBRO	-	X	-	X	-	X	-	X	-	-	X	-	X	X	-	X
MANU	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
MIST	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
NEWC	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
NOTT	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
OXFD	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
READ	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SALF	-	X	-	X	-	X	-	X	-	-	X	-	-	X	-	X
SHEF	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
SOTN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SURY	-	X	-	X	-	X	-	X	-	-	X	-	-	X	-	X
SUSX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
WARW	-	X	-	X	-	X	-	X	-	-	X	X	X	X	-	X
YORK	-	X	-	X	-	X	-	X	-	-	X	-	-	X	-	X
ABWY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BNGR	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
CARD	-	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-
SWAN	-	-	-	-	-	-	-	-	-	-	-	X	-	X	-	-
UWST	X	X	X	X	X	X	X	X	-	X	X	X	X	X	X	X
ABDN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DUND	-	-	-	-	-	-	-	-	-	-	-	X	-	X	-	-
EDIN	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
GLAS	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-
HWAT	-	X	-	X	-	X	-	X	-	-	X	X	-	X	-	X
ANDW	-	-	-	-	-	-	-	-	-	-	-	X	-	X	-	-
STIR	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
CLYD	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
BELF	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-

Figure 7.26. Factor Identification in Performance Profile for Example 'B' of the University Department Application.



Of the 46 DMU, only eight would adopt the 'Standard Performance Profile', and hence under the arguments put forward in Chapter Five (Section 5.4.3), with the data present for this application, the level of specialisation is far too high for these DMU to be assessed as one integral set.

As the 46 Decision Making Units cannot be assessed collectively, it is necessary to split them into distinct groups which can be internally assessed to produce significant results.

Further examination of Table 7.25 reveals that the variables with most missing values are the three variables representing taught postgraduates (I8C/I8P/I8S). Separation on the basis of the presence or absence of one or more of these three variables would not immediately lead to a sufficient fall in levels of specialisation amongst variables to one at which distinct sets of DMU which could be assessed, a minimum of two-thirds of DMU adopting the Standard Performance Profile. These three variables will, however, clearly play a pivotal role in the process of 'splitting' the DMU into separate groups.

As it will require more than one iteration of the process of separation to distinct sets of DMU before significant results can be gleaned, the order in which the division is carried out will not make any difference, the same sets of DMU will eventually be achieved.

Again referring to Table 7.25, the most logical first step would be to separate those DMU which participate in the variables of the cost centre 'Other Physical Sciences' from those which do not. The 'S sub-divisions' of variables account for a total of seven of the variables in which DMU exhibit specialisation.

Tables 7.27 and 7.28 reveal the effect of this breaking down of the DMU to those with data for one or more of the variables of the group I1S, I2S, I3S, I4S, I7S, I8S, and O7S (Table 7.27), and those DMU without data for any of these variables (Table 7.28). This divide, hence, distinguishes those DMU which have activity in the cost centre 'Other Physical Sciences', from those which do not.

In the Tables of this section the variables of the overall set of 30 which would be absent for data runs involving one of these newly formed groups of DMU are indicated by columns of asteri. In any actual data runs which involve these DMU groups, such 'deleted' variables would, of course, simply not be included.

Examining Table 7.27, the group of DMU still has the same variable set as the fifth data run, with all 30 variables present, hence the same 30-variable Standard Performance Profile would be utilised. This being the case, there naturally remains the same eight DMU free of specialisation in the group of 35 DMU that there were in the group of 46.

Turning to the group of Universities in Table 7.28, in a data run with the 'reduced' data set for these DMU, only five of the eleven would adopt the 23-

Table 7.27. Specialisation Amongst Variables in The 35 DMU Participating in 'Other Physical Sciences' Variables.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	I8C	I8P	I8S	O7P	O7S
BHAM	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BRAD	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
BRIS	-	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-
CAMB	-	-	-	-	-	-	-	-	X	-	-	X	-	-	-	-
DHAM	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
EANG	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
EXTR	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
HULL	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
KEEL	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
LANC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
LEED	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
LEIC	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
LIVR	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
LOND	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
MANU	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
MIST	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
NEWC	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
NOTT	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
OXFD	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
READ	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SHEF	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
SOTN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SUSX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ABWY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
BNGR	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	-
CARD	-	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-
SWAN	-	-	-	-	-	-	-	-	-	-	-	X	-	X	-	-
ABDN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
DUND	-	-	-	-	-	-	-	-	-	-	-	X	-	X	-	-
EDIN	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	-
GLAS	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-
ANDW	-	-	-	-	-	-	-	-	-	-	-	X	-	X	-	-
STIR	-	-	-	-	-	-	-	-	-	-	-	X	X	X	-	-
CLYD	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-
BELF	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-

Table 7.28. Specialisation Amongst Variables in the Eleven DMU Not Participating in 'Other Physical Sciences' Variables.

	I1P	*	I2P	*	I3P	*	I4P	*	I6	I7P	*	I8C	I8P	*	O7P	*
BATH	-	*	-	*	-	*	-	*	-	-	*	X	X	*	-	*
BRUN	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*
ESSX	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*
KENT	-	*	-	*	-	*	-	*	-	-	*	X	X	*	-	*
LBRO	-	*	-	*	-	*	-	*	-	-	*	-	X	*	-	*
SALF	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*
SURY	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*
WARW	-	*	-	*	-	*	-	*	-	-	*	X	X	*	-	*
YORK	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*
UWST	X	*	X	*	X	*	X	*	-	X	*	X	X	*	X	*
HWAT	-	*	-	*	-	*	-	*	-	-	*	X	-	*	-	*

variable Standard Performance Profile, these DMU would, hence, still be in a minority.

Neither of the groups in Tables 7.27 and 7.28 can be applied to the DEAPMAS process without failing the 'two-thirds rule' of DMU which would adopt the Standard Performance Profile, designed to ensure significance in the results obtained. Clearly, hence, further decomposition beyond the formation of the two sub-sets of DMU already produced is indicated.

Section 7.7.1 details the further division of the smaller of the two groups; the eleven DMU of Table 7.28, and the subsequent section (section 7.7.2), the more complex division of the 35 DMU of Table 7.27.

7.7.1. Decomposition of DMU Without 'Other Physical Sciences' Activity to Distinct Sets of Comparable DMU.

From examination of Table 7.28, a separation of DMU with or without one of the 'taught postgraduate' variables will clearly be the most effective. The effect of such a division is shown in Tables 7.29 and 7.30. These tables show the extent of specialisation amongst variables in the groups divided from those in Table 7.28 with (Table 7.29), and without (Table 7.30) 'Chemistry Taught Postgraduates'.

An extra column has been added to these tables and will also be present in all subsequent tables of this and the following section. This column reveals the percentage of total virtual inputs which is specialised for each of the DMU.

Recalling Section 5.4.2 of the fifth chapter, an absolute maximum figure of 50% of either total virtual inputs or total virtual outputs is permitted to ensure the viability of the group of DMU, in terms of the confidence in results for all constituent DMU. The figures for percentage of total virtual outputs are not shown as with the extent of specialisation in this application the maximum permitted figure could never be breached.

With only 'Loughborough' demonstrating specialisation amongst variables from the group of Six DMU in Table 7.29, and in only one variable (which represents 2.5% TVI), this distinct group can be assessed with a satisfactory level of confidence in the pareto efficiency ratings obtained.

Table 7.29. Specialisation Amongst Variables in the Six DMU of Table 7.28 Which Participate in 'I8C.POSTGRAD-TAUGHT'.

	I1P	*	I2P	*	I3P	*	I4P	*	I6	I7P	*	I8C	I8P	*	O7P	*	spec. TVI%
BRUN	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*	0
ESSX	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*	0
LBRO	-	*	-	*	-	*	-	*	-	-	*	-	X	*	-	*	2.5
SALF	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*	0
SURY	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*	0
YORK	-	*	-	*	-	*	-	*	-	-	*	-	-	*	-	*	0

Table 7.30. Specialisation Amongst Variables in the Five DMU of Table 7.28 Not Participating in 'I8C.POSTGRAD-TAUGHT'.

	I1P	*	I2P	*	I3P	*	I4P	*	I6	I7P	*	*	I8P	*	O7P	*	spec. TVI%
BATH	-	*	-	*	-	*	-	*	-	-	*	*	X	*	-	*	2.5
KENT	-	*	-	*	-	*	-	*	-	-	*	*	X	*	-	*	2.5
WARW	-	*	-	*	-	*	-	*	-	-	*	*	X	*	-	*	2.5
UWST	X	*	X	*	X	*	X	*	-	X	*	*	X	*	X	*	24.8
HWAT	-	*	-	*	-	*	-	*	-	-	*	*	-	*	-	*	0

There is only one University ('Heriot-Watt') in the group of DMU in Table 7.30 which would adhere to the 22-variable Standard Performance Profile which would be used for that collection of DMU. One final division can be made; between those DMU with or without the variable 'I8P.POSTGRAD-TAUGHT'.

Table 7.31 contains the four DMU without this variable, which in fact is a group with no taught postgraduates at all. This group with three of the Four DMU free of specialisation can be assessed as a coherent set of DMU. Note that 'University of Wales Institute of Science and Technology' exhibits a very

Table 7.31. Specialisation Amongst Variables in the Four DMU of Table 7.30 Not Participating in 'I8P.POSTGRAD-TAUGHT'.

	I1P	*	I2P	*	I3P	*	I4P	*	I6	I7P	*	*	*	*	O7P	*	spec. TVI%
BATH	-	*	-	*	-	*	-	*	-	-	*	*	*	*	-	*	0
KENT	-	*	-	*	-	*	-	*	-	-	*	*	*	*	-	*	0
WARW	-	*	-	*	-	*	-	*	-	-	*	*	*	*	-	*	0
UWST	X	*	X	*	X	*	X	*	-	X	*	*	*	*	X	*	22.3

high level of specialisation at 22.3%, but not sufficiently high to be excluded from the analysis.

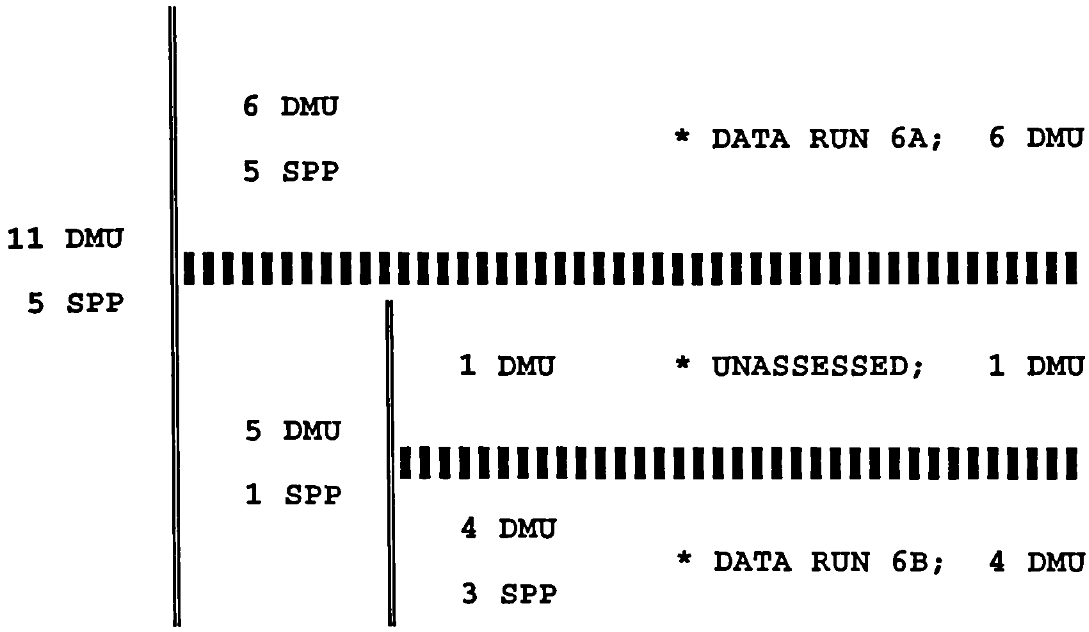
The sole DMU from this division that has the 'Physics Taught Postgraduate' variable, unfortunately cannot be practically assessed. The process of division has rendered it unique. DEA being based on comparison, 'Heriot-Watt' must therefore be excluded from the analysis.

Hence, two data runs are indicated from the division in this sub-section, one of six DMU, one member of which has specialisation, and another of four DMU, again with one member exhibiting specialisation. One further DMU is excluded from the analysis. These divisions are summarised in Figure 7.32.

Figure 7.32 shows the number of DMU in each group, along with the number of DMU which would adopt the Standard Performance Profile (SPP) in each case. It also reveals the member DMU of the groups that form the data runs which are reported in Section 7.8.

Figure 7.32. Division to Distinct Groups of DMU from

the Eleven DMU of Table 7.28.



DATA RUN 6A: BRUN, ESSX, LBRO, SALF, SURY, YORK.

DATA RUN 6B: BATH, KENT, WARW, UWST.

UNASSESSED: HWAT.

7.7.2. Decomposition of DMU With 'Other Physical Sciences' Activity to Distinct Sets of Comparable DMU.

The initial division of the original 46 Decision Making Units led to the creation of the separate set of 35 DMU which participate in the 'Other Physical Sciences' cost centre. The specialisation amongst variables within this grouping was illustrated in Table 7.27.

As explained in Section 7.7; the other set of DMU created in the initial split was the one which had the reduced variable set. The group of 35 DMU must have, given the unchanged variable set, the same number of DMU adopting the Standard Performance Profile as had the original 46 DMU. These eight DMU still represent only a small proportion of the, now reduced, set of 35 DMU, too small for a data run at this point to provide results with sufficient significance. A further division to separate groups of DMU is, hence, indicated.

The variable which the largest number of DMU do not participate in is 'I8C.POSTGRAD-TAUGHT', eighteen of the DMU lacking this variable. Sub-division to two distinct groups of DMU on the basis of whether or not each has 'Chemistry taught postgraduates' is, therefore, the obvious step.

Table 7.33 démonstrates the remaining specialisation amongst variables in the seventeen DMU which do have 'I8C.POSTGRAD-TAUGHT', with Table 7.34 illustrating the same information for the reduced-variable grouping of the remaining eighteen DMU.

Specialisation amongst variables by the 17 DMU of Table 7.33 is now limited to just two variables, each of which represents just 1.7% of Total Virtual Inputs.

The DMU of Table 7.33 are those, however, with the full 30-variable set intact. As such, there remains just eight DMU which would utilise the Standard Performance Profile in a data run, and as these DMU would still be in a

Table 7.33. Specialisation Amongst Variables in the Seventeen DMU of Table 7.27 Which Participate in 'I8C.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	I8C	I8P	I8S	O7P	O7S	spec. TVI %
BHAM	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
BRIS	-	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	3.4
EANG	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	1.7
HULL	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	1.7
LANC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
LEED	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	1.7
LOND	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
MIST	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	1.7
READ	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
SOTN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
SUSX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
ABWY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
CARD	-	-	-	-	-	-	-	-	-	-	-	-	X	X	-	-	3.4
ABDN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
GLAS	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	1.7
CLYD	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	-	1.7
BELF	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	1.7

Table 7.34. Specialisation Amongst Variables in the Seventeen DMU of Table 7.27 Not Participating in 'I8C.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	*	I8P	I8S	O7P	O7S	spec. TVI %
BRAD	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0.00
CAMB	-	-	-	-	-	-	-	-	X	-	-	*	-	-	-	-	5.00
DHAM	-	-	-	-	-	-	-	-	-	-	-	*	X	-	-	-	2.55
EXTR	-	-	-	-	-	-	-	-	-	-	-	*	X	X	-	-	5.10
KEEL	-	-	-	-	-	-	-	-	-	-	-	*	X	X	-	-	5.10
LEIC	-	-	-	-	-	-	-	-	-	-	-	*	X	-	-	-	2.55
LIVR	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0.00
MANU	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0.00
NEWC	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0.00
NOTT	-	-	-	-	-	-	-	-	-	-	-	*	X	-	-	-	2.55
OXFD	-	-	-	-	-	-	-	-	-	-	-	*	X	X	-	-	5.10
SHEF	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0.00
BNGR	-	-	-	-	-	-	-	-	-	-	-	*	X	-	-	-	2.55
SWAN	-	-	-	-	-	-	-	-	-	-	-	*	-	X	-	-	2.55
DUND	-	-	-	-	-	-	-	-	-	-	-	*	-	X	-	-	2.55
EDIN	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0.00
ANDW	-	-	-	-	-	-	-	-	-	-	-	*	-	X	-	-	2.55
STIR	-	-	-	-	-	-	-	-	-	-	-	*	X	X	-	-	5.10

minority, under the rules adopted within the DEAPMAS process, significant results could not be obtained. Further division is therefore necessary.

Of the two variables illustrated in Table 7.33 as not being participated in by some DMU, 'I8P.POSTGRADUATE-TAUGHT' is 'missing' for a greater number of DMU than the other 'I8S.POSTGRADUATE-TAUGHT' and therefore it is the Physics sub-division of the eighth input variable which forms the basis of the division to distinct groups.

Table 7.35 illustrates the specialisation amongst variables for the ten DMU of Table 7.33 which have 'Physics taught postgraduates' and Table 7.36 in turn illustrates the specialisation amongst variables of the seven DMU which do not participate in 'I8P.POSTGRADUATE-TAUGHT'.

Table 7.35. Specialisation Amongst Variables in the Ten DMU of Table 7.33 Which Participate in 'I8P.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	I8C	I8P	I8S	O7P	O7S	spec. TVI %
BHAM	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
LANC	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
LOND	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
READ	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
SOTN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
SUSX	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
ABWY	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
ABDN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0
GLAS	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	1.7
BELF	-	-	-	-	-	-	-	-	-	-	-	-	-	X	-	-	1.7

Table 7.36. Specialisation Amongst Variables in the Seven DMU of Table 7.33 Not Participating in 'I8P.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	I8C	*	I8S	O7P	O7S	spec. TVI %
BRIS	-	-	-	-	-	-	-	-	-	-	-	-	*	X	-	-	2.55
EANG	-	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	0
HULL	-	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	0
LEED	-	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	0
MIST	-	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	0
CARD	-	-	-	-	-	-	-	-	-	-	-	-	*	X	-	-	2.55
CLYD	-	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	0

With eight of the ten DMU listed in Table 7.35 participating in all of the 30-variable set, a distinct and comparable sub-grouping from the original 46 DMU has been achieved.

Equally, five of the seven DMU of Table 7.36 would adopt the 29-variable Standard Performance Profile for this group. This figure also exceeds the two-thirds required for confidence to exist in the significance of the results which could be obtained.

In terms of percentage of Total Virtual Inputs which are specialised out of for any particular DMU, in both of the sets of DMU contained in the two preceding tables, the very small figures (1.7% and 2.55% TVI) would not reduce the significance of pareto efficiency ratings obtained.

The data for both these sets of DMU can therefore be applied to data runs to produce satisfactorily significant results. The route of division to these groups of DMU is summarised in Figure 7.37, together with the number of DMU in each group which adopt the Standard Performance Profile and a listing of the members of these variable groups.

The results of Data Runs 6C and 6D are discussed in Section 7.8 together with Data Runs 6A and 6B developed in Section 7.7.1 and those containing the comparable groups which will now be developed from the eighteen DMU of Table 7.34.

<u>Figure 7.37. Division to Distinct Groups of DMU from the Seventeen DMU of Table 7.33.</u>

17 DMU 8 SPP	10 DMU 8 SPP	* DATA RUN 6C; 10 DMU
	7 DMU 5 SPP	* DATA RUN 6D; 5 DMU

DATA RUN 6C: BHAM, LANC, LOND, READ, SOTN, SUSX, ABWY, ABDN, GLAS, BELF.

DATA RUN 6D: BRIS, EANG, HULL, LEED, MIST, CARD, CLYD.

Table 7.34 illustrated the specialisation amongst variables by the eighteen DMU in Table 7.27 which did not participate in 'I8C.POSTGRADUATE-TAUGHT'. Referring back to this table, only six of the DMU would adopt the 29-variable Standard Performance Profile, and, hence, a further division to distinct groups is clearly indicated.

Again this division is centred on the taught postgraduate statistics, more of the group of eighteen DMU are without data for 'I8P.POSTGRADUATE-TAUGHT' than any other variable. Separating the DMU on this basis, Table 7.38 lists the group of ten DMU from Table 7.34 which have 'Physics taught postgraduates', and the specialisation amongst variables which exists within it. Table 7.39 supplies the same data concerning the eight DMU which do not have 'I8P.POSTGRADUATE-TAUGHT'.

Table 7.38. Specialisation Amongst Variables in the Ten DMU of Table 7.34 Which Participate in 'I8P.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	*	I8P	I8S	O7P	O7S	spec. TVI %
BRAD	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
CAMB	-	-	-	-	-	-	-	-	X	-	-	*	-	-	-	-	5.00
LIVR	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
MANU	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
NEWC	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
SHEF	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
SWAN	-	-	-	-	-	-	-	-	-	-	-	*	-	X	-	-	2.55
DUND	-	-	-	-	-	-	-	-	-	-	-	*	-	X	-	-	2.55
EDIN	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
ANDW	-	-	-	-	-	-	-	-	-	-	-	*	-	X	-	-	2.55

Table 7.39. Specialisation Amongst Variables in the Eight DMU of Table 7.34 Not Participating in 'I8P.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	*	*	I8S	O7P	O7S	spec. TVI %
DHAM	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0
EXTR	-	-	-	-	-	-	-	-	-	-	-	*	*	X	-	-	5.1
KEEL	-	-	-	-	-	-	-	-	-	-	-	*	*	X	-	-	5.1
LEIC	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0
NOTT	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0
OXFD	-	-	-	-	-	-	-	-	-	-	-	*	*	X	-	-	5.1
BNGR	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0
STIR	-	-	-	-	-	-	-	-	-	-	-	*	*	X	-	-	5.1

Unfortunately, these two newly created sets of DMU still cannot be satisfactorily assessed. The ten DMU of Table 7.38 narrowly fall short of the significance of results test pertaining to the proportion of DMU which would adopt the 29-variable Standard Performance Profile, with six of the group not demonstrating any specialisation amongst the variables. For the eight DMU of Table 7.39, this figure drops to just 50%, with in this case a 28-variable Standard Performance Profile applying.

