Integrating spare part inventory management and predictive maintenance as a digital supply chain solution

ABSTRACT

Purpose – The present study aims to assess the feasibility and effectiveness of incorporating predictive maintenance (PdM) into existing practices of spare part inventory management and pinpoint the barriers and identify economic values for such integration within the supply chain (SC).

Design/methodology/approach - A two-staged embedded multiple case study with multi-method data collection and a combined discrete/continuous simulation were conducted to diagnose obstacles and recommend a potential solution.

Findings - Several major organisational, infrastructure and cultural obstacles were revealed and an optimum scenario for the integration of spare part inventory management with PdM was recommended. **Practical implications -** The proposed solution can significantly decrease the inventory and SC costs as well as machinery downtimes through minimising unplanned maintenance and address shortage of spare parts.

Originality- This is the first study with the best of our knowledge that offers further insights for practitioners in the Industry 4.0 (I4.0) era looking into embarking on digital integration of PdM and spare part inventory management as an efficient and resilient SC practice for the automotive sector by providing empirical evidence.

Keywords – Inventory Management, Supply Chain Management, simulation, Procurement, Artificial Intelligence, Predictive Maintenance

1. Introduction

Despite the substantial advancements in research, practice and technology, the automotive supply chain (ASC) is still under a significant pressure to achieve higher efficiency and effectiveness (Balakrishnan and Ramanathan, 2021; Yang et al., 2024). Spare parts management plays a critical role in achieving such a goal as it is responsible for ordering and maintaining an adequate number of spare parts to improve mean times between system failures and reduce the associated costs and delays across the repair-and-reliability value chain (Hasan et al., 2020). The shortage of critical spare parts can have serious repercussions for operations continuity and working time of machines which would eventually curtail the company's profit (Mecheter et al., 2023). Wallin Blair et al. (2020) reported that 20-50% of all purchases (by value) in the manufacturing sector relate to spare parts for maintenance, repair, and operations, in which they account for 70-90% of purchase orders, shipment, inventory expenses, and processed invoices. Nonetheless, there are still many shortfalls in the ASC resilience in terms of forecasting the failure rates of machinery components and maintaining optimal levels of spare parts inventory (Balakrishnan and Ramanathan, 2021). Accurate planning for availability of spare parts and their replenishment for unexpected breakdowns is of paramount criticality to avoid downtimes and associated costs (Zhu et al., 2022; Eslami et al., 2023). Currently, lack of a centralised on-demand SC system and remarkably inefficient human-driven reactive maintenance strategies are resulting in significant machine downtimes which increases production costs (Aransyah et al., 2020; Balakrishnan and Ramanathan, 2021).

Ample evidence provided by SC and procurement managers manifests the pivotal role of digitalised inventory management for high value, high variety, and low volume spare parts to reduce total SC cost through a more efficient and effective ordering system (Ho et al., 2021; Herold et al., 2023). This means digitalised inventory management happens through utilising technologies such as blockchain to improve visibility alongside other technologies such as machine learning to improve inventory prediction that ultimately they lead into enhancing SC cost efficiency in the spares part inventory management (Ho et al., 2021). As a result, the importance of integrating predictive maintenance (PdM) into established digital tools and technologies in spare part SC and inventory has been recently highlighted to reduce the SC and inventory costs in the automotive manufacturing sector (Calatayud et al., 2019; Carvalho et al., 2019; and Kovács et al., 2020). Nevertheless, the evidence base in the literature and practice remains scarce regarding this integration for spare part inventory management within ASC, and cost-benefit analysis remains to be developed (Calatayud et al., 2019 and Kovács et al., 2020; İfraz et al., 2024). Insufficient investigation of practical implications such as obstacles and economic benefits prior to the digital integration of spare parts inventory management with PdM appears as a research gap and calls for further investigations (Kovács et al., 2020). Further evidence will shed light on the practical implications of such a digital integration and provide insights for coupling upstream ordering system with the PdM initiatives within manufacturing processes. Our findings have strong contribution into visionary leadership of organisations in the manufacturing SC for better collaborative decision making by triggering necessary investigation into digitalisation of the spare parts SC like consumable goods SC for better visibility, efficiency and environmental sustainability. This will initiate more research avenues for the scholars to develop our study further through different case studies in collaboration with the industry.