The final sub-divisions to distinct groups of comparable DMU will clearly, referring to the specialisation amongst variables portrayed in Tables 7.38 and 7.39, be on the basis of the same variable in both cases.

Division of the DMU of Table 7.38 on the basis of the presence (seven DMU) or absence (three DMU) of the variable 'I8S.POSTGRADUATE-TAUGHT' is shown in Tables 7.40 and 7.41 respectively. Similarly, division of the DMU of Table 7.39, on the same basis, leads to the creation of two groups of four DMU.

Table 7.40. Specialisation Amongst Variables in the Seven DMU of Table 7.38 Which Participate in 'I8S.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	*	I8P	I8S	O7P	O7S	spec. TVI %
BRAD	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
CAMB	-	-	-	-	-	-	-	-	X	-	-	*	-	-	-	-	5.00
LIVR	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
MANU	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
NEWC	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
SHEF	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0
EDIN	-	-	-	-	-	-	-	-	-	-	-	*	-	-	-	-	0

Table 7.41. Specialisation Amongst Variables in the Three DMU of Table 7.38 Not Participating in 'I8S.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	*	I8P	*	O7P	O7S	spec. TVI %
SWAN	-	-	-	-	-	-	-	-	-	-	-	*	-	*	-	-	5.10
DUND	-	-	-	-	-	-	-	-	-	-	-	*	-	*	-	-	5.10
ANDW	-	-	-	-	-	-	-	-	-	-	-	*	-	*	-	-	5.10

Table 7.42 displays the DMU participating in the Other Physical Sciences taught postgraduate variable, and Table 7.43, the half of the DMU which do not.

As can be seen in these four tables, separation to distinct groups for these DMU, which has been necessary four times since the original 46 DMU, has virtually led to the elimination of specialisation amongst variables within the resulting sets of DMU, though at considerable cost in terms of the limited comparison now possible.

Table 7.42. Specialisation Amongst Variables in the Four DMU of Table 7.39 Which Participate in 'I8S.POSTGRAD-TAUGHT'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	*	*	I8S	O7P	O7S	spec. TVI %
DHAM	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0
LEIC	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0
NOTT	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0
BNGR	-	-	-	-	-	-	-	-	-	-	-	*	*	-	-	-	0

Table 7.43. Specialisation Amongst Variables in the Four DMU of Table 7.39 Not Participating in 'I8S.POSTGRAD-TAUGHT'.

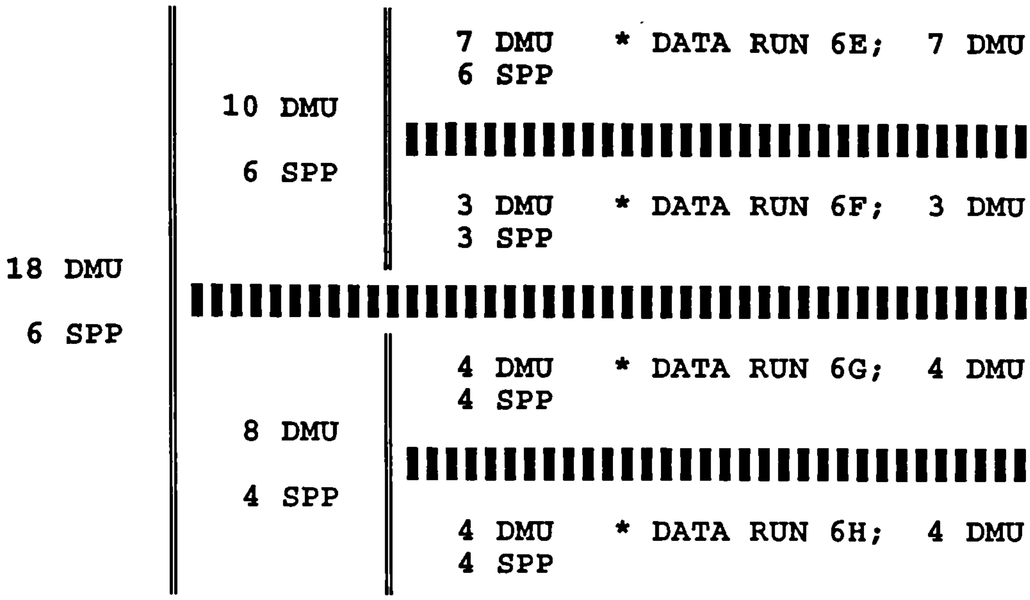
	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	*	*	*	O7P	O7S	spec. TVI %
EXTR	-	-	-	-	-	-	-	-	-	-	-	*	*	*	-	-	0
KEEL	-	-	-	-	-	-	-	-	-	-	-	*	*	*	-	-	0
OXFD	-	-	-	-	-	-	-	-	-	-	-	*	*	*	-	-	0
STIR	-	-	-	-	-	-	-	-	-	-	-	*	*	*	-	-	0

In three of the four groups, all DMU would adopt the Standard Performance Profile pertaining in each. In the remaining group, the DMU of Table 7.40, only one university, 'Cambridge', requires the specialisation amongst variables procedures of the DEAPMAS process, with a single missing value which represents just 5% of Total Virtual Inputs.

These four groups of DMU, hence, can each be applied to the DEAPMAS program with significant results being achieved. The DMU of the preceding four tables, 7.40 to 7.43, are applied as Data Runs 6E, 6F, 6G and 6H respectively. Figure 7.44 summarises the divisions of the DMU that resulted in these four

Figure 7.44. Division to Distinct Groups of DMU from

the Eighteen DMU of Table 7.34.



DATA RUN 6E: BRAD, CAMB, LIVR, MANU, NEWC, SHEF, EDIN.

DATA RUN 6F: SWAN, DUND, ANDW.

DATA RUN 6G: DHAM, LEIC, NOTT, BNGR.

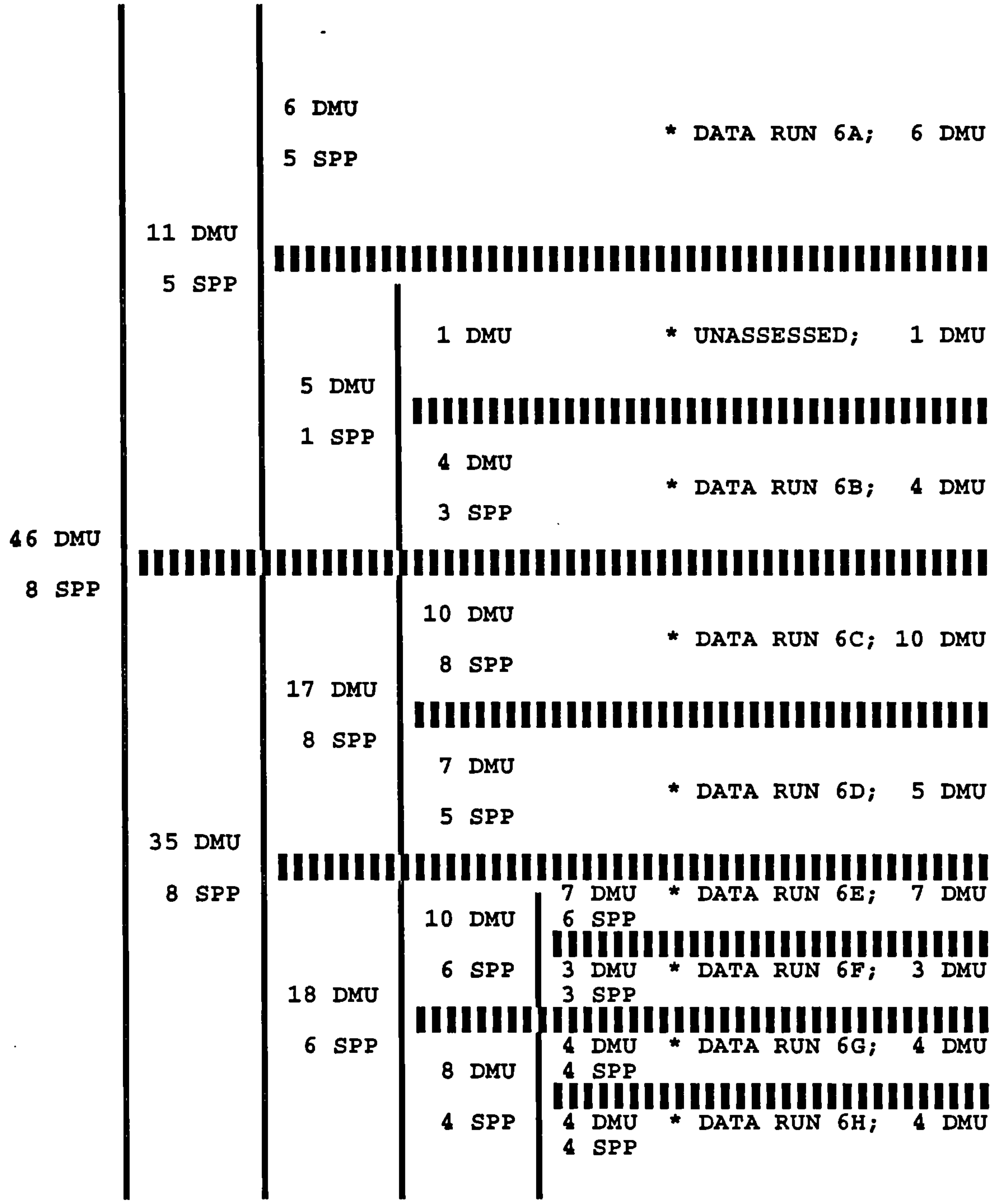
DATA RUN 6H: EXTR, KEEL, OXFD, STIR.

groups from the eighteen DMU of Table 7.34, and also lists the DMU involved in each of the four data runs which result.

The final diagram of this section, Figure 7.45, places Figure 7.44 in context, summarising all the sub-division of the 46 DMU of Example 'B' developed in Sections 7.7.1 and 7.7.2.

Figure 7.45. Division to Distinct Groups of DMU

from the 46 DMU of 'Example B'.



The next section, Section 7.8, presents the results of Data Run Six for each of the eight groupings of DMU of Figure 7.45, and then discusses an alternative course of action to the process of division and sub-division carried out within this section.

7.8. Pareto Efficiency Ratings for Example 'B' with Specialisation Amongst Variables.

In the previous section, Section 7.7, adherence to the procedures of the DEAPMAS process led to sub-division to smaller groups of DMU. The procedures which relate to the significance of results obtained when a substantial proportion of the Decision-Making Units exhibit specialisation amongst the variables created eight internally comparable groups.

Section 7.8.1 presents the pareto efficiency ratings obtained within each of these sub-divisions.

7.8.1. Results of Data Run Six of Example 'B'.

Each of the eight groups of DMU involves differing variable sets, the variables from the full set of 30 which are absent from each group's standard performance profile are shown in Table 7.46 together with the specialisation amongst variables now present in each group.

Table 7.46. Variables of Data Run Five Absent in Each Group of Data Run Six, and Specialisation Amongst Variables Present.

Group	Variables of Data Run Five Absent	Specialisation Amongst Variables
A	I1S I2S I3S I4S I7S I8S O7S	LBRO; No I8P
B	I1S I2S I3S I4S I7S I8C I8P I8S O7S	UWST; No I1P I2P I3P I4P I7P O7P
C	None	GLAS and BELF; No I8S
D	I8P	BRIS and CARD; No I8S
E	I8C	CAMB; No I6
F	I8C I8S	None
G	I8C I8P	None
H	I8C I8P I8S	None

The pareto efficiency ratings achieved in each of the eight data runs, of 'Data Run Six' of Example 'B', are then listed in Figure 7.47. As would be expected with such small groups of DMU being assessed over large variable sets, the results contain a predominance of pareto efficient DMU.

7.8.2. Rationalisation of Example 'B' Variable Set.

The results presented in Section 7.8.1 may not seem particularly satisfactory; the original 46 DMU being decomposed to eight distinct, separate groups, and one DMU, 'HWAT', not being assessed at all.

Figure 7.47. Combined Results of Data Run Six of Example 'B'.

DATA RUN 6A

ESSX	100%
LBRO	100%
SALF	100%
SURY	100%
BRUN	93%
YORK	75%

DATA RUN 6B

BATH	100%
WARW	100%
KENT	87%
UWST	66%

DATA RUN 6C

BHAM	100%
LANC	100%
LOND	100%
READ	100%
SOTN	100%
SUSX	100%
ABWY	100%
ABDN	100%
GLAS	100%
BELF	100%

DATA RUN 6D

BRIS	100%
EANG	100%
HULL	100%
LEED	100%
MIST	100%
CARD	100%
CLYD	49%

DATA RUN 6E

BRAD	100%
CAMB	100%
LIVR	100%
MANU	100%
NEWC	100%
SHEF	100%
EDIN	100%

DATA RUN 6F

SWAN	100%
ANDW	100%
DUND	64%

DATA RUN 6G

DHAM	100%
LEIC	100%
NOTT	100%
BNGR	86%

DATA RUN 6H

EXTR	100%
OXFD	100%
STIR	77%
KEEL	37%

(UNASSESSED HWAT)

It must be accepted, however, that if the set of relevant, significant variables is as selected for this application, then these results are, under the rules adopted within the DEAPMAS process, the only results of significance that can be proposed with any confidence.

The pareto efficiency ratings in Figure 7.47 can, therefore, be viewed as the 'final' results for example 'B'. Examination of the pattern of specialisation amongst variables suggests, however, that had the requirement to present input data for both taught and, separately, research postgraduates not been present, then the degree of specialisation would have been far lower.

If a single statistic had been selected to represent postgraduates, then wider comparison amongst the set of DMU may have been possible. For the purposes of study, the figures for research and taught postgraduates will be rationalised to a single postgraduate statistic. It must be noted, of course, that a different variable set is being used, and hence the application, as defined by the variables involved, is also different. Direct comparison, for example, could not be drawn between the first five data runs and any subsequent runs after rationalisation. Figure 7.48 illustrates the rationalisation by indicating the change in the variable set and the consequent changes to the performance profile.

Figure 7.48 Rationalisation of Research and Taught Postgraduate Inputs to Single Postgraduate Inputs.

Previous Inputs	Weight Limits (% of TVI)	Rationalised Inputs	Weight Limits (% of TVI)
I7C.POSTGRAD-RESEARCH	1.7-5.0	I7C.POSTGRAD-NUMBERS	3.4-10.0
I8C.POSTGRAD-TAUGHT	1.7-5.0		
I7P.POSTGRAD-RESEARCH	1.7-5.0	I7P.POSTGRAD-NUMBERS	3.4-10.0
I8P.POSTGRAD-TAUGHT	1.7-5.0		
I7S.POSTGRAD-RESEARCH	1.7-5.0	I7S.POSTGRAD-NUMBERS	3.4-10.0
I8S.POSTGRAD-TAUGHT	1.7-5.0		

7.8.3. Results of Data Run Seven Of Example 'B'.

Table 7.49 is adapted from Table 7.25 of Section 7.7, to show the extent of Specialisation Amongst Variables which exists in the 27-variable version of example 'B'.

As Table 7.49 reveals, there are now twelve DMU which do not participate in one or more of the variables in the table. Although these twelve DMU will require the creation of specialised performance profiles, the proportion of DMU which will adopt the Standard Performance Profile is well above the two-thirds figure set as being required within the DEAPMAS process in order to ensure satisfactory levels of confidence in the results obtained.

Figure 7.50, therefore, presents the results of Data Run Seven of example 'B', for the 46 DMU across the 27 variable set.

Table 7.49. Identification of Specialisation Amongst Variables in Rationalised Example 'B'.

	I1P	I1S	I2P	I2S	I3P	I3S	I4P	I4S	I6	I7P	I7S	O7P	O7S
BATH	-	X	-	X	-	X	-	X	-	-	X	-	X
BHAM	-	-	-	-	-	-	-	-	-	-	-	-	-
BRAD	-	-	-	-	-	-	-	-	-	-	-	-	-
BRIS	-	-	-	-	-	-	-	-	-	-	-	-	-
BRUN	-	X	-	X	-	X	-	X	-	-	X	-	X
CAMB	-	-	-	-	-	-	-	-	X	-	-	-	-
DHAM	-	-	-	-	-	-	-	-	-	-	-	-	-
EANG	-	-	-	-	-	-	-	-	-	-	-	-	-
ESSX	-	X	-	X	-	X	-	X	-	-	X	-	X
EXTR	-	-	-	-	-	-	-	-	-	-	-	-	-
HULL	-	-	-	-	-	-	-	-	-	-	-	-	-
KEEL	-	-	-	-	-	-	-	-	-	-	-	-	-
KENT	-	X	-	X	-	X	-	X	-	-	X	-	X
LANC	-	-	-	-	-	-	-	-	-	-	-	-	-
LEED	-	-	-	-	-	-	-	-	-	-	-	-	-
LEIC	-	-	-	-	-	-	-	-	-	-	-	-	-
LIVR	-	-	-	-	-	-	-	-	-	-	-	-	-
LOND	-	-	-	-	-	-	-	-	-	-	-	-	-
LBRO	-	X	-	X	-	X	-	X	-	-	X	-	X
MANU	-	-	-	-	-	-	-	-	-	-	-	-	-
MIST	-	-	-	-	-	-	-	-	-	-	-	-	-
NEWC	-	-	-	-	-	-	-	-	-	-	-	-	-
NOTT	-	-	-	-	-	-	-	-	-	-	-	-	-
OXFD	-	-	-	-	-	-	-	-	-	-	-	-	-
READ	-	-	-	-	-	-	-	-	-	-	-	-	-
SALF	-	X	-	X	-	X	-	X	-	-	X	-	X
SHEF	-	-	-	-	-	-	-	-	-	-	-	-	-
SOTN	-	-	-	-	-	-	-	-	-	-	-	-	-
SURY	-	X	-	X	-	X	-	X	-	-	X	-	X
SUSX	-	-	-	-	-	-	-	-	-	-	-	-	-
WARW	-	X	-	X	-	X	-	X	-	-	X	-	X
YORK	-	X	-	X	-	X	-	X	-	-	X	-	X
ABWY	-	-	-	-	-	-	-	-	-	-	-	-	-
BNGR	-	-	-	-	-	-	-	-	-	-	-	-	-
CARD	-	-	-	-	-	-	-	-	-	-	-	-	-
SWAN	-	-	-	-	-	-	-	-	-	-	-	-	-
UWST	X	X	X	X	X	X	X	X	-	X	X	X	X
ABDN	-	-	-	-	-	-	-	-	-	-	-	-	-
DUND	-	-	-	-	-	-	-	-	-	-	-	-	-
EDIN	-	-	-	-	-	-	-	-	-	-	-	-	-
GLAS	-	-	-	-	-	-	-	-	-	-	-	-	-
HWAT	-	X	-	X	-	X	-	X	-	-	X	-	X
ANDW	-	-	-	-	-	-	-	-	-	-	-	-	-
STIR	-	-	-	-	-	-	-	-	-	-	-	-	-
CLYD	-	-	-	-	-	-	-	-	-	-	-	-	-
BELF	-	-	-	-	-	-	-	-	-	-	-	-	-

Figure 7.50. Results of Data Run Seven of Example 'B'.

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SUMMARY OF RESULTS FOR
EXAMPLE B   DATA RUN 7

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****

PARETO EFFICIENT UNITS

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DMU	2	BHAM	100%
DMU	4	BRIS	100%
DMU	7	DHAM	100%
DMU	8	EANG	100%
DMU	10	EXTR	100%
DMU	15	LEED	100%
DMU	16	LEIC	100%
DMU	18	LOND	100%
DMU	20	MANU	100%
DMU	24	OXFD	100%
DMU	25	READ	100%
DMU	28	SOTN	100%
DMU	30	SUSX	100%
DMU	36	SWAN	100%
DMU	38	ABDN	100%
DMU	40	EDIN	100%

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****

PARETO INEFFICIENT UNITS

****

DMU	6	CAMB	99%
DMU	27	SHEF	95%
DMU	17	LIVR	93%
DMU	34	BNGR	92%
DMU	14	LANC	90%
DMU	23	NOTT	90%
DMU	33	ABWY	90%
DMU	41	GLAS	89%
DMU	29	SURY	87%
DMU	43	ANDW	86%
DMU	22	NEWC	84%
DMU	46	BELF	83%
DMU	21	MIST	82%
DMU	31	WARW	81%
DMU	3	BRAD	80%
DMU	35	CARD	77%
DMU	19	LBRO	76%
DMU	9	ESSX	75%
DMU	44	STIR	71%
DMU	1	BATH	69%
DMU	26	SALF	66%
DMU	42	HWAT	64%
DMU	13	KENT	62%
DMU	5	BRUN	61%
DMU	39	DUND	46%
DMU	37	UWST	44%
DMU	32	YORK	40%
DMU	12	KEEL	33%
DMU	45	CLYD	32%
DMU	11	HULL	29%

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****

Sixteen of the DMU are in the Pareto Efficient set, with ratings for the other DMU ranging from 99% PE down to 29% PE. The 29% PE rating was achieved by the DMU 'Hull', the detail of how the weights were optimised for this DMU is shown in Figure 7.51 as an example of the output from this data run.