Our study distinguishes itself from the extant literature by assessing the feasibility of deploying digital and analytical tools within the ASC and predicting demand (i.e., through PdM) and quantifying its impact on manufacturing efficiency (i.e., machine downtimes). The two-fold aim of this study, therefore, is to explore the practical obstacles and reliably quantify the economic value of integrating PdM with spare part inventory management as part of an industry-specific SC (i.e., the UK ASC). Thus, this research aims to address two research questions (RQs) as follows:

RQ1 - What are the obstacles in the current spare part inventory management and maintenance processes in a typical ASC that can hinder the integration of PdM and spare parts inventory management?

RQ2 – What is the potential economic value of integrating spare parts inventory management and PdM in ASC?

Hence, the key objectives of this study are as follows: i) to identify key practical obstacles in the maintenance practices of car manufacturers through participant observation, process mapping and analysis; ii) to ascertain key practical pain points (challenges) for SC solution and digital PdM providers through expert panel discussions; iii) to present the most ideal scenario with potentially highest economic values by running a combined discrete/continuous simulation. Answering RQ1 can offer valuable insights into embracing and embarking on digital SC transformation by focusing on upstream ordering and inventory management that has been under less attention by scholars (Eslami et al., 2023). Although the primary focus of this study was placed on car manufacturing industry, our findings for reducing unplanned downtimes can be generalised to other sectors that use manufacturing machines.

The rest of this paper is organised as follows: Section 2 includes a critical literature review to develop a knowledge and theoretical framework for studying a digital SC coupled with PdM. This is followed by the methodological discussions in section 3 revolving around the research design and approaches to address the research objectives through multiple case studies. The findings including the identified key paint points and estimated value of the best simulated scenario are presented in Section 4. Section 5 discusses the theoretical contributions and practical implications of the proposed solution. Finally, the conclusions and recommended directions for future research are presented in Section 6.

2. Literature Review

The notion of diagnosis and prognosis in maintenance of mechanical systems has been an active field of research for several decades and still it is attracting attention (Li et al., 2017; Maurya et al., 2024). However, due to uncertainties and multiplicity of variables, decision making and inventory planning for effective and efficient maintenance still entail several challenges. The uncertainties over the failure rates and patterns of component failure for novel technologies can be even more profound. Whilst inventory control of different spare parts may happen independently, the spare part inventory decision-making becomes inter-dependent as a consequence of one part being out of stock can depend on the availability of other parts (Zhu et al., 2022). In addition, insufficient failure data (Aivaliotis et al., 2021), absence of reliable protocols for exchanging data (Hasan et al., 2020), and lack of tailored analytical basis (Peruzzini and Stjepandić, 2018) can adversely affect the availability of spare parts. Unplanned downtimes (Yan et al., 2017; Bousdekis et al., 2019), secondary damage, long delivery lead-times (Yan et al., 2017; Bousdekis et al., 2019), redundancy (Li et al., 2017; Balakrishnan and Ramanathan, 2021), over-maintenance and obsolescence (Shi and Liu, 2020) are amongst the main consequences reported in the literature. These repercussions can further result in increased cost and time of manufacturing, degraded quality of products and affect the relationship with customers which subsequently threaten total return on investment (ROI).

2.1. The advantages of I4.0 technologies for enhancing PdM and SC performance

Implementing PdM for industrial robots and machines is inherently a challenging task (Aivaliotis et al., 2021). On the other hand, the diffusion of I4.0 across the manufacturing sector as well as enhancements in disruptive technologies (e.g., sensory, big data and Artificial Intelligence) and infrastructure (e.g., communication and data centres) offer a significant potential to broaden the range of feasible solutions and replace the traditional practices (Dubey et al., 2020; Balakrishnan and Ramanathan, 2021; Sharma et al., 2022; Eslami et al., 2023; Samani and Saghafi, 2024). Meanwhile, adoption and integration of disruptive technologies introduced by I4.0 carries its new challenges (Olsen and Tomlin, 2020; Queiroz et al., 2021; Tortorella et al., 2024). I4.0 entails not only technical aspects, but also a sociotechnical perspective, including technology, environment, organisation and humans (Hobscheidt et al., 2020). Therefore, a comprehensive analysis for identifying obstacles in the way of integrating PdM and spare parts inventory management within the SC needs to comprise factors from all the specified spheres above.