Figure 7.51. Output of Data Run Seven of Example 'B' Specific to 'Hull'.

```
****************************************************************
****************************************************************


     DMU  11       HULL          PARETO EFFICIENCY:    29%

****************************************************************

 ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.

****************************************************************
I1C)GEN-INCOME-RESEARCH
          -352.0      .000318      -.111928         3.300
I1P)GEN-INCOME-RESEARCH
          -424.0      .000664      -.281515         8.300
I1S)GEN-INCOME-RESEARCH
          -186.0      .000602      -.111928         3.300
I2C)GRANTS-RESEARCH
          -470.0      .000238      -.111928         3.300
I2P)GRANTS-RESEARCH
          -774.0      .000364      -.281515         8.300
I2S)GRANTS-RESEARCH
            -2.0      .140758      -.281515         8.300
I3C)GEN-INCOME-TEACHING
          -500.0      .000339      -.169587         5.000
I3P)GEN-INCOME-TEACHING
          -642.0      .000618      -.396834        11.700
I3S)GEN-INCOME-TEACHING
          -262.0      .000647      -.169587         5.000
I4C)ACADEMIC-STAFF
           -19.0      .003035      -.057660         1.700
I4P)ACADEMIC-STAFF
           -21.0      .008076      -.169587         5.000
I4S)ACADEMIC-STAFF
           -12.0      .004805      -.057660         1.700
I5)UNDERGRAD-NUMBERS
          -803.0      .000562      -.451102        13.300
I6)UNDERGRAD-ENTR-QUAL
            -9.4      .018041      -.169587         5.000
I7C)POSTGRAD-NUMBERS
           -39.0      .002957      -.115319         3.400
I7P)POSTGRAD-NUMBERS
           -34.0      .003392      -.115319         3.400
I7S)POSTGRAD-NUMBERS
           -32.0      .010599      -.339175        10.000
****************************************************************

                               TOTAL VIRTUAL INPUTS  -3.391747
```

```
***************************************************************
 ID      DATA VALUE   OPTIMUM VAL. VIRTUAL CONT.   PERC. TOT.
***************************************************************
O1)GRADS-KNOWN-DEST
              96.0     .000104       .010000        1.000
O2)GRADS-LONGTRM-EMPL
              59.0     .000678       .040000        4.000
O3)GRADS-SHORT-EMPLOY
               2.0     .000000       .000000         .000
O4)GRADS-EDUC-TRAINING
              25.0     .003200       .080000        8.000
O5)FIRST-DEG-GRADUATES
             109.0     .001101       .120000       12.000
O6)HIGHER-DEGREE-GRADS
              48.0     .009375       .450000       45.000
O7C)RESEARCH-COMPOSITE
             466.7     .000386       .180000       18.000
O7P)RESEARCH-COMPOSITE
             258.0     .000233       .060000        6.000
O7S)RESEARCH-COMPOSITE
               3.3     .018182       .060000        6.000
O8)CONT-EDUC-PROVISION
              43.0     .000000       .000000         .000
***************************************************************
                              TOTAL VIRTUAL OUTPUTS   1.000000
***************************************************************
```

7.9. The Identification and Incorporation of an Environmental Factor.

The way in which Environmental Factors are handled within an application of the DEAPMAS process was detailed in Chapter Five (Section 5.5), after the area was examined in the preceding chapter (Section 4.4). The principle of Affected Variable Adjustment (AVA) was applied to both Example 'A' and 'B', using the environmental factor identified in Section 7.9.1. Data Run Six of example 'A' and Data Run Seven of example 'B' being extended to include environmental factor consideration.

7.9.1. The 'Learning Environment'; An Environmental Factor.

Departments take advantage of and derive benefit from many aspects of a university that do not fall within their own budgets. Staff and students benefit from centrally provided services such as sports facilities, the university library and the quality of the buildings which they use. These and other facilities combine to make up the 'Learning Environment'. As the extent of the provision of such facilities is not homogenous across universities, it should be taken into account in any comparison of departments, cost centres or subject groups.

Fortunately, the major elements of the 'Learning Environment' are readily identifiable within the sources of data used for the input and output measures. The relevant elements of Table Six (Recurrent expenditure of each University analysed by purpose and type) in Volume Three of the UGC/USR publication (V3F: reference Section 6.2) are shown in Table 7.52 together with descriptive summaries of each, as the items within each element are not always apparent.

7.9.2. The Application of Affected Variable Adjustment (AVA).

The 'Learning Environment' could be deemed as affecting all the outputs from a Department, it is in this sense a 'Global' Environmental Factor in terms of the outputs.. It would be included as a variable in its own right (an input) were it not clearly outwith the subject matter; individual departments have no direct control over central expenditure.

Table 7.52. Elements of the 'Learning Environment'.

Title of Expenditure. Category (Purpose/Type).	Summary of Main Items. Within Category.
ACADEMIC SERVICES	Libraries, Central Computers, Museums, Educational Technology Units, Language Centres.
GENERAL EDUCATIONAL EXPENDITURE	Examinations, Fellowships, Scholarships, prizes, educational publications, UCCA subscriptions.
MAINTENANCE AND RUNNING OF PREMISES	Covers all premises (except internal maintenance of student residences and refectories). Overheads, cleaning and repairs. Also Roads and general grounds.
STAFF AND STUDENT AMENITIES AND FACILITIES	Careers Service, Student Union, Societies, Accommodation office, Health-care, sports facilities.

As the statistic has been compiled from data referring to the 'recurrent expenditure' of universities as a whole, it naturally follows that Cost Centre recurrent expenditure should be adjusted. In addition, the other non-student inputs will also be adjusted, as the benefits derived from these will be influenced by the quality of the learning environment.

There are then four 'Affected Variables' under the AVA principle used within the DEAPMAS process, those referring to total recurrent departmental expenditure from general income attributable to both research (I1.GEN-INCOME-TEACHING) and teaching (I3.GEN-INCOME-TEACHING), and the other non-student resources of (I2.GRANTS-RESEARCH) and (I4.ACADEMIC-STAFF).

Recalling Table 6.8 of Section 6.5, there are two separate time periods for the inputs to be adjusted. Generally the Environmental Factor (in cases where it is not static) should naturally refer to the same period as the variable.

Hence for each Department the four categories of Section 7.9.1 would be totalled for 1985-1986 (I3.GEN-INCOME-TEACHING and I4.ACADEMIC-STAFF), and for 1986-1987 (I1.GEN-INCOME-RESEARCH and I2.GRANTS-RESEARCH). A scaled percentage is then added to each, in this case the Environmental Factor divided by 1000. Figure 7.53 gives an example of this calculation for example 'A', with Figure 7.54 displaying the program output from the final data run of example 'A' which summarises the pre-adjustments.

Figure 7.53. The Mathematics of the Application of AVA Using the 'Learning Environment'.

ASTON.

ACADEMIC SERVICES	1441	
GENERAL EDUCATIONAL EXPENDITURE	1385	
MAINTENANCE AND RUNNING OF PREMISES	2626	
STAFF AND STUDENT AMENITIES AND FACILITIES	839	
'THE LEARNING ENVIRONMENT'	6291	(6.29%)

I3.GEN-INCOME-TEACHING	1352 + 6.29% = 1437
I4.ACADEMIC-STAFF	75 + 6.29% = 80

Figure 7.54. Output from the Final Data Run of Example 'A' Reporting Environmental Factor Adjustments (Edited to First Twelve DMU only).

****

ENVIRONMENTAL FACTOR 1

****

I3)GEN-INCOME-TEACHING

DMU		UNADJUSTED VALUE	PERCENTAGE ADJUSTMENT	NEW VALUE
1	ASTN	-1352.00	-6.29	-1437.04
2	BATH	-554.00	-5.91	-586.74
3	BRAD	-775.00	-6.86	-828.17
4	CITY	-1078.00	-7.78	-1161.87
5	HULL	-127.00	-5.86	-134.44
6	KENT	-92.00	-5.72	-97.26
7	LANC	-719.00	-6.76	-767.60
8	LEED	-244.00	-5.64	-257.76
9	LBUS	-671.00	-27.65	-856.53
10	LOND	-698.00	-9.61	-765.08
11	LBRO	-439.00	-6.81	-468.90
12	MBUS	-574.00	-14.79	-658.89...

I4)ACADEMIC-STAFF

DMU		UNADJUSTED VALUE	PERCENTAGE ADJUSTMENT	NEW VALUE
1	ASTN	-75.00	-6.29	-79.72
2	BATH	-33.00	-5.91	-34.95
3	BRAD	-52.00	-6.86	-55.57
4	CITY	-38.00	-7.78	-40.96
5	HULL	-9.00	-5.86	-9.53
6	KENT	-6.00	-5.72	-6.34
7	LANC	-50.00	-6.76	-53.38
8	LEED	-17.00	-5.64	-17.96
9	LBUS	-37.00	-27.65	-47.23
10	LOND	-45.00	-9.61	-49.32
11	LBRO	-29.00	-6.81	-30.97
12	MBUS	-40.00	-14.79	-45.92...

****

ENVIRONMENTAL FACTOR 2

****

I1)GEN-INCOME-RESEARCH

DMU	UNADJUSTED VALUE	PERCENTAGE ADJUSTMENT	NEW VALUE
1 ASTN	-881.00	-6.48	-938.09
2 BATH	-385.00	-6.35	-409.45
3 BRAD	-540.00	-7.15	-578.61
4 CITY	-849.00	-7.87	-915.82
5 HULL	-90.00	-5.88	-95.29
6 KENT	-81.00	-6.06	-85.91
7 LANC	-544.00	-6.86	-581.32
8 LEED	-181.00	-5.79	-191.48
9 LBUS	-552.00	-26.97	-700.87
10 LOND	-504.00	-10.34	-556.11
11 LBRO	-321.00	-7.64	-345.52
12 MBUS	-373.00	-17.68	-438.95...

I2)GRANTS-RESEARCH

DMU	UNADJUSTED VALUE	PERCENTAGE ADJUSTMENT	NEW VALUE
1 ASTN	-487.00	-6.48	-518.56
2 BATH	-312.00	-6.35	-331.81
3 BRAD	-197.00	-7.15	-211.09
4 CITY	-404.00	-7.87	-435.79
5 HULL	.00	-5.88	.00
6 KENT	-2.00	-6.06	-2.12
7 LANC	-222.00	-6.86	-237.23
8 LEED	-14.00	-5.79	-14.81
9 LBUS	-1374.00	-26.97	-1744.57
10 LOND	-275.00	-10.34	-303.44
11 LBRO	-146.00	-7.64	-157.15
12 MBUS	-463.00	-17.68	-544.86...

****

7.9.3. Results of the Final Data Run of Examples 'A' and 'B'.

The effect of including this particular environmental factor is fairly minor, suggesting that the differences found in the costs and level of provision of 'learning environment' do not have a critical influence in the range discovered. If a substantially wider range of costs had been encountered, then it is likely the influence would have been greater.

It should be noted that the pareto efficiencies which result in the final data runs for both examples, are, as for all data runs, rounded to the nearest whole decimal place. The ratings achieved will not be exactly the same for any DMU in the final two data runs, but for many the ratings are not altered sufficiently to move by a percentage point.

Figure 7.55 details the results of the final data run of 'Example A', with Figure 7.56, the final table of the chapter, displaying the result of the final data run of 'Example B'.

Figure 7.55. Results of the Final Data Run of Example 'A'.

****
****

PARETO EFFICIENT UNITS

****

DMU	4	CITY	100%
DMU	9	LBUS	100%
DMU	11	LBRO	100%
DMU	14	NEWC	100%
DMU	20	UWST	100%
DMU	21	EDIN	100%
DMU	22	GLAS	100%
DMU	24	STIR	100%
DMU	25	CLYD	100%
DMU	27	ULST	100%

****
****

PARETO INEFFICIENT UNITS

****

DMU	13	MIST	98%
DMU	1	ASTN	94%
DMU	7	LANC	93%
DMU	17	SURY	93%
DMU	8	LEED	91%
DMU	12	MBUS	88%
DMU	2	BATH	87%
DMU	3	BRAD	83%
DMU	19	CARD	82%
DMU	18	WARW	77%
DMU	5	HULL	74%
DMU	16	SOTN	68%
DMU	15	SHEF	67%
DMU	23	HWAT	62%
DMU	26	BELF	52%
DMU	6	KENT	45%
DMU	10	LOND	45%

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Figure 7.56. Results of the Final Data Run of Example 'B'.

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SUMMARY OF RESULTS FOR
EXAMPLE B DATA RUN 8

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****

****
****

PARETO EFFICIENT UNITS

****

DMU	2	BHAM	100%
DMU	4	BRIS	100%
DMU	6	CAMB	100%
DMU	7	DHAM	100%
DMU	8	EANG	100%
DMU	10	EXTR	100%
DMU	15	LEED	100%
DMU	16	LEIC	100%
DMU	18	LOND	100%
DMU	20	MANU	100%
DMU	24	OXFD	100%
DMU	25	READ	100%
DMU	28	SOTN	100%
DMU	30	SUSX	100%
DMU	36	SWAN	100%
DMU	38	ABDN	100%

****

****

PARETO INEFFICIENT UNITS

****

DMU	40	EDIN	99%
DMU	27	SHEF	95%
DMU	17	LIVR	94%
DMU	34	BNGR	91%
DMU	14	LANC	90%
DMU	23	NOTT	90%
DMU	33	ABWY	90%
DMU	41	GLAS	89%
DMU	29	SURY	87%
DMU	43	ANDW	87%
DMU	21	MIST	83%
DMU	22	NEWC	83%
DMU	46	BELF	83%
DMU	31	WARW	82%
DMU	3	BRAD	79%
DMU	35	CARD	77%
DMU	19	LBRO	76%
DMU	9	ESSX	75%
DMU	44	STIR	71%
DMU	1	BATH	70%
DMU	26	SALF	65%
DMU	42	HWAT	64%
DMU	13	KENT	62%
DMU	5	BRUN	60%
DMU	39	DUND	45%
DMU	37	UWST	44%
DMU	32	YORK	40%
DMU	12	KEEL	33%
DMU	45	CLYD	32%
DMU	11	HULL	30%

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****

8. CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER STUDY.

8.1. Review of Findings Relating to University Performance Measurement.

From the opening discussion of performance measurement and review of relevant literature on performance indicators which can be found in Chapters One and Two respectively, a number of observations can be made.

There is a lack of clear definition of the objectives of universities and of higher education in general. No consensus exists beyond broad, and largely unrecorded mission statements, which call for the activities of teaching and research to be carried out effectively and in a way which provides 'value for money'.

The primary objectives can, therefore, only be estimated by means of reasonable assumptions. It is assumed that teaching should provide qualified graduates who will succeed in their chosen field, that research should display high quality analytical skills which extend knowledge, and that there be additional, if intangible, benefits to society from the financing of universities.

Attempts to measure the performance of universities in achieving these, or any other set of similar objectives have focused increasingly in recent years on the production of input, process and output performance indicators.

Singly, these performance indicators were found to be ambiguous and commonly hindered by serious caveats on their use when applied for comparison between institutions. Many of those presented by Government funding bodies were found to be concerned with the control of expenditure, with little emphasis on ascertaining the effectiveness of institutions, partly as a consequence of the poor understanding of objectives.

It was concluded that the more relevant and appropriate measures would require simultaneous consideration to be of any practical use, however, no suitable and applicable mechanism through which this could be achieved could be identified.

Relevant indicators were identified as those which record the inputs of finance and other scarce resources, such as academic staff and students, and many of these were found to be readily available.

The 'products' of the university system were also found to be identifiable, but it was questioned whether many of these were final outputs, or merely intermediate outputs when considered against objectives. Teaching outputs were found to be more readily available and quantifiable than those of the research function.

Many process indicators are available and these operating measures are in common use in the internal management of universities, but confusion was found over both their role as comparative indicators between institutions and of the significance of particular measures.

Little evidence was uncovered of any defined productive relationship between the inputs and outputs of universities, the link between them was found to be intangible. This encouraged a view of the process of conversion from inputs to outputs as a closed system, a 'black box'.

By regarding the activities within universities as a 'black box', existing data could be relied upon to select data covering the principal inputs to, and outputs from, this system. The adoption of this approach also eliminated the need to consider the role of process measures.

In the third chapter, two potential approaches to improving the practicality of consideration of a set of performance indicators were examined. In the first, it was found that inputs and environmental factors could be used to attempt to explain some of the variation in particular indicators in a compensatory manner. This approach had much merit and made comparisons more feasible by allowing output measures of different institutions to be made on a more equitable basis.

Whilst continued research in this regression analysis based technique is to be encouraged, the approach is based solely on individual output measures and does not provide a way in which to 'bring together' a number of distinct performance indicators for concurrent consideration.

The most obvious way of achieving this simultaneous consideration is to apply a set of weights to the various measures. This implied high levels of subjectivity, however, which would make any results produced open to controversy and claims of in-built systematic bias.

The second approach introduced in Chapter Three was that of Data Envelopment Analysis (DEA). This technique allows performance measurement to be made by incorporating a range of input and output measures, which may be incommensurate, into a single ratio through the allocation of flexible weighting in an linear programming based optimization process.

The potential of this approach was felt to be sufficient to merit further investigation, as the technique of Data Envelopment Analysis required no definition of the relationship between the incorporated inputs and outputs. Neither regression analysis nor any other process is therefore necessary as there is no need to establish any relationships between the variables.

A thorough analysis of Data Envelopment Analysis can be found in Chapter Four. The investigation carried out within this chapter concluded that there were serious conceptual and practical drawbacks in the application of the technique. None of the problems, however, were found to be without satisfactory solution and the adjustments to the technique were developed and formalised in Chapter Five. These considerable developments are reviewed in Section 8.2.

In the Sixth Chapter it was reasoned that comparison between entire universities was unrealistic and tenuous due to the vastly differing subject mixes which exist in different institutions. There are wide variations between subjects in terms of resource use and typical output levels which can for particular universities either corrupt particular indicators or lead to figures which are simply averages, unrepresentative of the variety within.

It was concluded that direct comparison between institutions was more justifiable at subject or departmental basis where 'like could be compared with like'. In practice the basis chosen for comparison across universities was influenced to a degree by data availability. The use of two example applications was opted for, one at each of the main administrative levels in common use.

Cost Centre 32, 'Business and Management' was selected as example 'A' and Subject Group Five, 'Physical Sciences' was chosen as example 'B'. Universities were identified as involved or 'active' in these two examples by the presence of data at a specific point in time, and these numbered 27 for example 'A' and 46 for example 'B'.

'Ideal' measures were identified for both inputs and outputs that would adequately reflect the intermediate and final outputs of the 'universities', or more precisely sub-parts of universities, being assessed whilst also taking account of the principal resources consumed.

These factors identified, the data sources were examined and inevitably a significant degree of compromise was involved in selecting the 'actual' variables which were to be utilised. The extent of difference between the 'ideal' and 'actual' statistics varied, but included the introduction of a number of substitute measures.

The relevant caveats on the applied variables were given prominence within Chapter Six to emphasize the fact that the significance of the results obtained would directly relate to the importance attached to the caveats present by those wishing to utilise the findings.

A number of data collection and interpretation problems were encountered and, in addition to the caveats stated for the analysis as a whole, further caveats are listed for each of the two examples and for each individual variable. Naturally, none of the results should be considered without awareness of these caveats.

In utilising DEA, the element of subjectivity introduced to the technique (See Section 8.2) was viewed as beneficial as it allowed provision of very loose definition of the relevant importance of the different inputs and outputs, to enable determination of effectiveness.

This process of setting the limits of the perceived significance of each variable enabled not only identification of 'key' variables, but also consideration to be made of the extent to which the actual variables utilised varied from those which had been originally indicated as the 'ideal' measures.

The range of variables used numbered eight inputs and nine outputs (sub-divided in the larger example 'B'). Across this, relatively limited, range of data a degree of inconsistency was encountered, with some units not being measured or not participating in particular resources or activities. This complicated comparison, but after closer examination of the data, specialisation out of particular variables was permitted to allow comparison to be on as wide a basis as possible.

It was discovered that comparison at sub-institutional level, whilst more appropriate, overlooked the utilisation of resources which were not attributed within an institution but left as central costs.

The 'learning environment' was identified as the most relevant of such central costs. This environmental factor was identified as having a number of component parts such as library facilities, sports centres and medical provision. the non-student input statistics were adjusted in an attempt to reflect its influence by varying the adjustment according to the scale of the associated resource cost. The learning environment was not selected as an input in its own right as cost centres/subject groups have no direct control over its provision.

For example 'A', a number of data runs were developed and reported in Chapter Seven. These culminated in the identification of ten relatively efficient (and effective) cost centres, with a range of lesser ratings for the remaining seventeen from 98% down to 45%.

The results in Chapter Seven for example 'B' revealed that the extent of specialisation was too extreme for comparison of the set as a whole, and a number of sub-divisions to distinct, but comparable groups were carried out.

This process of division led to no less than eight distinct groups with between three and ten members in each. Each could only be compared internally, and two of the three groups with more than six members recorded maximum ratings for all constituents. One university was identified as 'individual' on the basis of the sub-division and could not be assessed at all.

To allow wider comparison, the variable set was rationalised to include only a single postgraduate input measure. Whilst altering the defined application, this did allow wider comparison, with all 46 units assessed against each other. Comparison on this basis revealed sixteen universities in the 'pareto efficient set', with the remaining 30 recording ratings from 99% to as low as 30%.

These results can potentially be applied to better inform the competitive allocation of resources, potential students or staff seeking information, (though only effectiveness is of primary importance to this group), and sponsors of research, particularly of a costly or long term nature. Decisions to specialise within universities and other internal management problems could also draw on such data.

Clearly, if the basis of calculation can be accepted, consideration of the single rating produced by this technique is of greater practical implication than consideration separately of a number of largely incomparable performance indicators.

8.2. Review of Findings relating to Data Envelopment Analysis.

In Chapter Four it was concluded that Data Envelopment Analysis could not be relied upon to produce significant results. The technique allowed complete flexibility in weight application, which enabled Decision-Making Units to base their ratings on small sub-sets of the variables, including just a single input and output.

This complete flexibility also effectively allowed DMU to 'ignore' aspects of their performance which were inferior. This is conceptually unsound where the 'ignored' variable is of great significance, the technique, however, treats all variables as equally important or unimportant. The only way that a variable can be shown to be less important than the others is by excluding it from the analysis altogether. With the ability to apply insignificant weight to any particular variable, during the process of optimization, any variable can, however, be effectively excluded from the assessment of a particular DMU.

Counter-intuitively, review of the literature revealed that a minimal variable set was recommended in order to ensure discrimination between the DMU involved. This study concluded that it was more appropriate to include all relevant variables and that if a large pareto efficient set was returned then this simply was a reflection on the data, the answer to the question 'as put'.

The practical solution adopted for the problems associated with complete weight flexibility was to limit the percentage of total virtual inputs or total virtual outputs which a variable and its weight can constitute. This involved setting a minimum and maximum level for each individual variable to reflect the importance of the particular measure.

This set of weight restrictions, which was termed a 'performance profile', hence defines within chosen margins the relative significance of the differing resources used and relative importance of the outputs produced. By this means, defining limits to the relative contribution which each variable can make; effectiveness was introduced into what was, at best, previously an efficiency model.

It was noted that the actual variables applied in any given example were in reality simply the points of measurement of activities. Hence in the process of analysing an application and considering the data to be included for the particular example, relevant 'factors' are selected. It is then from these factors that the actual statistics for inclusion are identified. One factor could be represented by a single variable, while for another there could be several individual statistics.

It was concluded that the performance profile should not be influenced by these data considerations and, therefore, that the weight limits in place on these factors should be considered with at least equal importance to those on individual variables.

The literature on this topic revealed that environmental factors were commonly included as 'contextual input variables'. It was noted that this improves the accuracy of determination of ratings for a unit which included a DMU, but not specifically of the DMU itself. This is because it involves the inclusion of a variable over which the DMU has no control.

With unrestricted DEA, a rating could conceivably be produced with 100% of input weights applied to the environmental factor. Under a 'performance profile' no rationale could be put forward for the appropriate limits to be put in place on such a variable.

After considerable analysis, the principle of 'Affected Variable Adjustment' (AVA) was developed. Here, the variables which the environmental factor influences are adjusted in a compensatory manner, the scale of which being linked to the environmental data.

In order to prepare and manage the suite of linear programs necessary to carry out Data Envelopment Analysis, and to incorporate the subsequent developments, computer software was developed.

This involved considerable effort, resulting in a FORTRAN 77 program of some two thousand lines of code (See Appendix B). The principles and procedures adopted within this program were developed and formalised in Chapter Five. The data runs of Chapter Seven all utilise this coding, which can simply emulate undeveloped DEA, or additionally carry out any combination of additional features.

The program and the process which it lies at the heart of, are both identified by the acronym DEAPMAS, which is derived from Data Envelopment Analysis; Performance Modelling and Specialisation.

A further problem resolved was the way in which to deal with incomplete data sets. The manipulations involved would have been entirely impractical without the development of computer coding to support it.

The area of specialisation amongst variables was examined in depth. A DMU could specialise out of one or more variables, as long as variable groups, or factors, had been identified as opposed to simply a list of individual variables. Each eliminated variables weight limits would be transferred to one or more other variables in order to enable a rating to established for the specialised DMU without a fall in the appropriateness of the performance profile in place.

It was observed, however, that any DMU which had specialised out of a variable, particularly where that variable had a high minimum weight restriction in the standard performance profile, would have no significant 'competitive' effect on those DMU without specialisation.

Clearly there would be a point at which the proportion of specialised to non-specialised DMU became large enough to affect the significance of the results obtained for the latter group. a rationale was adopted which erred on the side of caution in the proportion of DMU which could be permitted to make use of a 'specialised performance profile' before specialisation was rejected by the program and a sub-division to distinct groups was indicated.

During the development of the data runs discussed in Chapter Seven, a number of additional conceptual points were observed. Firstly, the larger example 'B' involved up to 33 variables, yet with a performance profile in place a majority of DMU were always recorded as pareto inefficient.

Clearly, therefore, the 'rules' governing variable selection are completely turned around; any and all relevant variables should be included with their relative significance identified within the performance profile.

Secondly, as DEA, and hence DEAPMAS, are derived from productive concepts, a productive relationship is assumed, though not defined, between inputs and outputs. Theoretically, doubling an input should double the, undefined, effect on the outputs. A consequence of this is that a finite ordinal scale of values cannot be incorporated, there cannot be an absolute upper bound on any variable.

If such a range of values is included then, for example, as discovered in Chapter Seven, a 'large' DMU with the upper limit of the finite output statistic will fair badly against a relatively 'small' DMU with the same or slightly lower value for that output.

Thirdly, and finally, specialisation procedures were considered where a 'zero' or missing value was encountered. Some DMU have 'almost' no statistic for particular variables, recording values which are a small fraction of those of the majority of DMU. In many cases this accounted for the lowest pareto efficiency ratings in some data runs.

Clearly, these DMU are not 'seriously' active in the particular variable and hence would have achieved a higher rating had they been allowed to specialise out of that variable. Although it could be viewed as a failing if they are not registering 'no statistic' in an area they would claim not to be active in, otherwise an additional step is clearly indicated in each application, of determining the threshold value below which specialisation is invoked for each variable.

The DEAPMAS process can hence be summarised as having the eight stages shown in Figure 8.1.

Figure 8.1. The DEAPMAS Process.

1. Clarification of objectives of DMU,
2. Identification of relevant factors,
3. Selection of representative variables/noting caveats,
4. Identification of environmental factors/variables affected,
5. Setting of weight limits on factors via the variables through the creation of a performance profile,
6. Determination of threshold values for specialisation,
7. Determination of acceptable specialisation and identification of appropriate transfer types,
8. Application of data to DEAPMAS program.

8.3. Recommendations for Further Study, Relating to Performance Measurement.

In the field of performance indicators, the increased measurement that has taken place should be coupled with increased conformity in accounting procedures, in Chapter Two, several quotes were adopted to indicate the wide differences in statistical reporting conventions which currently exist. Consideration should be given therefore to the establishment of more standardised procedures.

Some of the 'ideal' measures which were identified in Chapter Six, but which could not be adopted provide scope for further study into performance indicators. This is particularly true of determination of the 'final outputs'.

The success of graduates in society and the pay-back associated with study could both be examined beyond the unimaginative first destination surveys currently available.

The concept of project based research reports also merits further investigation. Universities should perhaps insist that departments provide evidence of their research effort internally, the same information could then be used externally for comparison. It could be argued that all research should be summarised in terms of success in meeting objectives and consequences of findings. Providing such data for only a small percentage of projects would not be impractical and would ensure that 'high risk, high reward' research was not discouraged.

Finally, one of the performance indicators introduced more recently in the UK-wide basis, but which has existed in some form for many years is 'completion rates'. These were not adopted in this study, but are clearly important in postgraduate research. It would be useful if further study could shed light on their significance, and more particularly when applied to taught postgraduate and undergraduate programmes where their significance is clearly more open to question.

8.4. Recommendations for Further Study, Relating to DEA and DEAPMAS.

Many conceptual questions were raised in the study of Data Envelopment Analysis and its development into the DEAPMAS process. The undeveloped technique, the application of DEA with unrestricted weights has been completely discredited, the results obtained having little or no significance. Further Study should, therefore, now concentrate on DEA with weight limitation in place.

Prolonged but essential study is now required into the relationship between the size of the variable set, the number of DMU, and the consequent patterns of pareto efficiencies which result. Any patterns identified would naturally be of great significance.

Similarly, the nature of the effect of differing proportions of fixed and flexible weighting needs to be explored in order that general rules can be applied. Equally, with specialisation, the true nature of the reduction in significance of the results obtained as the number of specialised DMU increases must be examined if more confidence is to be placed in the specified limits that specialisation can reach.

It was discovered that consideration of 'the learning environment' as implemented in Chapter Seven had a limited effect on the results obtained. Whilst more justifiable than the 'contextual input' approach, Affected Variable Adjustment remains open to criticism in terms of its apparently arbitrary nature, and research in this area would be of some importance.

It was also discovered in both Chapters Four and Seven, that some DMU are 'easily' pareto efficient, being dominant over particular other DMU on most single-ratios. An interesting experiment would be to examine the consequences of identifying and eliminating these DMU and effecting a second 'iteration' to determine if any DMU records a dramatic increase in their rating.

Finally, it might even be possible to formalise the 'balanced' approach to performance profile creation adopted as the central basis in Chapter Six. A fairly objective and quickly established set of weight limits could be achieved by identification of each variable as for example 'key', 'important', or just 'significant', with a fixed procedure for performance profile creation linked only to this information and the number of inputs and outputs present.

Appendix A.

Appendix A. Extended Data Envelopment Analysis Bibliography.

In addition to the references to work involving DEA at the end of Chapters Three, Four, and Five; the following works are also useful in attempting to gain a full understanding of the development and methodology of undeveloped Data Envelopment Analysis.

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Appendix B.

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      PROGRAM DEAPMAS3

CCCCCCC VER 3.7.2   APR 91

CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCC
CCCCCCC Data Envelopment Analysis;
CCCCCCC               Performance Modelling and Specialisation.
CCCCCCC ****************************************************************
CCCCCCC
CCCCCCC  R.H.Wilkinson, Division of Management, University of Stirling.
CCCCCCC
CCCCCCC  Written during 1989/90 on University of Stirling VAX
CCCCCCC
CCCCCCC
CCCCCCC                                  Copyright R.H.Wilkinson 1990.
CCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC


      INTEGER M,N,JAY,NUMI,NUMO,VAR,M1,N1,MTOT,MTOT1,GROUP,MATRIX,
     +        ANSWER(100),INDX(100),JJ(50),JJ1(51),CONTR,SCOPE,
     +        NAMES,RESULTS(100),VARDEF


      DOUBLE PRECISION A(252,50),B(252),C(50),X(50),DINV(50,50),S(50),
     +                 V(50),TEMP(50),DMUOBJ(100),A1(253,51),B1(253),
     +                 C1(51),X1(51),DINV1(51,51),S1(51),V1(51),
     +                 TEMP1(51),LIMITS(50,2),LIMSPEC(50,2),
     +                 OBJV,OBJV1,SPECMAT(252,50),AOLD(252,50)

      CHARACTER*25 DMU(100)*8,TITLE*50,
     +             NAMEINP(50),NAMEOUT(50),NAMEVAR(100)


      CALL INTRO

CCCCCCC  INTRO CALLS LINE

      CALL BASICS(JAY,NUMI,NUMO,VAR,M,N,M1,N1,MTOT,MTOT1,SCOPE,TITLE,
     +            GROUP,NAMES,MATRIX,VARDEF,NAMEINP,NAMEOUT,NAMEVAR)


CCCCCCC  BASICS CALLS LINE

      CALL ANALYSE(M,N,JAY,NUMI,NUMO,VAR,DMUOBJ,DMU,B,C,X,DINV,S,
     +             V,TEMP,JJ,OBJV,MTOT,A1,B1,C1,X1,DINV1,S1,V1,TEMP1,
     +             JJ1,OBJV1,M1,N1,MTOT1,CONTR,LIMITS,LIMSPEC,SCOPE,
     +             GROUP,NAMES,RESULTS,ANSWER,MATRIX,VARDEF,
     +             NAMEINP,NAMEOUT,NAMEVAR,A,SPECMAT,AOLD)


CCCCCCC   ANALYSE CALLS:
CCCCCCC                 SETDATA WHICH CALLS:
CCCCCCC                         GROUPMINMAX
CCCCCCC                         PRNGROUP WHICH CALLS LINE
CCCCCCC                 AVA WHICH CALLS LINE
CCCCCCC                 SPECINPUT
CCCCCCC                 NEXTDMU WHICH CALLS:
CCCCCCC                         GROUPMINMAX
CCCCCCC                         PRNGROUP WHICH CALLS LINE
CCCCCCC                         PERPROF
CCCCCCC                         SPECIALISE
CCCCCCC                         LINE
```

```
CCCCCCC                 LINPRO WHICH CALLS:
CCCCCCC                        OPTIMISE WHICH CALLS:
CCCCCCC                                 STP1
CCCCCCC                                 STP2
CCCCCCC                                 STP3
CCCCCCC                                 MATMOD
CCCCCCC                        MATMOD
CCCCCCC                 LPSHOW WHICH CALLS LINE
CCCCCCC                 LINE

      CALL PRNRANK(JAY,DMU,ANSWER,INDX,NAMES,TITLE)

CCCCCCC   PRNRANK CALLS LINE

      STOP
      END

*******


      SUBROUTINE INTRO

CCCCCCC   INTRO IS CALLED BY THE MAIN PROGRAM
CCCCCCC
CCCCCCC   INTRO CALLS LINE
CCCCCCC
CCCCCCC   THIS SUBROUTINE GENERATES THE INITIAL OUTPUT
CCCCCCC   OF THE PROGRAM, INCLUDING AUTHOR AND THE
CCCCCCC   COMPUTER ON WHICH THE ORIGINAL CODE WAS WRITTEN
CCCCCCC
CCCCCCC   LATER EDITING WAS CARRIED OUT ON THE UNIVERSITY
CCCCCCC   OF STIRLING UNIX AND NAPIER POLYTECHNIC PRIME
CCCCCCC   THIS VERSION IS WRITTEN TO MEET THE REQUIREMENTS OF
CCCCCCC   THE UNIX FORTRAN 77 COMPILER
CCCCCCC


      INTEGER LN


      WRITE(6,'(//)')
      CALL LINE(3)
      WRITE(6,*)
     +'****************************** ******************************'
      WRITE(6,*)
     +'***************************** * *****************************'
      WRITE(6,*)
     +'**************************** *** ****************************'
      WRITE(6,*)
     +'*************************** ***** ***************************'
      WRITE(6,*)
     +'************************** ******* **************************'
      WRITE(6,*)
     +'************************* ***  **** *************************'
      WRITE(6,*)
     +'************************ *****  **** ************************'
      WRITE(6,*)
     +'*********************** *******  **** ***********************'
      WRITE(6,*)
     +'********************** *****  **  **** **********************'
      WRITE(6,*)
     +'********************* *****  ****  **** *********************'
      WRITE(6,*)
     +'******************** *****  ******  **** ********************'
      WRITE(6,*)
```

```
+'******************** *****  ***  ***  **** *******************'
 WRITE(6,*)
+'******************* *****  *****  ***  **** ******************'
 WRITE(6,*)
+'****************** *****  *******  ***  **** *****************'
 WRITE(6,*)
+'***************** *****  ****  ***  ***  **** ****************'
 WRITE(6,*)
+'**************** *****  ****  *****  ***  **** ***************'
 WRITE(6,*)
+'*************** *****  ****  *******  ***  **** **************'
 WRITE(6,*)
+'************** *****  ****  *********  ***  **** *************'
 WRITE(6,*)
+'************* *****  ****  ***********  ***  **** ************'
 WRITE(6,*)
+'************ *****  ****  *************  ***  **** ***********'
 WRITE(6,*)
+'***********                                         **********'
 CALL LINE(3)
 WRITE(6,*)
+'****     ***       **** ****     *** ***** **** ******     ***'
 WRITE(6,*)
+'**** **** ** ********* * *** **** **  ***  *** * **** ********'
 WRITE(6,*)
+'**** ***** * ******** *** ** ***** * * * * ** *** ** *********'
 WRITE(6,*)
+'**** ***** * ******* ***** * **** ** ** ** * ***** ** ********'
 WRITE(6,*)
+'**** ***** *       *       *     *** ** ** *       ***   *****'
 WRITE(6,*)
+'**** ***** * ******* ***** * ******* ***** * ***** ****** ****'
 WRITE(6,*)
+'**** ***** * ******* ***** * ******* ***** * ***** ******* ***'
 WRITE(6,*)
+'**** **** ** ******* ***** * ******* ***** * ***** ****** ****'
 WRITE(6,*)
+'****     ***       * ***** * ******* ***** * ***** *     *****'
 CALL LINE(2)
 WRITE(6,*)
+'*****                                                    *****'
 WRITE(6,*)
+'*****  DATA RUN ON DEAPMAS 3                             *****'
 WRITE(6,*)
+'*****                                                    *****'
 WRITE(6,*)
+'*****  DATA ENVELOPMENT ANALYSIS                         *****'
 WRITE(6,*)
+'*****  PERFORMANCE MODELLING AND SPECIALISATION          *****'
 WRITE(6,*)
+'*****                                                    *****'
 CALL LINE(3)
 WRITE(6,*)
+'*****                                                    *****'
 WRITE(6,*)
+'*****  WRITTEN BY                                        *****'
 WRITE(6,*)
+'*****  R.H.WILKINSON, DIVISION OF MANAGEMENT SCIENCE,    *****'
 WRITE(6,*)
+'*****  DURING 1989/90, ON THE UNIV. OF STIRLING VAX      *****'
 WRITE(6,*)
+'*****                                                    *****'
 CALL LINE(2)
 WRITE(6,*)
+'*****  Copyright R.H.Wilkinson 1990.  ************************'
 CALL LINE(2)
 END
```

```
*******

      SUBROUTINE BASICS(JAY,NUMI,NUMO,VAR,M,N,M1,N1,MTOT,MTOT1,SCOPE,
     +                  TITLE,GROUP,NAMES,MATRIX,VARDEF,
     +                  NAMEINP,NAMEOUT,NAMEVAR)

CCCCCCC   BASICS IS CALLED BY THE MAIN PROGRAM
CCCCCCC
CCCCCCC   BASICS CALLS LINE
CCCCCCC
CCCCCCC   THIS SUBROUTINE READS IN THE TITLE, OPTION CODE,
CCCCCCC   NUMBER OF DMU'S, INPUTS AND OUTPUTS. IT CALCULATES
CCCCCCC   THE SPECIFIC COMBINATION OF OPTIONS REQUIRED AND
CCCCCCC   OUTPUTS A SUMMARY OF THESE AFTER THE TITLE. IT ALSO
CCCCCCC   SETS THE VARIABLES WHICH TAKE THEIR INITIALISATION
CCCCCCC   FROM THE INPUT DATA.
CCCCCCC
CCCCCCC
CCCCCCC  THE CHOICE OF FACILITIES WITHIN DEAPMAS-3 IS CONTROLLED
CCCCCCC  BY THE INPUT TO THE SCOPE VARIABLE AS FOLLOWS

CCCCCCC  (WHERE DEA= BASIC DATA ENVELOPMENT ANALYSIS
CCCCCCC         PROFILE=PERFORMANCE PROFILE
CCCCCCC         SPECIAL=SPECIALISED PERFORMANCE PROFILE
CCCCCCC         ENVIRON=ENVIRONMENTAL FACTOR CONSIDERATION

CCCCCCC             DEA     PROFILE    SPECIAL      ENVIRON
CCCCCCC  OPTION
CCCCCCC    1         *         *
CCCCCCC    2         *         *          *
CCCCCCC    3         *         *          *            *
CCCCCCC    4         *         *                       *
CCCCCCC    5         *                                 *

CCCCCCC  THE ABOVE ALL INCLUDE DEFINITION OF VARIABLE GROUPS,
CCCCCCC  WHERE THESE ARE NOT INCLUDED (MANDATORY ONLY WITH
CCCCCCC  SPECIALISATION), THE FOLLOWING INPUT IS USED

CCCCCCC  OPTION 1 ; ENTER "6"
CCCCCCC  OPTION 4 ; ENTER "7"
CCCCCCC  OPTION 5 ; ENTER "8"

CCCCCCC  OPTION 9 REPRESENTS BASIC DEA ONLY AND WITH NO GROUPS
CCCCCCC  N.B. VALUES 5,8 AND 9 WILL CAUSE A WARNING TO BE OUTPUT
CCCCCCC       QUESTIONING THE USE OF UNLIMITED VARIABLE WEIGHTS

CCCCCCC  WITH OPTIONS 1-9 NAMES FOR THE DMU'S AND VARIABLES ARE
CCCCCCC  EXPECTED, WHERE THE DMU'S ARE NOT PROVIDED WITH
CCCCCCC  NAMES, THE VALUE TO INPUT SHOULD BE GIVEN A TRAILING 0;
CCCCCCC  i.e. OPTION 1; ENTER "10" OPTION 2; ENTER "20" AND SO ON

CCCCCCC  WHERE NAMES ARE NOT PROVIDED FOR THE VARIABLES EITHER, A
CCCCCCC  SECOND TRAILING ZERO SHOULD BE ADDED TO THE OPTION;
CCCCCCC  i.e. OPTION 1; ENTER "100" OPTION 2; "200" AND SO ON

CCCCCCC  WHERE AN EXAMPLE LP MATRIX IS REQUIRED; "0" SHOULD FIRST
CCCCCCC  BE ENTERED FOR SCOPE, A SECOND INPUT IS THEN REQUIRED
CCCCCCC  AS PER THE OPTIONS SET OUT ABOVE. NOTE THAT THIS OPTIONAL
CCCCCCC  "DOUBLE INPUT" SHOULD BE PRIOR TO THE INPUT OF ANY OTHER
CCCCCCC  VARIABLES: i.e. PRIOR TO JAY,NUMI, AND NUMO
CCCCCCC  THE FIRST INPUT TO THE DEAPMAS PROGRAM IS A HEADING LINE
CCCCCCC  IN THE INPUT FILE: THIS IS USED AS A TITLE FOR THE DATA
CCCCCCC  RUN. THE SCOPE DATA MUST THEN FOLLOW ON A FRESH LINE.
```

```
      INTEGER JAY,NUMI,NUMO,VAR,M,N,M1,N1,MTOT,MTOT1,SCOPE,
     +        GROUP,NAMES,MATRIX,VARDEF

      CHARACTER*25 NAMEINP(NUMI),NAMEOUT(NUMO),NAMEVAR(VAR),
     +             TITLE*50

      READ(5,*) TITLE
      READ(5,*) SCOPE
      MATRIX=0
      IF (SCOPE.EQ.0) THEN
         MATRIX=1
         READ(5,*)SCOPE
      END IF
      NAMES=1
      VARDEF=1
      IF(SCOPE.GT.99) THEN
         VARDEF=0
         SCOPE=SCOPE/10
      END IF
      IF(SCOPE.GT.9)THEN
         NAMES=0
         SCOPE=SCOPE/10
      END IF
      GROUP=1
      IF(SCOPE.GT.5) THEN
         GROUP=0
         IF (SCOPE.EQ.6) SCOPE=1
         IF (SCOPE.EQ.7) SCOPE=4
         IF (SCOPE.EQ.8) SCOPE=5
      END IF
      WRITE(6,'(////)')
      CALL LINE(2)
      WRITE(6,'(/,4X,A,//)') TITLE
      CALL LINE(2)
      WRITE(6,'(/'' Criteria Summary''/)')
      IF (SCOPE.EQ.5.OR.SCOPE.EQ.9)  THEN
         WRITE(6,'(11X,'' BASIC DATA ENVELOPMENT ANALYSIS'')')
      ELSE
         WRITE(6,'(11X,'' DEA WITH'')')
      END IF
      IF (SCOPE.EQ.1.OR.SCOPE.EQ.4) THEN
         WRITE(6,'(11X,'' PERFORMANCE PROFILE'')')
      ELSE IF (SCOPE.EQ.2.OR.SCOPE.EQ.3) THEN
         WRITE(6,'(11X,'' SPECIALISED PERFORMANCE PROFILE'')')
      END IF
      IF (SCOPE.EQ.5)  THEN
         WRITE(6,'(11X,'' WITH ENVIRONMENTAL FACTOR CONSIDERATION'')')
      ELSE IF (SCOPE.EQ.3.OR.SCOPE.EQ.4) THEN
         WRITE(6,'(11X,'' AND ENVIRONMENTAL FACTOR CONSIDERATION'')')
      END IF
      WRITE(6,'(/)')
      CALL LINE(1)
      IF (SCOPE.NE.9) THEN
         WRITE(6,'(/,'' involving:''/)')
      END IF
      IF (SCOPE.NE.5.AND.SCOPE.NE.9) THEN
         WRITE(6,'(5X,'' 1) Variable weight restriction'')')
      END IF
      IF (SCOPE.EQ.2.OR.SCOPE.EQ.3) THEN
         WRITE(6,'(5X,'' 2) Variable specialisation'')')
      END IF
      IF (SCOPE.GT.2.AND.SCOPE.NE.9) THEN
         WRITE(6,'(5X,'' 3) Affected variable adjustment (A.V.A.)'')')
      END IF
      WRITE(6,'(//)')
      CALL LINE(2)
      WRITE(6,'(//)')
```