Wide range of sensors together with analytical algorithms can develop complex predictive tools for monitoring network asset performance (Golightly et al., 2018). Data-driven approaches towards condition monitoring of industrial robots have been proven to be effective means in detecting anomalies (Aivaliotis et al., 2021). Indispensable elements in SC, such as manufacturing and transport, are also rapidly and extensively turning into data-driven tools for management and maintenance of modern assets. Despite the capabilities and tremendous potentials, incorporation of the technology and analytical tools faces organisational, technical, and human hurdles that can compromise the pledged benefits (Golightly et al., 2018). A production system cannot be studied as an individual entity only, but rather as an organisation of people and decision makers (Sony and Naik, 2020). This necessitates setting up a theoretical framework that accounts for influential factors and variables across the above domains and allow for interdisciplinary exploration.

Balakrishnan and Ramanathan (2021) investigated the impacts of digitalisation of SC on resilience within the automotive sector. Digitalisation in this context refers to the implementation and impact of adopting digital technologies on organisational and societal performance of a firm (Queiroz et al., 2021). Their analysis shows that the integration of digital technologies and solutions into the SC improves resilience and performance (Balakrishnan and Ramanathan, 2021). Those findings are consistent with the work of Sharma et al. (2022) and Eslami et al. (2023). In addition, Carvalho et al. (2019) conducted a systematic literature review on the applications of machine learning (ML) techniques in PdM in the I4.0 era and advocated that coupling PdM and ML can bring about economic benefits for manufacturers and service providers. Also, Li et al. (2017) studied how data mining (DM) and ML can contribute to fault diagnosis and prognosis in machine centres, and they proposed a framework that contained the whole fault analysis processes from data acquisition through sensors to maintenance schedule optimisation.

Furthermore, Yan et al. (2017) explored the implications of big data processing-based PdM within the context of I4.0 and identified ten different sources of data at technical, operator, organisational and environmental levels that constitute industrial big data. Their discussions indicate that multisource heterogeneous data can further improve PdM practices. In a recent systematic literature review by Perano et al. (2023), Artificial Intelligence (AI), blockchain, and Internet of Things (IoT) were found to be among the dominant technologies to digitalise SC and inventory management. Andersson and Jonsson (2018) investigated how product-in-use or consumable data can be applied to address the problem of spare parts forecasting for automotive aftermarket services. Their findings suggest that causal-based forecasting strategies can effectively improve the demand planning for low-frequency spare parts. The application of blockchain in SC practices has recently gained momentum (Hasan et al., 2020; Sony and Naik, 2020; Qader et al., 2022). Wamba and Queiroz (2022) looked into the diffusion of blockchain and its capacity for transforming SC relationships and underlined 'information sharing amongst SC parties' as a major advantage of that cutting-edge technology. Nevertheless, there remains several gaps to be addressed. For instance, the impact of digitalisation on SC sustainability and carbon emissions as well as economic gains for manufacturers need in-depth analysis (Kovács et al., 2020).

2.2. A socio-technical approach towards ASC

One of the main contributors to the complexity of a general supply network is lack of transparency in decision making hierarchy (de Kok and Fransoo, 2003). This can be even exacerbated when an organisation expands and in consequence its hierarchy, operational activities and technological developments become even more interdependent (Pereira et al., 2021). This can vividly demonstrate the important role of humans and organisational structure/culture in a socio-technical system or entity such as a manufacturing firm (Bortolotti et al., 2015; Cadden et al., 2021). Therefore, inclusion of human and organisational factors can broaden the scope for identification of obstacles across the ASC. To this end, a socio-technical theory approach was adopted to identify the obstacles in the studied SCs and assess the organisational capabilities in integrating spare part inventory management with PdM.