```
      IF (SCOPE.EQ.5.OR.SCOPE.EQ.9) THEN
       WRITE(6,'(5X,'' ********************************************'')')
       WRITE(6,'(5X,'' * WARNING:                                 *'')')
       WRITE(6,'(5X,'' * Results obtained by DEA without variable *'')')
       WRITE(6,'(5X,'' * weight restriction must be treated with  *'')')
       WRITE(6,'(5X,'' * extreme caution and are unlikely to have *'')')
       WRITE(6,'(5X,'' * any significant practical use.           *'')')
       WRITE(6,'(5X,'' ********************************************'')')
      END IF
      WRITE(6,'(//)')
      CALL LINE(2)
      WRITE(6,'(//)')
      READ (5,*) JAY,NUMI,NUMO
      VAR=(NUMI+NUMO)
      M=((3*VAR)+JAY+2)
      N=VAR
      M1=M+1
      N1=N+1
      MTOT=M
      MTOT1=M1
      END

*******

      SUBROUTINE ANALYSE(M,N,JAY,NUMI,NUMO,VAR,DMUOBJ,DMU,B,C,X,
     +        DINV,S,V,TEMP,JJ,OBJV,MTOT,A1,B1,C1,X1,DINV1,S1,V1,
     +        TEMP1,JJ1,OBJV1,M1,N1,MTOT1,CONTR,LIMITS,
     +        LIMSPEC,SCOPE,GROUP,NAMES,RESULT,ANSWER,MATRIX,
     +        VARDEF,NAMEINP,NAMEOUT,NAMEVAR,A,SPECMAT,AOLD)

CCCCCCC   ANALYSE IS CALLED BY THE MAIN PROGRAM
CCCCCCC
CCCCCCC   ANALYSE CALLS:
CCCCCCC                  SETDATA WHICH CALLS:
CCCCCCC                          GROUPMINMAX
CCCCCCC                          PRNGROUP WHICH CALLS LINE
CCCCCCC                  AVA WHICH CALLS LINE
CCCCCCC                  SPECINPUT
CCCCCCC                  NEXTDMU WHICH CALLS:
CCCCCCC                          GROUPMINMAX
CCCCCCC                          PRNGROUP WHICH CALLS LINE
CCCCCCC                          PERPROF
CCCCCCC                          SPECIALISE
CCCCCCC                          LINE
CCCCCCC                  LINPRO WHICH CALLS:
CCCCCCC                         OPTIMISE WHICH CALLS:
CCCCCCC                                 STP1
CCCCCCC                                 STP2
CCCCCCC                                 STP3
CCCCCCC                                 MATMOD
CCCCCCC                         MATMOD
CCCCCCC                  LPSHOW WHICH CALLS LINE
CCCCCCC                  LINE
CCCCCCC
CCCCCCC   THIS SUBROUTINE AND THE SUBROUTINES WHICH IT CALLS
CCCCCCC   READ IN ALL THE INPUT DATA (OTHER THAN THAT
CCCCCCC   ALREADY INPUT WITHIN BASICS). ENVIRONMENTAL FACTORS
```

```
CCCCCCC   ARE DEALT WITH IF INDICATED BY A CALL TO AVA. THE
CCCCCCC   MAIN LOOP OF THE SUBROUTINE THEN CALCULATES AND OUTPUTS
CCCCCCC   THE RESULTS FOR EACH OF THE DMU'S IN DETAIL INCLUDING
CCCCCCC   THE VIRTUAL INPUTS AND VIRTUAL OUTPUTS.
CCCCCCC


      INTEGER M,N,JAY,NUMI,NUMO,JTH,VAR,CONTR,M1,N1,MTOT,MTOT1,
     +        SCOPE,NAMES,JJ(N),JJ1(N1),SPECTOT,SPECGROUP(50),
     +        SPECID(50,100),SPECDELNUM(50),SPECDELVAR(50,50),
     +        MINTYPE(50,50),MINTOT(50,50),MINDEST(50,50,50),
     +        MAXTYPE(50,50),MAXDEST(50,50),
     +        GROUP,LEVELS,SETS(100),TOTSET,SETNUMVAR(100),
     +        SETIDVAR(100,100),RESULT(JAY),ANSWER(JAY),Y,Z,MATRIX,
     +        I,DEL,VARDEF,K,SKIP

      DOUBLE PRECISION A(MTOT,N),B(MTOT),C(N),X(N),DINV(N,N),S(N),
     +                 V(N),TEMP(N),A1(MTOT1,N1),B1(MTOT1),C1(N1),
     +                 X1(N1),DINV1(N1,N1),S1(N1),V1(N1),TEMP1(N1),
     +                 DMUOBJ(JAY),OBJV,OBJV1,LIMITS(VAR,2),
     +                 LIMSPEC(VAR,2),SETMIN(100),SETMAX(100),
     +                 ICONTOT,OCONTOT,SPECMAT(MTOT,N),AOLD(MTOT,N)

      CHARACTER*25 DMU(JAY)*8,
     +             NAMEINP(NUMI),NAMEOUT(NUMO),NAMEVAR(VAR)

      CALL SETDATA(JAY,DMU,NUMI,NUMO,VAR,M,N,A,B,C,MTOT,GROUP,
     +             LEVELS,SETS,TOTSET,SETMIN,SETMAX,SETNUMVAR,
     +             SETIDVAR,LIMITS,SCOPE,NAMES,VARDEF,NAMEINP,
     +             NAMEOUT,NAMEVAR)
      IF (SCOPE.GT.2.AND.SCOPE.LT.9) THEN
       CALL AVA(A,M,N,JAY,NUMI,NUMO,MTOT,NAMEVAR,AOLD,DMU,NAMES,VARDEF)
      END IF
      IF (SCOPE.EQ.2.OR.SCOPE.EQ.3) THEN
         CALL SPECINPUT(SPECTOT,SPECGROUP,SPECID,SPECDELNUM,
     +                  SPECDELVAR,MINTYPE,MINTOT,MINDEST,
     +                  MAXTYPE,MAXDEST,JAY)
      END IF
      DO 200 JTH=1,JAY
         CALL NEXTDMU(A,C,JTH,M,N,NUMI,VAR,MTOT,SCOPE,LIMSPEC,LIMITS,
     +                JAY,SPECTOT,SPECGROUP,SPECID,SPECDELNUM,SPECDELVAR,
     +                MINTYPE,MINTOT,MINDEST,MAXTYPE,MAXDEST,DMU,NAMES,
     +                LEVELS,SETS,TOTSET,SETNUMVAR,SETIDVAR,SETMIN,
     +                SETMAX,NUMO,NAMEINP,NAMEOUT,NAMEVAR,VARDEF)
         IF (JTH.EQ.1) THEN
            IF (MATRIX.EQ.1) CALL LPSHOW(A,B,M,N,JAY,VAR,MTOT)
            CALL LINE(2)
            WRITE(6,'(///,6X,''DETAILS OF RESULTS FOR EACH DMU'')')
            WRITE(6,'(///)')
         END IF
         WRITE(6,'(//)')
         CALL LINE(2)
         SKIP=0
         DO 50 Y=1,M
           DO 50 Z=1,N
50           SPECMAT(Y,Z)=A(Y,Z)
         IF (SCOPE.EQ.2.OR.SCOPE.EQ.3) THEN
           DO 100 Y=1,SPECTOT
             DO 100 Z=1,SPECGROUP(Y)
100            IF(SPECID(Y,Z).EQ.JTH) SKIP=Y
            DO 120 Y=1,SPECTOT
              IF (Y.EQ.SKIP) THEN
                DO 115 Z=1,SPECDELNUM(Y)
                  DO 110 K=1,(JAY+2)
                    SPECMAT(K,(SPECDELVAR(Y,Z)))=0.D0
110               CONTINUE
```

```
115            CONTINUE
             END IF
120        CONTINUE
            DO 150 Y=1,SPECTOT
              IF (Y.EQ.SKIP) GO TO 150
              DO 130 Z=1,SPECGROUP(Y)
                DO 130 K=1,N
130             SPECMAT((SPECID(Y,Z)+2),K)=0.D0
150         CONTINUE
          END IF
         CALL LINPRO(M,N,OBJV,SPECMAT,B,C,X,DINV,S,V,TEMP,JJ,
     +               MTOT,A1,B1,C1,X1,DINV1,S1,V1,TEMP1,JJ1,OBJV1,
     +               M1,N1,MTOT1,CONTR)
         DMUOBJ(JTH)=1.D0/OBJV
         RESULT(JTH)=NINT(DMUOBJ(JTH)*100)
         ANSWER(JTH)=RESULT(JTH)
         IF(NAMES.EQ.1) THEN
            WRITE(6,'(//,5X,'' DMU '',I3,6X,A,
     +            6X,''PARETO EFFICIENCY: '',I4,''%'',/)')
     +      JTH,DMU(JTH),RESULT(JTH)
         ELSE
            WRITE(6,'(//,5X,'' DMU '',I3,6X,
     +            ''PARETO EFFICIENCY: '',I4,''%'',/)')
     +      JTH,RESULT(JTH)
         END IF
         CALL LINE(1)
         ICONTOT=0.D0
         OCONTOT=0.D0
         DO 160 I=1,NUMI
            ICONTOT=ICONTOT+((A(JTH+2,I))*(X(I)))
160      CONTINUE
         DO 170 I=(NUMI+1),VAR
            OCONTOT=OCONTOT+((A(JTH+2,I))*(X(I)))
170      CONTINUE
         WRITE(6,'(/,2X,''ID     DATA VALUE   OPTIMUM VAL.'',
     +            '' VIRTUAL CONT.   PERC. TOT.''/)')
         CALL LINE(1)
         DO 180 I=1,NUMI
         WRITE(6,'('' '',A)') NAMEINP(I)
         WRITE(6,'(8X,F10.1,3X,F10.6,3X,F10.6,3X,F10.3)')
     +          (A(JTH+2,I)),X(I),((A(JTH+2,I))*(X(I))),
     +          ((((A(JTH+2,I))*(X(I)))/ICONTOT)*100)
180      CONTINUE
         CALL LINE(1)
         WRITE(6,'(/,30X,''TOTAL VIRTUAL INPUTS '',F10.6,/)') ICONTOT
         CALL LINE(1)
         WRITE(6,'(/,2X,''ID     DATA VALUE   OPTIMUM VAL.'',
     +            '' VIRTUAL CONT.   PERC. TOT.''/)')
         CALL LINE(1)
         DO 190 I=(NUMI+1),VAR
         WRITE(6,'('' '',A)') NAMEOUT(I-NUMI)
         WRITE(6,'(8X,F10.1,3X,F10.6,3X,F10.6,3X,F10.3)')
     +          (A(JTH+2,I)),X(I),
     +          ((A(JTH+2,I))*(X(I))),
     +          ((((A(JTH+2,I))*(X(I)))/OCONTOT)*100)
190      CONTINUE
         CALL LINE(1)
        WRITE(6,'(/,30X,''TOTAL VIRTUAL OUTPUTS '',F10.6,/)') OCONTOT
         CALL LINE(1)
         WRITE(6,'(//)')
200      CONTINUE
         END
```

****

```
      SUBROUTINE PRNRANK(JAY,DMU,ANSWER,INDX,NAMES,TITLE)

CCCCCCC    PRNRANK IS CALLED BY THE MAIN PROGRAM
CCCCCCC
CCCCCCC    PRNRANK CALLS LINE
CCCCCCC
CCCCCCC    THIS SUBROUTINE SORTS THE RATINGS OF THE DMU'S
CCCCCCC    INTO DESCENDING ORDER AND OUTPUTS FIRST THE PARETO
CCCCCCC    EFFICIENT UNITS FOLLOWED BY THE PARETO INEFFICIENT
CCCCCCC    IN ORDER, PROVIDING A SUMMARY OF RESULTS.
CCCCCCC

      INTEGER JAY,ANSWER(JAY),FLAG,MEMORY,Y,Z,INDX(JAY),SIGN,NAMES

      CHARACTER*8 DMU(JAY),TITLE*50

      DO 100 Y=1,JAY
100      INDX(Y)=Y
200   FLAG=0
      DO 300 Y=1,(JAY-1)
         IF (ANSWER(Y).LT.ANSWER(Y+1)) THEN
            MEMORY=ANSWER(Y+1)
            ANSWER(Y+1)=ANSWER(Y)
            ANSWER(Y)=MEMORY
            MEMORY=INDX(Y+1)
            INDX(Y+1)=INDX(Y)
            INDX(Y)=MEMORY
            FLAG=1
          END IF
          IF (FLAG.EQ.1) GO TO 200
300   CONTINUE
      WRITE(6,'(//)')
      CALL LINE(3)
      WRITE(6,'(///)')
      CALL LINE(2)
      WRITE(6,'(//,12X,'' SUMMARY OF RESULTS FOR'')')
      WRITE(6,'(13X,A,//)') TITLE
      CALL LINE(2)
      IF (ANSWER(1).LT.100) GO TO 600
      WRITE(6,'(///)')
      CALL LINE(2)
      WRITE(6,'(//'' PARETO EFFICIENT UNITS''/)')
      CALL LINE(1)
      WRITE(6,'(//)')
      DO 500 Y=1,JAY
         IF (ANSWER(Y).LT.100) GO TO 600
         IF (NAMES.EQ.1) THEN
            WRITE(6,'(5X,'' DMU '',I3,4X,A,
     +            I4,''%'')')INDX(Y),DMU(INDX(Y)),ANSWER(Y)
         ELSE
            WRITE(6,'(5X,'' DMU '',I3,4X,I4,''%'')')INDX(Y),ANSWER(Y)
         END IF
500   CONTINUE
600   CONTINUE
      WRITE(6,'(//)')
      CALL LINE(2)
      WRITE(6,'(//'' PARETO INEFFICIENT UNITS''/)')
      CALL LINE(1)
      WRITE(6,'(//)')
      SIGN=0
      DO 700 Z=Y,JAY
         SIGN=1
         IF(NAMES.EQ.1) THEN
```

```
          WRITE(6,'(5X,'' DMU '',I3,4X,A,
     +          I4,''%'')')INDX(Z),DMU(INDX(Z)),ANSWER(Z)
        ELSE
          WRITE(6,'(5X,'' DMU '',I3,4X,I4,''%'')')INDX(Z),ANSWER(Z)
        END IF
700   CONTINUE
      IF (SIGN.EQ.0) WRITE(6,'(/'' (NONE)''//)')
      WRITE(6,'(//)')
      CALL LINE(4)
      END


*******


      SUBROUTINE SETDATA(JAY,DMU,NUMI,NUMO,VAR,M,N,A,B,C,MTOT,GROUP,
     +                  LEVELS,SETS,TOTSET,SETMIN,SETMAX,SETNUMVAR,
     +                  SETIDVAR,LIMITS,SCOPE,NAMES,VARDEF,
     +                  NAMEINP,NAMEOUT,NAMEVAR)

CCCCCCC  SETDATA IS CALLED BY ANALYSE
CCCCCCC
CCCCCCC  SETDATA CALLS:
CCCCCCC                 GROUPMINMAX
CCCCCCC                 PRNGROUP WHICH CALLS LINE
CCCCCCC
CCCCCCC  THIS SUBROUTINE READS IN DMU AND VARIABLE NAMES
CCCCCCC  WHERE THESE ARE PRESENT AND VARIABLE GROUP STRUCTURE
CCCCCCC  WHERE GROUPS HAVE BEEN DEFINED
CCCCCCC
CCCCCCC  GROUPMINMAX IS CALLED TO CALCULATE THE LIMITS AND
CCCCCCC  PRNGROUP THEN DISPLAYS THESE LIMITS


      INTEGER JAY,NUMI,NUMO,VAR,M,N,I,J,MTOT,GROUP,LEVELS,
     +        SETS(100),TOTSET,SETNUMVAR(100),SETIDVAR(100,100),SCOPE,
     +        NAMES,VARDEF,DELVAR(100)

      DOUBLE PRECISION A(MTOT,N),B(MTOT),C(N),LIMITS(VAR,2),
     +                 SETMIN(100),SETMAX(100)

      CHARACTER*25 DMU(JAY)*8,
     +             NAMEINP(NUMI),NAMEOUT(NUMO),NAMEVAR(VAR)

      IF(NAMES.EQ.1) READ(5,*) (DMU(I),I=1,JAY)
      IF(VARDEF.EQ.1) THEN
         READ(5,*) (NAMEVAR(I),I=1,VAR)
         DO 15 I=1,NUMI
15          NAMEINP(I)=NAMEVAR(I)
         DO 30 I=(NUMI+1),VAR
30          NAMEOUT(I-NUMI)=NAMEVAR(I)
      END IF
      DO 200 I=3,(JAY+2)
            READ(5,*) (A(I,J),J=1,VAR)
         DO 100 J=1,VAR
            IF (J.LE.NUMI) THEN
               A(I,J)=-A(I,J)
            ELSE
            IF (A(I,J).LT.1.D-3) THEN
               A(I,J)=1.D-1
            END IF
         END IF
100      CONTINUE
200   CONTINUE
```

```
      DO 300 I=3,M
300      B(I)=0.D0
      B(1)=1.D0
      B(2)=-1.D0
      DO 400 I=1,N
         A(1,I)=0.D0
400      A(2,I)=0.D0
      DO 500 I=1,N
500      C(I)=0.D0
      IF(SCOPE.EQ.5.OR.SCOPE.EQ.9) THEN
         DO 600 I=1,VAR
            LIMITS(I,1)=0.D0
600         LIMITS(I,2)=1.D2
      ELSE
         READ(5,*) ((LIMITS(I,J),J=1,2),I=1,VAR)
      END IF
      IF(GROUP.NE.0) THEN
         TOTSET=0
         READ(5,*) LEVELS,(SETS(I),I=1,LEVELS)
         DO 700 I=1,LEVELS
700         TOTSET=TOTSET+SETS(I)
         READ(5,*) (SETNUMVAR(I),I=1,TOTSET)
         DO 800 I=1,TOTSET
800         READ(5,*) (SETIDVAR(I,J),J=1,SETNUMVAR(I))
         CALL GROUPMINMAX(NUMI,VAR,LIMITS,TOTSET,SETNUMVAR,SETIDVAR,
     +                    SETMIN,SETMAX)
      DO 900 I=1,VAR
900      DELVAR(I)=0
         CALL PRNGROUP(A,M,N,NUMI,NUMO,VAR,MTOT,LEVELS,TOTSET,SETS,
     +                 SETMIN,SETMAX,SETNUMVAR,SETIDVAR,LIMITS,
     +                 NAMEINP,NAMEOUT,NAMEVAR,DELVAR)
      END IF
      END


*******


      SUBROUTINE AVA(A,M,N,JAY,NUMI,NUMO,MTOT,NAMEVAR,AOLD,
     +               DMU,NAMES,VARDEF)

CCCCCCC AVA IS CALLED BY ANALYSE
CCCCCCC
CCCCCCC AVA CALLS LINE
CCCCCCC
CCCCCCC THIS SUBROUTINE READS IN ENVIRONMENTAL FACTOR DATA
CCCCCCC AND CARRIES OUT THE PRE-ADJUSTMENT TO THE INPUTS AND OUTPUTS

      INTEGER M,N,JAY,NUMI,NUMO,MTOT,NUMEF,NUMAV(50),DMUADJ(50),
     +        EFTYPE(50),AFFVAR(50,50),AFFDMU(50,200),
     +        I,J,K,L,NAMES,VARDEF

      DOUBLE PRECISION A(MTOT,N),AOLD(MTOT,N),AVADATA(50,200),
     +                 SCALE(50)

      CHARACTER*25 NAMEVAR(100),DMU(JAY)*8

CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
CCCCCCC ENVIRONMENTAL FACTOR CONSIDERATION BY
CCCCCCC AFFECTED VARIABLE ADJUSTMENT
CCCCCCC
CCCCCCC THIS ADJUSTMENT IS DIRECTLY TO THE INPUT DMU DATA
```