The socio-technical system philosophy concerns with the integration between machine, or in a broader term technology, and humans in designing operational processes and/or systems (Sony and Naik, 2020). The concept of the socio-technical system emphasises the bilateral interactions between humans and machines to foster both efficiency and labour capabilities in a way that they do not contradict each other (Geddes, 2021). Apart from technological/technical, organisational and human factors that can affect productivity and efficiency of a socio-technical system, environmental dynamism (ED) is recognised as a core element in dynamic capabilities (DC) theory (Dubey et al., 2020; Herold et al., 2023). ED is mainly driven by unpredictability and lack of failure patterns (Zimmermann et al., 2020). DC in this context refer to an organisation's ability to develop, structure, reconfigure and integrate internal and external competencies/capacities to operate in a dynamic, uncertain, and volatile environment (Eslami et al., 2021). The inclusion of ED here is because the operational performances stemming from organisational capabilities can be influenced by the dynamic nature of an enterprise's external environment (Pfaff, 2023).

The SC of a manufacturing firm extends to its environment and plays a crucial role in the firm's operations since external uncertainties can propagate across the organisation through the SC (Shan et al., 2021). The semiconductor shortage in 2021 which impacted several industries including automaking perfectly exemplifies the notion of risk propagation through and beyond a supply chain (Ramani et al., 2022). This approach remains consistent with the technology-organisation-environment (TOE) framework which provides a useful lens for investigating the adoption and diffusion of technology and innovation (Al Hadwer et al., 2021). Moreover, organisations that effectively promote collaboration within a firm's supply network gain advantage for enhancing and implementing lean operations more successfully (Farajpour et al., 2022). Bortolotti, et al., (2015) maintained that customer-supplier collaboration is critical to tackle quality and delivery problems in SC and flourish lean production.

2.3. Transformation of organisational capabilities through digitalising SC

The emergence of I4.0 has drawn the attention of scholars and practitioners to redefine organisational capabilities and deploy them to upgrade organisational performance (Münch et al., 2022). Big data and the combination of physical and virtual systems are two prominent facets of I4.0 (Sony and Naik, 2020; Ulhe et al., 2023). Dubey et al. (2020) and Belhadi et al. (2024) reported that different parts of SCs are increasingly becoming digitalised and a sheer volume of data is now being generated as a result. An immediate benefit of SC and inventory management digitalisation will be providing a ground for applying predictive analytics (Dubey et al., 2020; Kumari and Kulkarni, 2022) and subsequently overcome the challenges of implementing PdM. Other than manufacturing, the consolidated IoT applications with cloud-based computing and big data analytics are becoming popular in healthcare, transportation, retail, agriculture, and education where non-technological levers also influence the adoption of those technologies (Al Hadwer et al., 2021). Utilising state-of-the-art analytics and big data tools enables companies to forecast potential future trends regarding customers, suppliers and manufacturing assets thereby mobilising their reactive capability to respond to forthcoming volatilities (Perano et al., 2023). Qader et al. (2022) asserted that firms that were equipped with I4.0 technologies had a stronger performance is responding to the disruptions caused by COVID-19. Furthermore, incorporating such technologies into SC operations and management as well as obtaining real-time data can effectively assist executives in strategic planning (Eslami et al., 2023).

Sony and Naik (2020) identified three types of operational capabilities (OCs) that automation can enhance: i) cyber-physical, ii) sensing, and iii) cognitive. In a broader term, OC can be defined as the ability of firms to generate value-adding tasks (Victer, 2020). From an OC perspective, SC integration is seen as internal and external integrative capabilities that (in)directly influence organisational performance (Münch et al., 2022). The integrated capabilities from across the supply network can expand cyber-physical (e.g., assets/inventory), sensing (e.g., condition monitoring), and cognitive capacities and competencies. Hautala-Kankaanpää (2023) asserted that digitalisation can increase a firm's ability to utilise data and seize data-related business opportunities.

Considering that SCs are complex socio-technical systems (Tortorella et al., 2024) and their relations to the organisational capabilities and performance of a firm are determining, we based our theoretical framework on socio-technical system and organisational capability theories. The combination of the two theories allows us to take the environment of an organisation into account, specifically its SC, and study its interdependencies with organisational capabilities besides their key performance indicators (KPIs). With the recent diffusion of I4.0, this approach is gaining more attention (Sony and Naik, 2020; Münch et al., 2022). Furthermore, previous studies have reported a direct relationship between the organisational capability, mitigating digitalisation challenges and the overall organisational performance, which can be quantified in terms of both process efficiencies and DC (Hallikas et al., 2021).

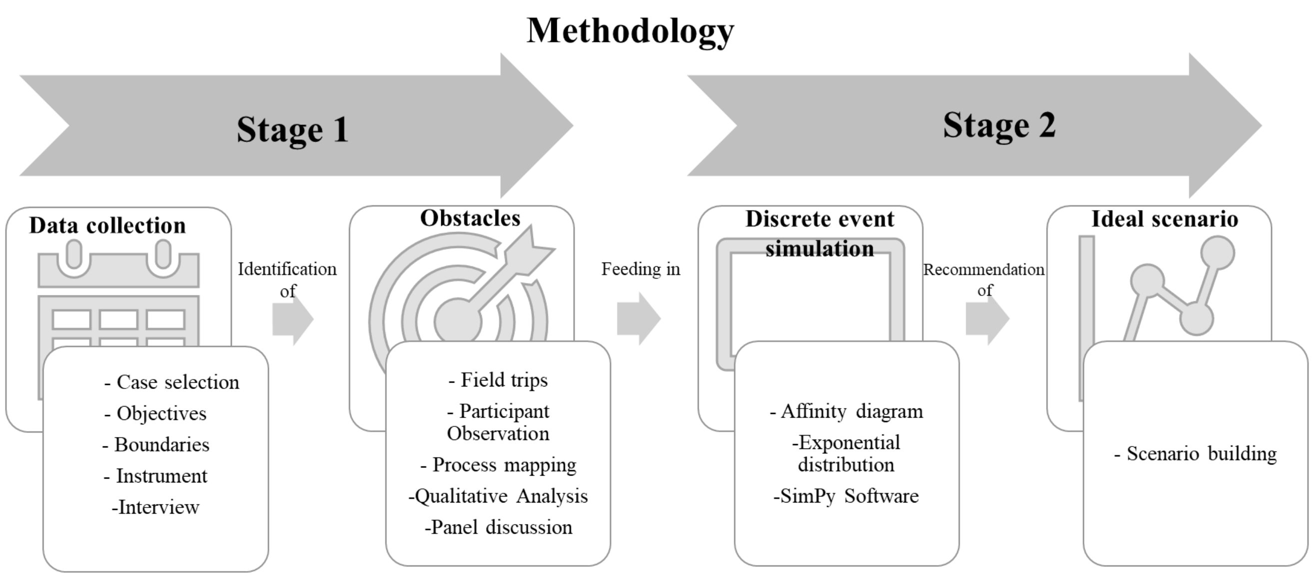
To the best of our knowledge, no academic study has yet adopted a socio-technical lens to ascertain the underlying pain points in the SC of high variety, high value, and low volume spare parts for manufacturing assets in the automotive sector. Moreover, the feasibility of integrating big data analytics, PdM, and supply chain management (SCM) needs to be assessed in monetary terms and its impacts on organisational capabilities for manufacturers. This emphasises the existence of a clear research gap about identifying the obstacles and financial values of integrating PdM with digital inventory management of spare parts in the automotive manufacturing SC (Kovács et al., 2020; Tortorella et al., 2024). Table I compares the most relevant and recent research in the realm of SC digitalisation with the present study in terms of characteristics, gaps, and contributions of the present study.