```
CCCCCCC BY ADDITION OR SUBTRACTION OF A PERCENTAGE REPRESENTED
CCCCCCC EITHER BY THE ENVIRONMENTAL FACTOR DATA OR THE RESULT
CCCCCCC OF ITS INVERSION
CCCCCCC
CCCCCCC THE FOLLOWING INPUT CODES ARE USED:
CCCCCCC
CCCCCCC DMUADJ (ID OF DMU'S WITH VARIABLE(S) TO BE ADJUSTED)
CCCCCCC
CCCCCCC 0: ALL DMUS
CCCCCCC X: WHERE X REPRESENTS A LESSER NUMBER OF DMUS
CCCCCCC
CCCCCCC EFTYPE (THE FORM OF ADJUSTMENT NECESSARY)
CCCCCCC
CCCCCCC 1: ADD PERCENTAGE
CCCCCCC 2: SUBTRACT PERCENTAGE
CCCCCCC 3: INVERT FACTOR AND ADD PERCENTAGE
CCCCCCC 4: INVERT FACTOR AND SUBTRACT PERCENTAGE
CCCCCCC
CCCCCCC SCALE (SCALING FACTOR FOR APPLICATION TO EF DATA)
CCCCCCC
CCCCCCC X: WHERE FACTOR IS DIVIDED BY 10 RAISED TO THE POWER OF X
CCCCCCC
CCCCCCC NOTE: WHERE AN EF AFFECTS BOTH AN INPUT AND OUTPUT IT
CCCCCCC       SHOULD BE TREATED AS TWO EF'S, ONE FOR INPUTS
CCCCCCC       AND ONE FOR OUTPUTS
CCCCCCC
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
      READ(5,*) NUMEF
      DO 500 I=1,NUMEF
         READ(5,*) NUMAV(I),DMUADJ(I),EFTYPE(I),SCALE(I)
         SCALE(I)=1.D1**SCALE(I)
         READ(5,*) (AFFVAR(I,J),J=1,NUMAV(I))
         IF(DMUADJ(I).EQ.0) THEN
           DMUADJ(I)=JAY
           DO 100 K=1,JAY
100        AFFDMU(I,K)=K
         ELSE
            READ(5,*) (AFFDMU(I,K),K=1,DMUADJ(I))
         END IF
         READ(5,*) (AVADATA(I,K),K=1,DMUADJ(I))
         IF(EFTYPE(I).EQ.3.OR.EFTYPE(I).EQ.4) THEN
            DO 200 K=1,DMUADJ(I)
            AVADATA(I,K)=(1/AVADATA(I,K))
200         CONTINUE
         END IF
         IF(EFTYPE(I).EQ.2.OR.EFTYPE(I).EQ.4) THEN
         DO 300 K=1,DMUADJ(I)
            AVADATA(I,K)=(-AVADATA(I,K))
300      CONTINUE
         END IF
         IF(AFFVAR(I,1).LE.NUMI) THEN
         DO 400 K=1,DMUADJ(I)
            AVADATA(I,K)=(-AVADATA(I,K))
400         CONTINUE
         END IF
500   CONTINUE
      DO 600 I=3,JAY+2
         DO 600 J=1,N
600         AOLD(I,J)=A(I,J)
      DO 800 I=1,NUMEF
         DO 800 J=1,NUMAV(I)
            DO 700 K=1,DMUADJ(I)
               A((AFFDMU(I,K)+2),(AFFVAR(I,J)))=
     +         A((AFFDMU(I,K)+2),(AFFVAR(I,J)))+
     + ((DABS(A((AFFDMU(I,K)+2),(AFFVAR(I,J)))))*
     +  (AVADATA(I,K)/SCALE(I)))
700         CONTINUE
```

```
800       CONTINUE
          CALL LINE(2)
          WRITE(6,'(//'' SUMMARY OF ENVIRONMENTAL FACTOR'',
     +            '' CONSIDERATION''//)')
          CALL LINE(2)
          DO 1000 I=1,NUMEF
             WRITE(6,'(//)')
             CALL LINE(1)
             WRITE(6,'(/'' ENVIRONMENTAL FACTOR '',I3)') I
             WRITE(6,'(/)')
             CALL LINE(1)
             WRITE(6,'(//)')
             DO 1000 J=1,NUMAV(I)
                IF(VARDEF.EQ.0) THEN
                WRITE(6,'(/'' VARIABLE'',I3)') AFFVAR(I,J)
                ELSE
                WRITE(6,'(/,X,A)') NAMEVAR(AFFVAR(I,J))
                END IF
                WRITE(6,'(/,15X,''UNADJUSTED  PERCENTAGE      NEW'')')
                WRITE(6,'('' DMU'',11X,''VALUE'',8X,''ADJUSTMENT'',
     +                    4X,''VALUE'')')
                DO 1000 K=1,JAY
                   DO 900 L=1,DMUADJ(I)
                      IF(AFFDMU(I,L).EQ.K) THEN
                        IF(NAMES.EQ.0) THEN
                         WRITE(6,'(I3,9X,F10.2,7X,F6.2,6X,F10.2)')
     +                         K,(AOLD((K+2),AFFVAR(I,J))),
     +                         (AVADATA(I,K)/SCALE(I)*100),
     +                         (A((K+2),AFFVAR(I,J)))
                  ELSE
                        WRITE(6,'(I3,X,A,F10.2,7X,F6.2,6X,F10.2)')
     +                    K,DMU(K),(AOLD((K+2),AFFVAR(I,J))),
     +                    (AVADATA(I,K)/SCALE(I)*100),
     +                    (A((K+2),AFFVAR(I,J)))
                  END IF
                         GO TO 1000
                      END IF
900                CONTINUE
                   IF (NAMES.EQ.0) THEN
                   WRITE(6,'(I3,10X,F10.2,9X,''0.00'',6X,F10.2)')
     +                   K,(AOLD((K+2),AFFVAR(I,J))),
     +                   (A((K+2),AFFVAR(I,J)))
                   ELSE
                    WRITE(6,'(I3,X,A,F10.2,9X,''0.00'',6X,F10.2)')
     +                   K,DMU(K),(AOLD((K+2),AFFVAR(I,J))),
     +                   (A((K+2),AFFVAR(I,J)))
                   END IF
1000       CONTINUE
           WRITE(6,'(//)')
           CALL LINE(1)
           WRITE(6,'(///)')
           CALL LINE(3)
      END


*******

      SUBROUTINE SPECINPUT(SPECTOT,SPECGROUP,SPECID,SPECDELNUM,
     +                     SPECDELVAR,MINTYPE,MINTOT,MINDEST,
     +                     MAXTYPE,MAXDEST,JAY)

CCCCCCC   SPECINPUT IS CALLED BY ANALYSE
CCCCCCC
CCCCCCC   SPECINPUT CALLS NO OTHER SUBROUTINE
CCCCCCC
```

```
CCCCCCC  THIS SUBROUTINE READS IN SPECIALISATION DATA
CCCCCCC  AND ISSUES WARNINGS WHERE THE SIGNIFICANCE
CCCCCCC  OF RESULTS IS LIKELY TO BE AFFECTED

      INTEGER SPECTOT,SPECGROUP(50),SPECID(50,100),SPECDELNUM(50),
     +        SPECDELVAR(50,50),MINTYPE(50,50),MINTOT(50,50),
     +        MINDEST(50,50,50),MAXTYPE(50,50),
     +        MAXDEST(50,50),Y,Z,I,CHECK,JAY


         CHECK=0
         READ(5,*) SPECTOT
         DO 100 Y=1,SPECTOT
            READ(5,*) SPECGROUP(Y)
            CHECK=CHECK+SPECGROUP(Y)
100      CONTINUE
         DO 200 Y=1,SPECTOT
200         READ(5,*) (SPECID(Y,Z),Z=1,SPECGROUP(Y))
         DO 300 Y=1,SPECTOT
300         READ(5,*) SPECDELNUM(Y)
         DO 400 Y=1,SPECTOT
400         READ(5,*) (SPECDELVAR(Y,Z),Z=1,SPECDELNUM(Y))
         DO 500 Y=1,SPECTOT
500         READ(5,*) (MINTYPE(Y,Z),Z=1,SPECDELNUM(Y))
         DO 600 Y=1,SPECTOT
            DO 600 Z=1,SPECDELNUM(Y)
               IF(MINTYPE(Y,Z).NE.2) GO TO 600
               READ(5,*) MINTOT(Y,Z)
600      CONTINUE
         DO 700 Y=1,SPECTOT
            DO 700 Z=1,SPECDELNUM(Y)
               IF(MINTYPE(Y,Z).NE.2) GO TO 700
               READ(5,*) (MINDEST(Y,Z,I),I=1,MINTOT(Y,Z))
700      CONTINUE
         DO 800 Y=1,SPECTOT
800         READ(5,*) (MAXTYPE(Y,Z),Z=1,SPECDELNUM(Y))
         DO 1000 Y=1,SPECTOT
            DO 1000 Z=1,SPECDELNUM(Y)
               IF(MAXTYPE(Y,Z).EQ.3.OR.MAXTYPE(Y,Z).EQ.1) GO TO 1000
               READ(5,*) MAXDEST(Y,Z)
1000      CONTINUE
         IF((CHECK/JAY).LE.(1/3)) GO TO 1100
         WRITE(6,'(//)')
         CALL LINE(2)
         WRITE(6,'(/,20X,''*****WARNING*****'',/)')
         CALL LINE(2)
         WRITE(6,'(//)')
         IF((CHECK/JAY).GT.0.5) THEN
            WRITE(6,*)'DMU''S WITH STANDARD PERFORMANCE PROFILE'
            WRITE(6,*)'ARE A MINORITY. THE FOLLOWING RESULTS WILL'
            WRITE(6,*)'THEREFORE HAVE SEVERELY REDUCED SIGNIFICANCE'
         ELSE
            WRITE(6,*)'AS NO MORE THAN 2 OUT OF 3 DMU''S CONFORM TO'
            WRITE(6,*)'THE STANDARD PERFORMANCE PROFILE, THE'
            WRITE(6,*)'FOLLOWING RESULTS ARE LIKELY TO HAVE REDUCED'
            WRITE(6,*)'SIGNIFICANCE'
         END IF
         WRITE(6,'(//)')
         CALL LINE(2)
1100     CONTINUE
         END
```

****

```
      SUBROUTINE NEXTDMU(A,C,JTH,M,N,NUMI,VAR,MTOT,SCOPE,LIMSPEC,LIMITS,
     +                   JAY,SPECTOT,SPECGROUP,SPECID,SPECDELNUM,
     +                   SPECDELVAR,MINTYPE,MINTOT,MINDEST,MAXTYPE,
     +                   MAXDEST,DMU,NAMES,LEVELS,SETS,TOTSET,SETNUMVAR,
     +                   SETIDVAR,SETMIN,SETMAX,NUMO,NAMEINP,
     +                   NAMEOUT,NAMEVAR,VARDEF)

CCCCCCC  NEXTDMU IS CALLIED BY ANALYSE
CCCCCCC
CCCCCCC  NEXTDMU CALLS:
CCCCCCC                 GROUPMINMAX
CCCCCCC                 PRNGROUP WHICH CALLS LINE
CCCCCCC                 PERPROF
CCCCCCC                 SPECIALISE
CCCCCCC                 LINE
CCCCCCC
CCCCCCC  THE PURPOSE OF THIS SUBROUTINE IS TO ALTER THE
CCCCCCC  LINEAR PROGRAM READY FOR OPTIMISATION FOR THE
CCCCCCC  NEXT DMU, IT ALSO ESTABLISHES THE PERFORMANCE
CCCCCCC  PROFILE FOR EACH DMU BY A CALL TO PERPROF
CCCCCCC  AND CALLS SPECIALISE IF SPECIALISATION
CCCCCCC  PRESENT, PRINTING OUT DETAILS OF THE SPECIALISED
CCCCCCC  PERFORMANCE PROFILE


      INTEGER JTH,Y,Z,NUMI,NUMO,M,N,VAR,MTOT,SCOPE,JAY,SPECTOT,
     +        SPECGROUP(50),SPECID(50,100),SPECDELNUM(50),
     +        SPECDELVAR(50,50),LEVELS,SETS(100),TOTSET,SETNUMVAR(100),
     +        SETIDVAR(100,100),MINTYPE(50,50),MINTOT(50,50),
     +        MINDEST(50,50,50),MAXTYPE(50,50),MAXDEST(50,50),
     +        DELVAR(100),NAMES,VARDEF


      DOUBLE PRECISION A(MTOT,N),C(N),LIMSPEC(VAR,2),LIMITS(VAR,2),
     +                 SETMIN(100),SETMAX(100)


      CHARACTER*25 NAMEINP(NUMI),NAMEOUT(NUMO),NAMEVAR(VAR),
     +             DMU(JAY)*8

      DO 100 Y=1,NUMI
100      C(Y)=-A((JTH+2),Y)
      DO 200 Y=(NUMI+1),VAR
200      A(1,Y)=A((JTH+2),Y)
      DO 300 Y=(NUMI+1),VAR
300      A(2,Y)=-A((JTH+2),Y)
      IF (SCOPE.EQ.2.OR.SCOPE.EQ.3) GO TO 380
      CALL PERPROF(NUMI,VAR,JAY,A,M,N,JTH,LIMITS,MTOT)
      RETURN
380   CONTINUE
      DO 400 Y=1,VAR
         DO 400 Z=1,2
400         LIMSPEC(Y,Z)=LIMITS(Y,Z)
      DO 500 Y=1,SPECTOT
         DO 500 Z=1,SPECGROUP(Y)
            IF(SPECID(Y,Z).EQ.JTH) THEN
               CALL SPECIALISE(SPECTOT,SPECGROUP,SPECID,SPECDELNUM,
     +                         SPECDELVAR,JTH,Y,Z,LEVELS,SETS,TOTSET,
     +                         SETNUMVAR,SETIDVAR,SETMIN,SETMAX,
     +                         VAR,LIMSPEC,NUMI,JAY,MINTYPE,MINTOT,
     +                         MINDEST,MAXTYPE,MAXDEST)
            END IF
500   CONTINUE
      CALL PERPROF(NUMI,VAR,JAY,A,M,N,JTH,LIMSPEC,MTOT)
      DO 525 Z=1,VAR
525      DELVAR(Z)=0
```

```
      DO 600 Y=1,SPECTOT
         IF(SPECID(Y,1).EQ.JTH) THEN
            CALL LINE(2)
            WRITE(6,'(/)')
            WRITE(6,'(/'' PERFORMANCE PROFILE SPECIFIC TO:''/)')
            IF(NAMES.EQ.1) THEN
              DO 530 Z=1,SPECGROUP(Y)
                 WRITE(6,'(28X,''DMU'',I3,3X,A)')
     +           SPECID(Y,Z),DMU(SPECID(Y,Z))
530           CONTINUE
            ELSE
            WRITE(6,'(28X,''DMU'',I3)')
     +           (SPECID(Y,Z),Z=1,SPECGROUP(Y))
            END IF
            IF(SPECDELNUM(Y).EQ.1) THEN
              WRITE(6,'(/'' AFTER DELETION OF VARIABLE:'')')
            ELSE
              WRITE(6,'(/'' AFTER DELETION OF VARIABLES:'')')
            END IF
            WRITE(6,'()')
            IF(VARDEF.EQ.1) THEN
              DO 535 Z=1,SPECDELNUM(Y)
                 WRITE(6,'(28X,A)') NAMEVAR(SPECDELVAR(Y,Z))
535           CONTINUE
            ELSE
               WRITE(6,'(28X,I3)')
     +      .     (SPECDELVAR(Y,Z),Z=1,SPECDELNUM(Y))
            END IF
            WRITE(6,'(//)')
            CALL LINE(1)
            DO 550 Z=1,SPECDELNUM(Y)
550            DELVAR(SPECDELVAR(Y,Z))=1
         CALL GROUPMINMAX(NUMI,VAR,LIMSPEC,TOTSET,SETNUMVAR,SETIDVAR,
     +                    SETMIN,SETMAX)
         CALL PRNGROUP(A,M,N,NUMI,NUMO,VAR,MTOT,LEVELS,TOTSET,SETS,
     +                 SETMIN,SETMAX,SETNUMVAR,SETIDVAR,LIMSPEC,
     +                 NAMEINP,NAMEOUT,NAMEVAR,DELVAR)
      ELSE
        DO 575 Z=1,SPECGROUP(Y)
          IF (SPECID(Y,Z).EQ.JTH) THEN
            CALL LINE(2)
             IF(NAMES.NE.1) THEN
              WRITE(6,'(/'' SEE DMU'',I3,'' FOR DETAILS OF''
     +      '' SPECIALISED PERFORMANCE PROFILE PERTAINING''
     +      '' TO THIS DMU.''/)') SPECID(Y,1)
          ELSE
      WRITE(6,'(/'' SEE DMU'',I3,X,A)') SPECID(Y,1),DMU(SPECID(Y,1))
      WRITE(6,'('' FOR DETAILS OF '')')
      WRITE(6,'('' SPECIALISED PERFORMANCE PROFILE'')')
      WRITE(6,'('' PERTAINING TO THIS DMU.'',/)')
          END IF
          END IF
575     CONTINUE
      END IF
600   CONTINUE
      END
```

****

```
      SUBROUTINE SPECIALISE(SPECTOT,SPECGROUP,SPECID,SPECDELNUM,
     +                      SPECDELVAR,JTH,IDTOT,IDGRP,LEVELS,
     +                      SETS,TOTSET,SETNUMVAR,SETIDVAR,SETMIN,
```

```
     +                          SETMAX,VAR,LIMSPEC,NUMI,JAY,MINTYPE,
     +                          MINTOT,MINDEST,MAXTYPE,MAXDEST)

CCCCCCC  SPECIALISE IS CALLED BY NEXTDMU
CCCCCCC
CCCCCCC  SPECIALISE CALLS NO OTHER SUBROUTINE
CCCCCCC
CCCCCCC  THIS SUBROUTINE CARRIES OUT THE TRANSFERS INVOLVED
CCCCCCC  IN SPECIALISATION PROCEDURES

      INTEGER SPECTOT,SPECGROUP(50),SPECID(50,100),SPECDELNUM(50),
     +        SPECDELVAR(50,50),MINTYPE(50,50),MINTOT(50,50),
     +        MINDEST(50,50,50),MAXTYPE(50,50),
     +        MAXDEST(50,50),Y,Z,JTH,IDTOT,IDGRP,VAR,NUMI,
     +        FIRST,LAST,CHECK,JAY,I,LEVELS,SETS,TOTSET,
     +        SETNUMVAR(100),SETIDVAR(100,100)

      DOUBLE PRECISION  SETMIN(100),SETMAX(100),LIMSPEC(VAR,2),
     +                  TOTLOWLIM,TOTHIGHLIM,TEMP


CCCCCCC SPECIALISATION CODES USED AS FOLLOWS

CCCCCCC   MINIMUM LIMIT TRANSFER TYPES;
CCCCCCC
CCCCCCC      1= TO ENTIRE CLASS PRO RATA
CCCCCCC      2= TO SPECIFIED VARIABLE GROUPS PRO RATA
CCCCCCC      3= DIRECT INPUT OF ALL LOWER LIMITS

CCCCCCC   MAXIMUM LIMIT TRANSFER TYPES;
CCCCCCC
CCCCCCC      1= NONE
CCCCCCC      2= MAINTENANCE OF SPECIFIED GROUPS
CCCCCCC      3= DIRECT INPUT OF ALL UPPER LIMITS

CCCCCCC   VARIABLES MINTYPE AND MAXTYPE RESPECTIVELY ARE USED

      DO 1200 Y=1,SPECDELNUM(IDTOT)
         TOTLOWLIM=0.D0
         IF(MINTYPE(IDTOT,Y).EQ.1)THEN
            IF(SPECDELVAR(IDTOT,Y).LE.NUMI) THEN
               FIRST=1
               LAST=NUMI
            ELSE
               FIRST=(NUMI+1)
               LAST=VAR
            END IF
         DO 300 Z=FIRST,LAST
            IF(Z.EQ.SPECDELVAR(IDTOT,Y)) GO TO 300
            TOTLOWLIM=(TOTLOWLIM+LIMSPEC(Z,1))
300      CONTINUE
         DO 400 Z=FIRST,LAST
            IF(Z.EQ.SPECDELVAR(IDTOT,Y)) GO TO 400
            LIMSPEC(Z,1)=(LIMSPEC(Z,1)+((LIMSPEC(Z,1)/TOTLOWLIM)*
     +                    LIMSPEC(SPECDELVAR(IDTOT,Y),1)))
400      CONTINUE
         ELSE IF(MINTYPE(IDTOT,Y).EQ.2) THEN
            DO 600 Z=1,MINTOT(IDTOT,Y)
               DO 500 I=1,SETNUMVAR(MINDEST(IDTOT,Y,Z))
                  IF(SETIDVAR((MINDEST(IDTOT,Y,Z)),I).EQ.
     +               SPECDELVAR(IDTOT,Y)) GO TO 500
                  TOTLOWLIM=(TOTLOWLIM+
     +            LIMSPEC(SETIDVAR((MINDEST(IDTOT,Y,Z)),I),1))
500            CONTINUE
600         CONTINUE
            DO 800 Z=1,MINTOT(IDTOT,Y)
               DO 700 I=1,SETNUMVAR(MINDEST(IDTOT,Y,Z))
```

```
                 IF(SETIDVAR((MINDEST(IDTOT,Y,Z)),I).EQ.
     +              SPECDELVAR(IDTOT,Y)) GO TO 700
                 TEMP=LIMSPEC(SETIDVAR((MINDEST(IDTOT,Y,Z)),I),1)
                 TEMP=TEMP+((TEMP/TOTLOWLIM)*
     +           LIMSPEC(SPECDELVAR(IDTOT,Y),1))
                 LIMSPEC(SETIDVAR((MINDEST(IDTOT,Y,Z)),I),1)=TEMP
700           CONTINUE
800         CONTINUE
         ELSE IF (MINTYPE(IDTOT,Y).EQ.3) THEN
               READ(5,*) (LIMSPEC(Z,1),Z=1,VAR)
         ELSE
            WRITE(6,'(''*** MINTYPE MUST EQ 1,2 OR 3.   '',I3)')
     +              MINTYPE(IDTOT,Y)
            STOP
         END IF
         LIMSPEC((SPECDELVAR(IDTOT,Y)),1)=0.D0
1200  CONTINUE
      DO 2000 Y=1,SPECDELNUM(IDTOT)
         TOTHIGHLIM=0.D0
         IF(MAXTYPE(IDTOT,Y).EQ.1) THEN
            LIMSPEC((SPECDELVAR(IDTOT,Y)),2)=0.D0
            RETURN
         ELSE IF (MAXTYPE(IDTOT,Y).EQ.2) THEN
            DO 1300 Z=1,SETNUMVAR(MAXDEST(IDTOT,Y))
               IF (SETIDVAR((MAXDEST(IDTOT,Y)),Z).EQ.SPECDELVAR
     +         (IDTOT,Y)) GO TO 1300
               TOTHIGHLIM=(TOTHIGHLIM+
     +         LIMSPEC((SETIDVAR((MAXDEST(IDTOT,Y)),Z)),2))
1300         CONTINUE
            DO 1400 Z=1,SETNUMVAR(MAXDEST(IDTOT,Y))
               IF(SETIDVAR((MAXDEST(IDTOT,Y)),Z).EQ.
     +         SPECDELVAR(IDTOT,Y)) GO TO 1400
               TEMP=LIMSPEC((SETIDVAR((MAXDEST(IDTOT,Y)),Z)),2)
               TEMP=TEMP+((TEMP/TOTHIGHLIM)*
     +         LIMSPEC(SPECDELVAR(IDTOT,Y),2))
               LIMSPEC((SETIDVAR((MAXDEST(IDTOT,Y)),Z)),2)=TEMP
1400        CONTINUE