Table I appears here

3. Research Design and Methods

Due to the implicit and ever-changing workflows, tacit knowledge of practitioners (e.g., maintenance technicians and supervisors), and scarcity of empirical data it was decided to conduct a multi-method data collection including participant observation with embedded multiple case studies and a scenario-based simulation to firstly diagnose the pain points and secondly quantify the economic benefit of the plausible scenarios for integrating PdM across the SC. To achieve this, it was important to incorporate the knowledge and experience of the domain experts into the data preparation, simulation, and evaluation phases in the designed approach (Bekar et al., 2019). Since the integration of spare part inventory management and PdM in ASC is a novel practice (Kovács et al., 2020; Zangiacomi et al., 2020) and the exploratory nature of this research, the multiple case study approach constitutes a suitable approach for such a study (Yin, 2009). It was argued earlier that SCs are complex and multi-faceted socio-technical systems. Jayaram et al. (2014) recommended case study research for constructing new or extend theory of complex social phenomena and that it can provide insights through in-depth details by collecting primary data. This facilitates cross-case comparison and includes the perspectives (or perceptions) of several actors across the ASC (Zangiacomi et al., 2020). Accordingly, a research protocol was developed to enhance the validity and reliability of the findings (Zangiacomi et al., 2020), encompassing the overall design of the case study, the data collection, the data analysis as well as the results formalisation (Yin, 2009). A schematic overview of the steps in the embedded multiple case studies is provided in Figure 1.

Figure 1- schematic of the research steps



Data collection framework in this study comprises of two stages: Stage 1) primary data was collected through field trips to study the existing processes of spare parts procurement and storage and equipment maintenance in OEMs. More primary data was collected in the second step of this stage through expert panel discussion with managers in the automotive SC discussing around potential roadblocks of the spare part inventory management with the maintenance process in a digital SC. Stage 2) Secondary data from the existing literature was used for running different scenarios through simulation. Further details are provided as below.

3.1. Stage 1 – Process Mapping and Obstacles Identification

Four companies identified with various sizes based on the number of employees as key players in the spare part of ASC have been approached to identify the major SC and PdM integration requirements and barriers through participant observation and expert elicitations (Table II).

Table II appears here

A careful participant observation and expert discussion as a part of the field trips took place at two OEMs (Company A and B). Company visits included the following activities: a) close observation of operations and documentation; b) note taking; and c) liaison with the operatives and production, maintenance, inventory and procurement managers. Accordingly, we had discussions with 3 operatives and production, logistics and maintenance managers of one production line in each company to create the existing processes and capture necessary information about current maintenance and spare part ordering procedures. This was to carefully capture all real-world step-by-step processes of the maintenance of machinery and spare part management, including the ordering system. Next, two separate process maps were developed in Microsoft Visio to identify potential and actual obstacles for PdM integration with digital spare part SC and inventory management. Non-value adding activities or paint points in Companies A and B as potential detrimental factors for embarking on digital integration of spare part inventory management with PdM and maintenance processes were identified through process mapping analysis (Figures 2 and 3).

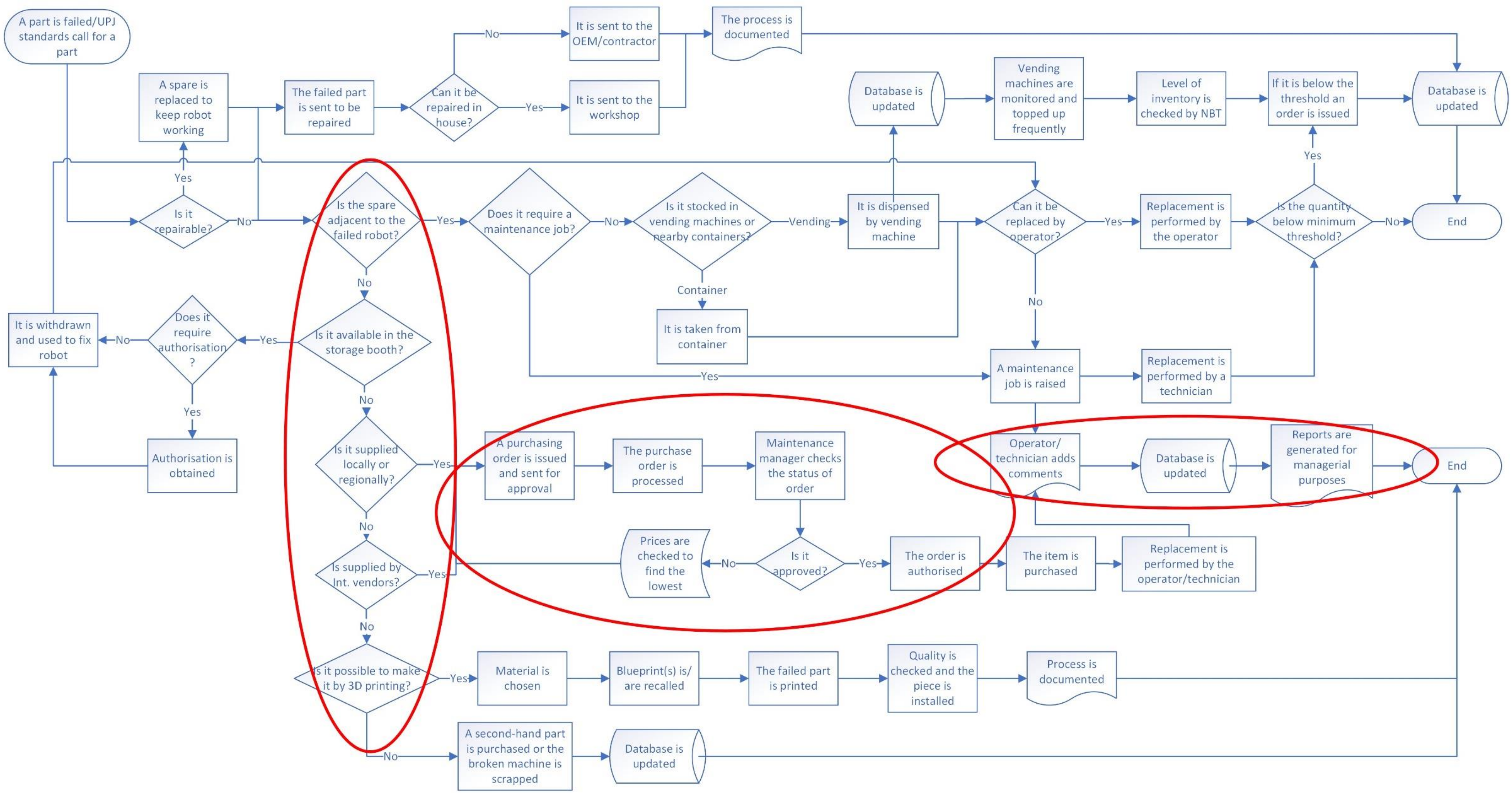


Figure 2- process map for spare part inventory management and maintenance of assets at Company A with indication of obstacles