         ELSE IF (MAXTYPE(IDTOT,Y).EQ.3) THEN
               READ(5,*) (LIMSPEC(Z,2),Z=1,VAR)
         ELSE
            WRITE(6,*)'******** MAXTYPE MUST EQUAL 1,2 OR 3'
            STOP
         END IF
         LIMSPEC((SPECDELVAR(IDTOT,Y)),2)=0.D0
2000   CONTINUE
       END


*******


      SUBROUTINE GROUPMINMAX(NUMI,VAR,LIMITS,TOTSET,SETNUMVAR,
     +                       SETIDVAR,SETMIN,SETMAX)

CCCCCCC  GROUPMINMAX IS CALLED BY:
CCCCCCC                              SETDATA
CCCCCCC                              NEXTDMU
CCCCCCC
CCCCCCC  GROUPMINMAX CALLS NO OTHER SUBROUTINE
CCCCCCC
CCCCCCC  THIS SUBROUTINE CALCULATES THE ACTUAL LIMITS
CCCCCCC  IN PLACE ON VARIABLE GROUPS

      INTEGER I,K,TOTSET,UPORLO,IMPREF,J,SETNUMVAR(100),VAR,
```

```
     +        SETIDVAR(100,100),NUMI,FIRST,LAST

      DOUBLE PRECISION ACTUAL,IMPLIED,LIMITS(VAR,2),
     +                 SETMIN(100),SETMAX(100)


      DO 400 I=1,TOTSET
         DO 400 UPORLO=1,2
            IF(UPORLO.EQ.1) THEN
               IMPREF=2
            ELSE
               IMPREF=1
            END IF
            ACTUAL=0.D0
            DO 100 J=1,SETNUMVAR(I)
100            ACTUAL=ACTUAL+LIMITS(SETIDVAR(I,J),UPORLO)
            IF(ACTUAL.GT.1.D2.AND.UPORLO.EQ.1) GO TO 500
            IF(ACTUAL.GT.1.D2) ACTUAL=1.D2
            IF(SETIDVAR(I,1).GT.NUMI)THEN
               FIRST=NUMI+1
               LAST=VAR
            ELSE
               FIRST=1
               LAST=NUMI
            END IF
            IMPLIED=0.D0
            DO 300 J=FIRST,LAST
               DO 200 K=1,SETNUMVAR(I)
200               IF(J.EQ.SETIDVAR(I,K)) GO TO 300
               IMPLIED=IMPLIED+LIMITS(J,IMPREF)
300         CONTINUE
            IMPLIED=(1.D2-IMPLIED)
            IF(UPORLO.EQ.2.AND.IMPLIED.LE.0.D0) GO TO 500
            IF(UPORLO.EQ.1) THEN
               SETMIN(I)=DMAX1(ACTUAL,IMPLIED)
            ELSE
               SETMAX(I)=DMIN1(ACTUAL,IMPLIED)
            END IF
400   CONTINUE
      RETURN
500   WRITE(6,'(//2X,'' PROFILE NOT MATHEMATICALLY POSSIBLE;'')')
      WRITE(6,'(2X,'' RE-EXAMINE GROUP DATA'')')
      STOP
      END


*******


      SUBROUTINE PRNGROUP (A,M,N,NUMI,NUMO,VAR,MTOT,LEVELS,TOTSET,
     +                     SETS,SETMIN,SETMAX,SETNUMVAR,SETIDVAR,
     +                     LIMITS,NAMEINP,NAMEOUT,NAMEVAR,DELVAR)

CCCCCCC  PRNGROUP IS CALLED BY:
CCCCCCC                         SETDATA
CCCCCCC                         NEXTDMU
CCCCCCC
CCCCCCC  PRNGROUP CALLS LINE
CCCCCCC
CCCCCCC  THIS SUBROUTINE PRINTS OUT ALL THE LEVELS
CCCCCCC  OF VARIABLE GROUPS AND THEIR WEIGHT LIMITS
CCCCCCC  AND SUMMARISES THE FIXED/FLEXIBLE WEIGHTING

      INTEGER M,N,NUMI,NUMO,VAR,LEVELS,TOTSET,SETS(100),MTOT,
     +        SETNUMVAR(100),SETIDVAR(100,100),DELVAR(VAR),
```

```
+         I,J,Y,K
      DOUBLE PRECISION LIMITS(VAR,2),A(MTOT,N),SETMIN(100),SETMAX(100),
     +                 INPREST,OUTREST
      CHARACTER*25  NAMEINP(NUMI),NAMEOUT(NUMO),NAMEVAR(VAR)

      WRITE(6,'(/)')
      WRITE(6,'(//,'' DETAILS OF PERFORMANCE PROFILE''///)')
      CALL LINE(2)
      WRITE(6,'(/,2X,'' INDIVIDUAL VARIABLES:''/)')
      CALL LINE(2)
      WRITE(6,'(//)')
      WRITE(6,'(20X,''INPUTS'',/)')
      WRITE(6,'(/)')
      DO 100 I=1,VAR
         IF (I.EQ.(NUMI+1)) WRITE(6,'(//,20X,''OUTPUTS'',//)')
         WRITE(6,'(3X,A)') NAMEVAR(I)
         IF (DELVAR(I).EQ.1) THEN
           WRITE(6,'(3X,''NOT PRESENT IN SPECIALISED '',
     +               ''PERFORMANCE PROFILE.'')')
         ELSE
         WRITE(6,'(3X,''RESTRICTED TO BETWEEN'',
     +         F6.2,''%'',1X,''AND'',F6.2,''%'')')
     +         LIMITS(I,1),LIMITS(I,2)
         END IF
         WRITE(6,'(/)')
100   CONTINUE
      WRITE(6,'(//)')
      CALL LINE(2)
      WRITE(6,'(/,2X,'' VARIABLE GROUPS:''/)')
      CALL LINE(2)
      WRITE(6,'(/)')
      Y=0
      DO 300 I=1,LEVELS
         WRITE(6,'(/)')
         CALL LINE(1)
         WRITE(6,'(/'' LEVEL'',1X,I2/)')I
         CALL LINE(1)
         WRITE(6,'(/)')
         DO 300 K=1,SETS(I)
            Y=Y+1
            WRITE(6,'(//,'' GROUP CONTAINING:'',1X,/)')
            DO 200 J=1,SETNUMVAR(Y)
               IF (DELVAR(SETIDVAR(Y,J)).NE.1) THEN
                  WRITE(6,'(3X,A,X)') NAMEVAR(SETIDVAR(Y,J))
               END IF
200         CONTINUE
            WRITE(6,'(/,'' RESTRICTED TO BETWEEN'',I3,''%'',1X,''AND'',
     +            I3,''%'',/)')SETMIN(Y),SETMAX(Y)
300   CONTINUE
      WRITE(6,'(/)')
      CALL LINE(2)
      WRITE(6,'(//)')
      INPREST=0.D0
      DO 400 I=1,NUMI
400      INPREST=INPREST+LIMITS(I,1)
      OUTREST=0.D0
      DO 500 I=(NUMI+1),VAR
500      OUTREST=OUTREST+LIMITS(I,1)
      WRITE(6,'(5X,'' TOTAL FIXED INPUT WEIGHTS:'',F6.2,''%; '',
     +        ''LEAVING'',F6.2,''%'',1X)') INPREST,(1.D2-INPREST)
      WRITE(6,'(/,5X,'' FREE FOR OPTIMISATION'',
     +        '' WITHIN PERFORMANCE PROFILE''//)')
      CALL LINE(2)
      WRITE(6,'(//,5X,'' TOTAL FIXED OUTPUT WEIGHTS:'',F6.2,''%; '',
```

```
     +         ''LEAVING'',F6.2,''%'',1X)') OUTREST,(1.D2-OUTREST)
      WRITE(6,'(/,5X,'' FREE FOR OPTIMISATION'',
     +         '' WITHIN PERFORMANCE PROFILE''//)')
      CALL LINE(3)
      WRITE(6,'(//)')
      END


*********


      SUBROUTINE PERPROF(NUMI,VAR,JAY,A,M,N,JTH,LIMITS,MTOT)

CCCCCCC  PERPROF IS CALLED BY NEXTDMU
CCCCCCC
CCCCCCC  PERPROF CALLS NO OTHER SUBROUTINE
CCCCCCC
CCCCCCC  THE PURPOSE OF THIS SUBROUTINE IS TO USE
CCCCCCC  THE INPUT WEIGHT LIMITS TO BUILD ADDITIONAL
CCCCCCC  CONSTRAINTS ONTO THE LP MODEL

      INTEGER DEX,UPORLO,JAY,M,N,JTH,NUMI,Y,Z,VAR,
     +        FIRST,LAST,MTOT

      DOUBLE PRECISION LIMITS(VAR,2),A(MTOT,N)



      DO 500 Y=1,VAR
            IF (LIMITS(Y,2).GE.LIMITS(Y,1)) GOTO 200
            WRITE(6,'(/'' ***************************************'')')
            WRITE(6,'('' DEA NOT POSSIBLE; ERROR IN DATA'')')
            WRITE(6,'(/'' UPPER WEIGHTING CONSTRAINTS MUST NOT'')')
            WRITE(6,'('' BE LESS THAN LOWER CONSTRAINTS'')')
            WRITE(6,'('' ***************************************''/)')
            STOP
200         CONTINUE
            DO 300 Z=1,2
               IF (LIMITS(Y,Z).LT.0.D0) GOTO 400
300            IF (LIMITS(Y,Z).GT.1.D2) GOTO 400
            GOTO 500
400         WRITE(6,'(/'' ***************************************'')')
            WRITE(6,'('' DEA NOT POSSIBLE; ERROR IN DATA'')')
            WRITE(6,'(/'' ALL WEIGHT CONSTRAINTS MUST BE'')')
            WRITE(6,'('' PERCENTAGES BETWEEN 0 AND 100'')')
            WRITE(6,'('' ***************************************''/)')
            STOP
500   CONTINUE
      DEX=JAY+2
      DO 1400 Y=1,VAR
         DO 1400 UPORLO=1,2
            FIRST=1
            LAST=NUMI
            DEX=DEX+1
            DO 600 Z=1,N
600            A(DEX,Z)=0.D0
            IF (LIMITS(Y,UPORLO).LT.1.D-4) THEN
               A(DEX,Y)=-1.D0
               IF(UPORLO.EQ.2) A(DEX,Y)=1.D0
               GO TO 1400
            END IF
            IF (Y.GT.NUMI) THEN
               FIRST=(NUMI+1)
               LAST=VAR
```

```
            END IF
            A(DEX,Y)=-(((1.D2-LIMITS(Y,UPORLO))/LIMITS(Y,UPORLO))
     +                 * A((JTH+2),Y))
            IF(Y.LE.NUMI) THEN
               A(DEX,Y)=-A(DEX,Y)
            END IF
            IF (Y.EQ.FIRST) GO TO 800
               DO 700 Z=FIRST,(Y-1)
                  A(DEX,Z)=A((JTH+2),Z)
                  IF(Y.LE.NUMI) THEN
                     A(DEX,Z)=-A(DEX,Z)
                  END IF
700         CONTINUE
800         CONTINUE
            IF (Y.EQ.LAST) GO TO 1000
            DO 900 Z=Y+1,LAST
               A(DEX,Z)=A((JTH+2),Z)
               IF(Y.LE.NUMI) THEN
                  A(DEX,Z)=-A(DEX,Z)
               END IF
900         CONTINUE
1000     CONTINUE
      IF(UPORLO.EQ.2) THEN
         DO 1100 Z=1,N
1100        A(DEX,Z)=-A(DEX,Z)
      END IF
1400  CONTINUE
      DO 1600 Y=1,VAR
         DEX=DEX+1
         DO 1500 Z=1,N
1500        A(DEX,Z)=0.D0
         A(DEX,Y)=-1.D0
1600  CONTINUE
      END



*******

CCCCCCC THE LP SUBROUTINES WHICH FOLLOW ARE TREATED
CCCCCCC AS A BLACK BOX AND GIVEN DATA OF THE CORRECT
CCCCCCC FORM WOULD OPERATE INDEPENDENTLY OF THE REST
CCCCCCC OF THE PROGRAM


      SUBROUTINE LINPRO(M,N,OBJV,A,B,C,X,DINV,S,V,TEMP,JJ,MTOT,A1,B1,
     +                  C1,X1,DINV1,S1,V1,TEMP1,JJ1,OBJV1,M1,N1,
     +                  MTOT1,CONTR)


      INTEGER M,N,M1,N1,CONTR,I,J,K,NXTCOL,JJ(N),JJ1(N1),MTOT,MTOT1

      DOUBLE PRECISION A(MTOT,N),B(MTOT),C(N),X(N),DINV(N,N),S(N),
     +                 V(N),TEMP(N),A1(MTOT1,N1),B1(MTOT1),
     +                 C1(N1),X1(N1),DINV1(N1,N1),S1(N1),V1(N1),
     +                 TEMP1(N1),VERYSM,ALPHA,CCK0,OBJV,OBJV1


      VERYSM=1.D-6
      DO 200 I=1,M
         DO 100 J=1,N
100         A1(I,J)=A(I,J)
200      A1(I,N1)=-1.D0
      DO 300 I=1,N
300      A1(M1,I)=0.D0
         A1(M1,N1)=-1.D0
```

```
      DO 400 I=1,M
400      B1(I)=B(I)
      B1(M1)=0.D0
      DO 500 I=1,N
         C1(I)=0.D0
500      X1(I)=0.D0
      C1(N1)=1.D0
      ALPHA=-1.D30
      DO 700 I=1,M
         IF(ALPHA.GT.(-B(I))) GO TO 700
         ALPHA=-B(I)
700   CONTINUE
      ALPHA=DMAX1(0.D0,ALPHA)
      X1(N1)=ALPHA
      DO 800 I=1,N1
         DO 800 J=1,N1
800         DINV1(I,J)=0.D0
      DO 900 I=1,N1
         DINV1(I,I)=1.D0
900      JJ1(I)=0
      CALL OPTIMISE(A1,B1,C1,X1,DINV1,S1,V1,TEMP1,JJ1,OBJV,
     +              M1,N1,MTOT1,CONTR)
      IF (OBJV.LE.VERYSM) GO TO 1000
      WRITE(6,'(/'' ******************************************'')')
      WRITE(6,'('' DEA NOT POSSIBLE; ERROR IN DATA (CODE C3)'')')
      WRITE(6,'('' ******************************************''/)')
      STOP
1000  CONTINUE
      DO 1100 I=1,N
1100     X(I)=X1(I)
      DO 1200 I=1,N1
         IF (JJ1(I).EQ.M1) GO TO 1500
1200  CONTINUE
      CCK0=-1.D0
      K=0
      DO 1300 I=1,N1
         IF (DABS(DINV1(N1,I)).LT.CCK0) GO TO 1300
         CCK0=DABS(DINV1(N1,I))
         K=I
1300  CONTINUE
      DO 1400 I=1,N
1400  TEMP1(I)=0.D0
      TEMP1(N1)=-1.D0
      CALL MATMOD(DINV1,TEMP1,K,N1)
      JJ1(K)=M1
1500  CONTINUE
      NXTCOL=1
      DO 1700 J=1,N1
         IF(JJ1(J).EQ.M1) GO TO 1700
         DO 1600 I=1,N
1600        DINV(I,NXTCOL)=DINV1(I,J)
         JJ(NXTCOL)=JJ1(J)
         NXTCOL=NXTCOL+1
1700  CONTINUE
      CALL OPTIMISE(A,B,C,X,DINV,S,V,TEMP,JJ,OBJV,M,N,MTOT,CONTR)
      END

*******

      SUBROUTINE OPTIMISE(A,B,C,X,DINV,S,V,TEMP,JJ,OBJV,M,N,
     +                    MTOT,CONTR)

      INTEGER ELL,ITER,I,M,N,CONTR,K,JJ(N),MTOT
```

```
      DOUBLE PRECISION A(MTOT,N),B(MTOT),C(N),X(N),DINV(N,N),S(N),
     +                 V(N),TEMP(N),OBJV,SUM,SIGJ

      ITER=0
      SUM=0.D0
      DO 100 I=1,N
100      SUM=SUM+C(I)*X(I)
      OBJV=SUM
200   CONTINUE
      CALL STP1(C,S,V,DINV,N,K,CONTR,JJ)
      IF(CONTR.EQ.1) RETURN
      CALL STP2(A,B,X,S,JJ,SIGJ,ELL,M,N,MTOT,CONTR)
      CALL STP3(X,C,S,DINV,A,TEMP,SIGJ,OBJV,JJ,ELL,K,M,N,MTOT,ITER)
      GO TO 200
      END


*******


      SUBROUTINE STP1(C,S,V,DINV,N,K,CONTR,JJ)

      INTEGER CONTR,I,N,J,K,JJ(N)

      DOUBLE PRECISION C(N),S(N),V(N),DINV(N,N),VERYSM,SUM,VMAXA,VMAX

      VERYSM=1.D-6
      CONTR=0
      DO 100 I=1,N
         IF(JJ(I).EQ.0) GO TO 200
100   CONTINUE
      GO TO 900
200   CONTINUE
      DO 400 I=1,N
         IF(JJ(I).NE.0) GO TO 400
         SUM=0.D0
         DO 300 J=1,N
300         SUM=SUM+C(J)*DINV(J,I)
         V(I)=SUM
400   CONTINUE
      VMAXA=-1.D0
      K=0
      DO 500 I=1,N
         IF(JJ(I).NE.0) GO TO 500
         IF(DABS(V(I)).LE.VMAXA) GO TO 500
         VMAXA=DABS(V(I))
         K=I
500   CONTINUE
      IF(VMAXA.LE.VERYSM) GO TO 900
      IF(V(K).LT.0.D0) GO TO 700
      DO 600 I=1,N
600      S(I)=DINV(I,K)
      RETURN
700   CONTINUE
      DO 800 I=1,N
800      S(I)=-DINV(I,K)
      RETURN
900   CONTINUE
      DO 1100 I=1,N
         IF(JJ(I).EQ.0) GO TO 1100
         SUM=0.D0
         DO 1000 J=1,N
```

```
1000          SUM=SUM+C(J)*DINV(J,I)
           V(I)=SUM
1100    CONTINUE
        VMAX=-1.D30
        DO 1200 I=1,N
           IF(JJ(I).EQ.0) GO TO 1200
           IF(V(I).LE.VMAX) GO TO 1200
           VMAX= V(I)
           K=I
1200    CONTINUE
        IF(VMAX.GE.VERYSM) GO TO 1300
        CONTR=1
        RETURN
1300    CONTINUE
        DO 1400 I=1,N
1400       S(I)=DINV(I,K)
        END
```

****

```
      SUBROUTINE STP2(A,B,X,S,JJ,SIGJ,ELL,M,N,MTOT,CONTR)


      INTEGER CONTR,ELL,M,N,MTOT,I,INDEX,JJ(N)

      DOUBLE PRECISION A(MTOT,N),B(MTOT),S(N),X(N),
     +                 VERYSM,SIGJ,BOT,TOP,RATIO


      CONTR=0
      VERYSM=1.D-6
      SIGJ=1.D35
      ELL=0
      DO 400 I=1,M
         DO 100 INDEX=1,N
            IF(JJ(INDEX).EQ.I) GO TO 400
100      CONTINUE
         BOT=0.D0
         DO 200 INDEX=1,N
200         BOT=BOT+A(I,INDEX)*S(INDEX)
         IF(BOT.GE.-VERYSM) GO TO 400
         TOP=-B(I)
         DO 300 INDEX=1,N
300         TOP=TOP+A(I,INDEX)*X(INDEX)
         RATIO=TOP/BOT
         IF(RATIO.GE.SIGJ) GO TO 400
         SIGJ=RATIO
         ELL=I
400   CONTINUE
      IF(ELL.EQ.0) THEN
         WRITE(6,'(/'' ***********************************************'')')
         WRITE(6,'('' DEA NOT POSSIBLE; ERROR IN DATA (CODE C2)'')')
         WRITE(6,'('' ***********************************************''/)')
         STOP
      END IF
      END
```

****

```
      SUBROUTINE STP3(X,C,S,DINV,A,TEMP,SIGJ,OBJV,JJ,ELL,
     +                K,M,N,MTOT,ITER)


      INTEGER ELL,K,M,N,MTOT,ITER,I,JJ(N)

      DOUBLE PRECISION X(N),C(N),S(N),DINV(N,N),A(MTOT,N),TEMP(N),
     +                 SIGJ,SUM,OBJV


      DO 100 I=1,N
100      X(I)=X(I)-SIGJ*S(I)
      SUM=0.D0
      DO 200 I=1,N
200      SUM=SUM+C(I)*X(I)
      OBJV=SUM
      DO 300 I=1,N
300      TEMP(I)=A(ELL,I)
      CALL MATMOD(DINV,TEMP,K,N)
      JJ(K)=ELL
      ITER=ITER+1
      END
```

****

```
      SUBROUTINE MATMOD(DINV,D,K,ROWS)


      INTEGER I,J,K,ROWS

      DOUBLE PRECISION DINV(ROWS,ROWS),D(ROWS),VERYSM,SUMSTP3,TRANS


      VERYSM=1.D-6
      SUMSTP3=0.D0
      DO 100 I=1,ROWS
100      SUMSTP3=SUMSTP3+D(I)*DINV(I,K)
      IF(DABS(SUMSTP3).GE.VERYSM) GO TO 200
      WRITE(6,'(/'' *******************************************'')')
      WRITE(6,'('' DEA NOT POSSIBLE; ERROR IN DATA (CODE S3)'')')
      WRITE(6,'('' ********************************************''/)')
      STOP
200   CONTINUE
      SUMSTP3=1.D0/SUMSTP3
      DO 300 I=1,ROWS
300      DINV(I,K)=DINV(I,K)*SUMSTP3
      DO 600 J=1,ROWS
         IF (J.EQ.K) GO TO 600
         TRANS=0.D0
         DO 400 I=1,ROWS
400         TRANS=TRANS+D(I)*DINV(I,J)
         DO 500 I=1,ROWS
500         DINV(I,J)=DINV(I,J)-TRANS*DINV(I,K)
600   CONTINUE
      END
```

****

```
      SUBROUTINE LINE(LN)

      INTEGER LN,I

      DO 100 I=1,LN
         WRITE(6,*)
     +'******************************************************************'
100   CONTINUE
      END

*******


      SUBROUTINE LPSHOW(A,B,M,N,JAY,VAR,MTOT)

      INTEGER I,M,N,JAY,VAR,J,MTOT

      DOUBLE PRECISION A(MTOT,N),B(MTOT)


CCCCCC   OPTIONAL LP MATRIX OUTPUT GENERATOR
CCCCCC
CCCCCC   EXAMPLE WILL BE FIRST DMU
CCCCCC
CCCCCC   OUTPUT WILL BE SUPPRESSSED WHEN MATRIX SET TO VALUE
CCCCCC   OTHER THAN ONE
CCCCCC

         CALL LINE(2)
         WRITE(6,'(/,'' FULL DEAPMAS LINEAR PROGRAM MATRIX'',/)')
         CALL LINE(2)
         DO 100 I=1,M
            CALL LINE(1)
            WRITE(6,'(//)')
            IF (I.EQ.1)  THEN
               CALL LINE(1)
               WRITE(6,'('' SUBJECT OUTPUT UNITY CONSTRAINTS'')')
               CALL LINE(1)
            ELSE IF (I.EQ.3)  THEN
               CALL LINE(1)
        WRITE(6,'('' INPUTS - OUTPUTS NON-NEGATIVITY CONSTRAINTS'')')
               CALL LINE(1)
            ELSE IF (I.EQ.(JAY+2)+1) THEN
               CALL LINE(1)
               WRITE(6,'('' PERFORMANCE PROFILE CONSTRAINTS'')')
               CALL LINE(1)
            ELSE IF (I.EQ.(M-VAR)+1) THEN
               CALL LINE(1)
               WRITE(6,'('' VARIABLES POSITIVITY CONSTRAINTS'')')
               CALL LINE(1)
            END IF
            WRITE(6,'(/,I3,/)') I
            J=1
80          CONTINUE
            WRITE(6,'(6F10.2)') A(I,J),A(I,J+1),A(I,J+2),
     +                A(I,J+3),A(I,J+4),A(I,J+5)
            J=J+6
            IF(J.LE.VAR) GO TO 80
            WRITE(6,'(/,45X,''<=  '',F10.6,//)') B(I)
100      CONTINUE
         END
```

Appendix C.

Appendix C. The Research Selectivity Exercise 1989: The Rating Scale.

The Universities Funding Council's advisory groups and panels used the following five-point scale:

5= Research quality that equates to attainable levels of international excellence in some sub-areas of activity and to attainable levels of national excellence in virtually all others.

4= Research quality that equates to attainable levels of national excellence i n virtually all sub-areas of activity, possibly showing some evidence of international excellence, or to international excellence in some and at least national level in a majority.

3= Research quality that equates to attainable levels of national excellence in a majority of the sub-areas of activity, or to international levels in some.

2= Research quality that equates to attainable levels of national excellence in up to half of the sub-areas of activity.

1= Research quality that equates to attainable levels of national excellence in none, or virtually none, of the sub-areas of activity.

For the purposes of the UFC's review, 'Research' equals original investigation undertaken in order to gain knowledge and understanding.

Appendix D.

Appendix D. Original Input Data For Examples 'A' and 'B'.

Example 'A'.

```
I1)GEN-INCOME-RESEARCH
I2)GRANTS-RESEARCH
I3)GEN-INCOME-TEACHING
I4)ACADEMIC-STAFF
I5)UNDERGRAD-NUMBERS
I6)UNDERGRAD-ENTR-QUAL
I7)POSTGRAD-RESEARCH
I8)POSTGRAD-TAUGHT

O1)GRADS-KNOWN-DEST
O2)GRADS-LONGTRM-EMPL
O3)GRADS-SHORT-EMPLOY
O4)GRADS-EDUC-TRAINING
O5)FIRST-DEG-GRADUATES
O6)HIGHER-DEGREE-GRADS
O7)RESEARCH-QUALITY
O8)RESEARCH-TURNOVER
O9)CONT-EDUC-PROVISION


ASTN
881 487 1352 75 660 11.2 58 204
148 124 3 11 166 213 2 405 25

BATH
385 312 554 33 288 12.8 60 40
50 39 1 6 57 61 3 364 1

BRAD
540 197 775 52 363 10.8 35 233
76 55 4 9 84 79 3 305 96

CITY
849 404 1078 38 256 11.5 29 279
111 92 2 9 138 184 3 432 182

HULL
90 0 127 9 76 10.4 8 22
26 16 1 7 29 17 2 0 94

KENT
81 2 92 6 65 11.3 2 21
19 12 0 5 26 31 1 1 107
```

LANC
544 222 719 50 285 10.7 31 155
73 45 1 16 87 114 3 268 21

LEED
181 14 244 17 238 7.6 3 26
27 17 0 6 31 30 1 20 208

LBUS
552 1374 671 37 0 0 36 359
0 0 0 0 0 169 5 1286 27

LOND
504 275 698 45 175 12.1 57 187
15 9 0 3 22 210 3 341 312

LBRO
321 146 439 29 450 12.0 5 51
110 80 6 14 124 32 3 179 60

MBUS
373 463 574 40 0 0 30 242
0 0 0 0 0 109 3 612 50

MIST
602 494 868 53 600 11.4 70 105
120 84 4 17 154 83 4 555 29

NEWC
40 14 55 3 11 11.0 0 25
35 24 1 6 40 22 2 63 42

SHEF
334 16 483 35 463 11.6 7 60
80 48 5 18 88 28 2 0 62

SOTN
71 22 98 5 84 12.3 2 12
18 111 4 22 10 3 12 133

SURY
308 51 415 21 259 10.9 7 59
52 37 3 10 64 32 3 87 279

WARW
452 944 571 35 288 12.2 25 135
97 65 7 20 121 31 5 1096 56

CARD
70 31 112 8 93 9.4 5 12
44 23 2 15 51 8 2 31 72

UWST
355 48 467 37 258 10.6 12 159
63 43 3 12 75 85 0 94 22

EDIN
243 122 329 22 366 12.2 7 45
60 36 2 15 69 62 2 131 84

GLAS
186 180 215 11 51 12.5 11 81
29 17 1 9 33 38 2 252 90

HWAT
185 130 241 16 197 10.9 6 33
53 39 1 9 68 11 1 132 22

STIR
242 313 289 16 188 9.7 19 89
52 35 1 9 60 48 2 427 45

CLYD
974 676 1385 77 652 9.7 47 374
89 62 1 18 105 316 3 796 73

BELF
108 30 171 12 127 12.0 4 67
26 15 0 8 29 19 0 17 78

ULST
978 383 1309 100 1180 9.2 1 269
223 147 14 36 252 39 1 426 64

Example 'B'.

```
I1C)GEN-INCOME-RESEARCH
I1P)GEN-INCOME-RESEARCH
I1S)GEN-INCOME-RESEARCH
I2C)GRANTS-RESEARCH
I2P)GRANTS-RESEARCH
I2S)GRANTS-RESEARCH
I3C)GEN-INCOME-TEACHING
I3P)GEN-INCOME-TEACHING
I3S)GEN-INCOME-TEACHING
I4C)ACADEMIC-STAFF
I4P)ACADEMIC-STAFF
I4S)ACADEMIC-STAFF
I5)UNDERGRAD-NUMBERS
I6)UNDERGRAD-ENTR-QUAL
I7C)POSTGRAD-RESEARCH
I7P)POSTGRAD-RESEARCH
I7S)POSTGRAD-RESEARCH
I8C)POSTGRAD-TAUGHT
I8P)POSTGRAD-TAUGHT
I8S)POSTGRAD-TAUGHT

O1)GRADS-KNOWN-DEST
O2)GRADS-LONGTRM-EMPL
O3)GRADS-SHORT-EMPLOY
O4)GRADS-EDUC-TRAINING
O5)FIRST-DEG-GRADUATES
O6)HIGHER-DEGREE-GRADS
O7C)RESEARCH-QUALITY
O7P)RESEARCH-QUALITY
O7S)RESEARCH-QUALITY
O8C)RESEARCH-TURNOVER
O8P)RESEARCH-TURNOVER
O8S)RESEARCH-TURNOVER
O9)CONT-EDUC-PROVISION


BATH
268 211 0 279 205 0 392 326 0 20 17 0 857 11.9 41 12 0 0 0 0
93 72 2 11 105 20 2 2 0 299 235 0 0

BHAM
584 1042 206 267 1436 112 66 1547 295 40 71 14 1442 11.9 66 55
139 3 16 19
164 103 6 38 219 36 3 5 3 554 1511 189 124

BRAD
245 122 221 71 38 153 358 215 264 16 11 15 589 9.5 19 10 60 0
3 2
73 53 4 8 80 15 1 0 2 120 39 176 2
```

BRIS
817 648 195 1014 890 30 1168 937 278 46 39 12 1643 13.2 110 48
17 27 0 0
213 137 6 45 238 73 5 5 3 1075 969 69 154

BRUN
274 196 0 384 103 0 407 272 0 19 11 0 668 10.0 30 18 0 18 8 0
43 34 1 7 47 32 2 2 0 366 86 0 5

CAMB
891 1070 778 960 2900 1380 1276 1500 1082 41 50 46 2599 0 154
162 1329 0 4 9
190 98 8 66 223 119 5 5 5 1041 3371 1825 50

DHAM
411 394 217 527 751 80 599 576 310 29 26 17 1323 12.9 42 33
123 0 0 13
190 114 5 57 228 48 4 4 3 555 795 124 27

EANG
462 209 466 499 39 629 694 273 657 26 12 30 922 10.1 65 10 453
31 0 19
103 58 6 27 125 90 4 2 5 597 58 815 8

ESSX
248 234 0 536 343 0 361 329 0 18 16 0 555 7.8 40 21 0 5 17 0
45 24 2 14 59 31 2 3 0 471 311 0 21

EXTR
394 372 127 181 284 32 567 520 184 25 23 8 1141 10.4 25 14 19
0 0 0
117 73 6 27 123 20 4 3 1 288 628 126 40

HULL
352 424 186 470 774 2 500 642 19 21 12 803 9.4 30 34 14 9 0 18
96 59 2 25 109 48 3 2 1 359 215 3 43

KEEL
176 200 193 199 215 19 249 269 261 8 12 11 692 9.2 10 12 34 0
0 0
7 3 0 2 9 12 2 2 3 231 158 26 59

KENT
267 286 0 100 266 0 352 382 0 16 15 0 761 8.8 31 16 0 0 0 0
39 25 1 10 54 11 2 3 0 198 340 0 87

LANC
274 369 270 168 383 171 406 509 368 21 25 20 755 9.4 14 27 117
11 10 1
74 45 1 16 88 37 1 3 5 227 461 223 7

LEED
1018 507 341 696 536 138 1465 728 485 51 30 22 1947 102 65 28
120 9 0 35
167 104 3 37 192 89 4 4 5 898 499 183 80

LEIC
368 356 355 387 901 218 521 478 506 22 20 23 995 10.0 42 28
277 0 0 22
132 72 2 42 151 48 4 4 3 395 1197 172 92

LIVR
504 558 343 486 764 196 743 742 504 24 29 17 1689 9.9 55 25
275 0 14 4
187 112 9 42 217 36 4 5 5 634 785 296 79

LOND
2915 4057 1666 2678 8416 1258 4114 6015 2206 154 255 91 7528
10.8 347 352 1864
36 69 158
626 396 19 139 938 510 3 4 3 2964 9414 1240 125

LBRO
483 176 0 381 339 0 643 239 0 30 13 0 554 11.0 53 8 0 26 0 0
37 27 2 5 42 36 2 1 0 384 621 0 38

MANU
768 1559 368 502 2274 33 1028 2231 506 40 76 26 2100 11.4 82
59 198 0 28 14
204 132 8 41 232 74 4 5 5 707 2281 433 149

MIST
703 334 174 1118669 201 1066 496 229 40 21 9 1040 10.1 88 27
50 9 0 13
66 47 2 9 85 44 3 3 0 1170 596 200 20

NEWC
484 403 191 522 95 59 688 583 276 26 30 14 1177 10.0 54 30 54
0 7 6
102 70 2 18 117 40 4 3 5 640 80 76 70

NOTT
564 475 149 509 881 25 782 671 201 34 29 9 1353 11.6 76 31 18
0 0 13
186 123 6 34 223 30 5 5 1 494 676 30 252

OXFD
1335 1852 348 1632 4761 273 1901 2602 416 64 97 18 2562 14.3
196 202 79 0 0 0
447 237 26 159 544 115 5 5 5 1607 4674 293 72

READ
363 391 360 321 450 350 542 561 516 26 23 23 820 9.6 33 28 163
5 26 23
90 58 3 20 106 56 2 3 5 558 515 434 46

SALF
597 332 0 568 269 0 823 487 0 35 21 0 866 9.7 108 22 0 18 17 0
58 47 0 7 77 75 3 2 0 477 346 0 35

SHEF
538 359 254 230 327 111 783 554 375 30 23 17 1730 11.3 48 15
43 0 1 10
167 101 10 38 183 34 4 2 1 287 207 197 71

SOTN
648 360 438 1164 897 188 941 501 523 40 25 23 1380 12.6 121 51
175 2 9 20
150 95 8 34 184 69 5 4 3 1190 1015 293 53

SURY
276 370 0 340 495 0 386 499 0 15 22 0 628 9.7 19 41 0 2 37 0
46 32 3 8 56 50 2 4 0 411 522 0 53

SUSX
530 500 50 545 540 89 754 744 68 31 33 4 956 10.0 92 47 102 13
13 10
89 48 5 25 112 102 4 3 3 518 621 87 68

WARW
371 404 0 354 687 0 534 548 0 22 22 0 1090 10.4 31 25 0 0 0 0
69 46 5 14 85 21 4 4 0 722 1164 0 29

YORK
379 293 0 706 296 0 541 386 0 24 15 0 955 11.9 37 20 0 7 3 0
107 62 5 25 116 8 3 4 0 806 376 0 7

ABWY
148 178 186 102 265 35 232 245 274 10 10 14 697 8.5 7 10 14 1
2 9
79 32 5 31 92 8 0 2 3 147 176 51 17

BNGR
144 123 239 122 153 329 206 185 316 10 9 18 521 6.9 9 4 10 0 0
17
40 20 2 14 45 8 2 0 3 54 178 386 24

CARD
340 193 160 247 517 78 503 285 238 20 14 12 974 8.8 42 13 16 3
0 0
99 51 5 33 114 10 4 3 3 372 361 49 73

SWAN
306 206 284 301 281 328 452 277 395 21 13 16 1082 8.9 26 18 23
0 7 0
118 66 9 30 139 29 3 2 1 204 349 401 31

UWST
224 0 0 168 0 0 319 0 0 14 0 0 341 10.2 23 0 0 0 0 0
49 34 2 9 58 5 0 0 0 236 0 0 1

ABDN
412 237 248 344 79 90 593 365 350 27 14 14 1158 10.4 22 4 16 2
1 22
50 29 1 16 58 35 2 1 3 370 114 97 59

DUND
248 228 91 132 116 21 413 332 122 16 16 8 528 10.7 12 9 6 0 20
0
22 13 1 6 25 19 1 0 0 25 87 14 29

EDIN
552 527 488 792 1037 913 769 724 641 35 35 31 1767 11.9 83 36
65 0 1 5
136 80 4 34 155 65 4 3 4 682 1035 490 29

GLAS
901 805 208 355 1522 62 1308 1060 413 49 44 18 2216 11.0 73 42
31 7 2 0
112 66 2 35 125 52 3 4 4 592 1736 78 130

HWAT
307 397 0 314 720 0 451 508 0 19 24 0 722 11.2 22 23 0 0 1 0
45 33 1 8 58 19 2 3 0 288 948 0 40

ANDW
278 415 284 387 487 34 397 455 301 16 21 13 4049 11.2 23 21 20
0 13 0
69 36 5 21 81 35 2 3 3 263 483 35 13

STIR
168 82 130 105 72 10 238 134 130 11 6 7 591 9.2 19 7 8 0 0 0
29 20 1 5 34 6 1 2 2 189 75 24 10

CLYD
686 477 108 899 474 8 1031 649 152 39 38 8 1291 11.4 76 29 12
15 0 3
99 69 1 20 117 50 3 3 2 1078 391 3 28

BELF
456 485 159 195 249 19 668 693 221 28 33 12 1210 9.0 32 26 12
8 13 0
95 53 2 30 108 41 2 4 1 175 391 17 59

Appendix E.

Appendix E. Example Output of DEAPMAS Program

Variable Group Summary.

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   VARIABLE GROUPS:

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 LEVEL  1

***************************************************************



 GROUP CONTAINING:

   I1)GEN-INCOME-RESEARCH
   I2)GRANTS-RESEARCH

 RESTRICTED TO BETWEEN 20% AND 50%


 GROUP CONTAINING:

   I3)GEN-INCOME-TEACHING

 RESTRICTED TO BETWEEN 15% AND 35%


 GROUP CONTAINING:

   I4)ACADEMIC-STAFF

 RESTRICTED TO BETWEEN  5% AND 15%
```

GROUP CONTAINING:

I5)UNDERGRAD-NUMBERS
I6)UNDERGRAD-ENTR-QUAL

RESTRICTED TO BETWEEN 10% AND 30%

GROUP CONTAINING:

I7)POSTGRAD-RESEARCH
I8)POSTGRAD-TAUGHT

RESTRICTED TO BETWEEN 10% AND 30%

GROUP CONTAINING:

O1)GRADS-KNOWN-DEST
O2)GRADS-LONGTRM-EMPL
O3)GRADS-SHORT-EMPLOY
O4)GRADS-EDUC-TRAINING

RESTRICTED TO BETWEEN 9% AND 23%

GROUP CONTAINING:

O5)FIRST-DEG-GRADUATES

RESTRICTED TO BETWEEN 12% AND 25%

GROUP CONTAINING:

O6)HIGHER-DEGREE-GRADS

RESTRICTED TO BETWEEN 21% AND 45%

GROUP CONTAINING:

O7)RESEARCH-COHORT

RESTRICTED TO BETWEEN 18% AND 58%

GROUP CONTAINING:

O8)CONT-EDUC-PROVISION

RESTRICTED TO BETWEEN 0% AND 10%

****

LEVEL 2

****

GROUP CONTAINING:

I1)GEN-INCOME-RESEARCH
I2)GRANTS-RESEARCH
I3)GEN-INCOME-TEACHING

RESTRICTED TO BETWEEN 35% AND 75%

GROUP CONTAINING:

I4)ACADEMIC-STAFF

RESTRICTED TO BETWEEN 5% AND 15%

GROUP CONTAINING:

I5)UNDERGRAD-NUMBERS
I6)UNDERGRAD-ENTR-QUAL
I7)POSTGRAD-RESEARCH
I8)POSTGRAD-TAUGHT

RESTRICTED TO BETWEEN 20% AND 60%

GROUP CONTAINING:

O1)GRADS-KNOWN-DEST
O2)GRADS-LONGTRM-EMPL
O3)GRADS-SHORT-EMPLOY
O4)GRADS-EDUC-TRAINING
O5)FIRST-DEG-GRADUATES

RESTRICTED TO BETWEEN 21% AND 48%

GROUP CONTAINING:

O6)HIGHER-DEGREE-GRADS

RESTRICTED TO BETWEEN 21% AND 45%

GROUP CONTAINING:

O7)RESEARCH-COHORT

RESTRICTED TO BETWEEN 18% AND 58%

GROUP CONTAINING:

O8)CONT-EDUC-PROVISION

RESTRICTED TO BETWEEN 0% AND 10%

****

LEVEL 3

****

GROUP CONTAINING:

I1)GEN-INCOME-RESEARCH
I2)GRANTS-RESEARCH
I3)GEN-INCOME-TEACHING

RESTRICTED TO BETWEEN 35% AND 75%

GROUP CONTAINING:

I4)ACADEMIC-STAFF
I5)UNDERGRAD-NUMBERS
I6)UNDERGRAD-ENTR-QUAL
I7)POSTGRAD-RESEARCH
I8)POSTGRAD-TAUGHT

RESTRICTED TO BETWEEN 25% AND 65%

GROUP CONTAINING:

O1)GRADS-KNOWN-DEST
O2)GRADS-LONGTRM-EMPL
O3)GRADS-SHORT-EMPLOY
O4)GRADS-EDUC-TRAINING
O5)FIRST-DEG-GRADUATES
O6)HIGHER-DEGREE-GRADS

RESTRICTED TO BETWEEN 42% AND 82%

GROUP CONTAINING:

O7)RESEARCH-COHORT

RESTRICTED TO BETWEEN 18% AND 58%

GROUP CONTAINING:

O8)CONT-EDUC-PROVISION

RESTRICTED TO BETWEEN 0% AND 10%

****
****

TOTAL FIXED INPUT WEIGHTS: 60.00%; LEAVING 40.00%

FREE FOR OPTIMISATION WITHIN PERFORMANCE PROFILE

****
****

TOTAL FIXED OUTPUT WEIGHTS: 60.00%; LEAVING 40.00%

FREE FOR OPTIMISATION WITHIN PERFORMANCE PROFILE

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****
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