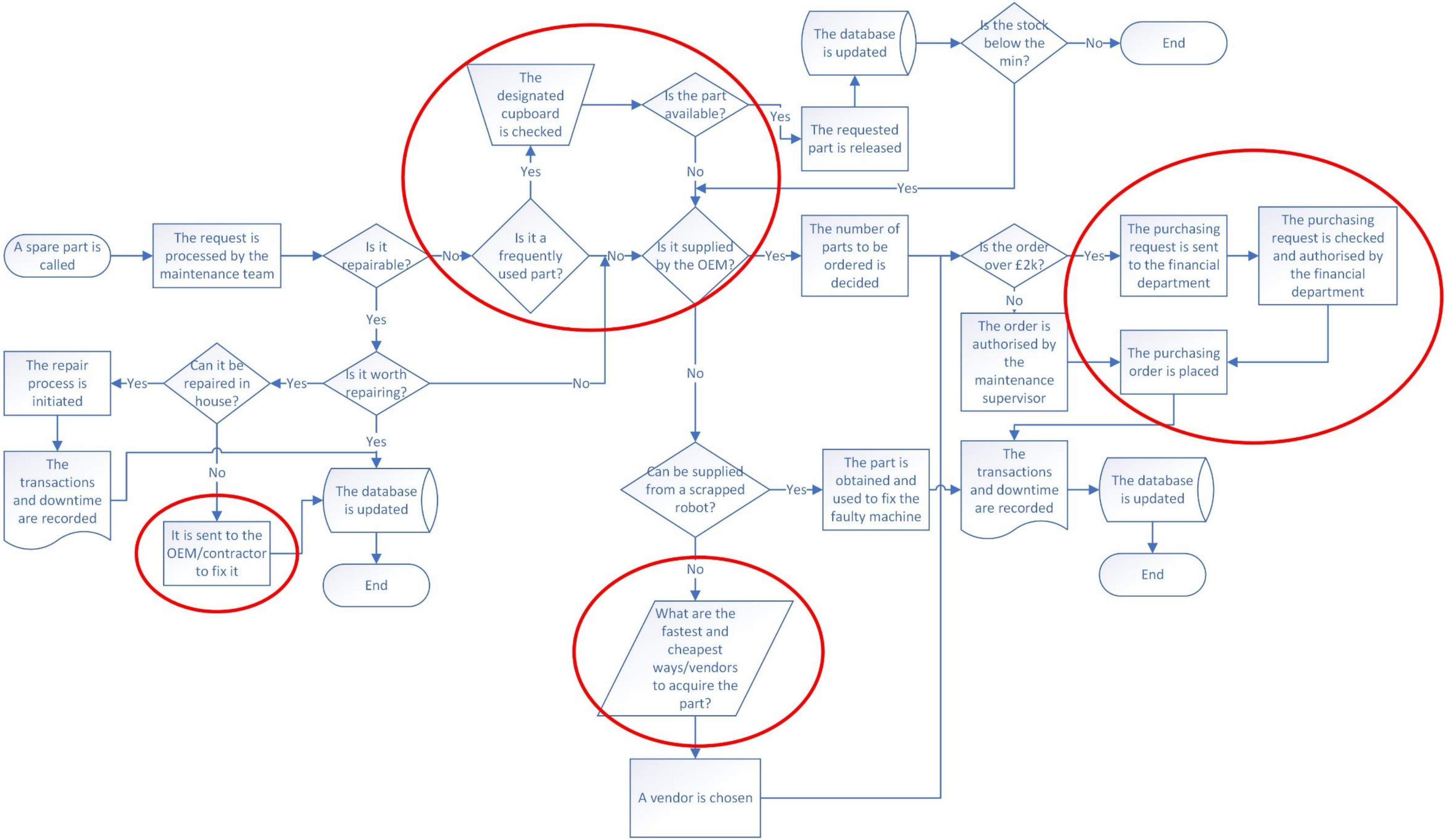


Figure 3- process map for spare part inventory management and maintenance of assets at Company B with indication of obstacles

This was followed by a real-time SC and PdM data collection through expert panel discussions in Companies C and D as the key players in providing solutions for PdM (Company D) and spare part inventory management (Company C). Three expert panel discussions were held with the chair, chief executive officer (CEO), data manager, procurement and logistics managers and software developer in Company C to identify the current bottlenecks in their spart part management and the perceived obstacles in their way towards adopting the proposed integration. This practice was replicated for Company D where the CEO, chief technology officer, and product associate participated in the expert elicitation sessions.

3.2. Stage 2 – Scenario Building and Discrete-Continuous Event Simulation

Motivated by the participant observations, expert panel discussions and process mapping from the first stage, in the second stage, we used discrete-continuous event simulation to model the maintenance processes in manufacturing factories of varying sizes, both with and without a unified SC and a PdM system. This was performed to quantify the economic values of the integration in terms of KPIs such as machine downtime and failure costs. The merit of this approach is that we can model and evaluate different scenarios that may not exist yet and we can quantify the economical values of them under different parameter settings (e.g., factory size, spare parts failure rate) (Calatayud et al., 2019). We used the open-source Python-based SimPy library to implement the simulations because of its flexibility in programming and the intricate details of simulations. It can also be integrated with a range of state-of-the-art AI software libraries (e.g., TensorFlow by Google, Meta AI).

The emphasis in this study was placed on simulating machine downtimes using various strategies, without directly estimating the total cost of spare parts in a particular inventory or estimating the cost of implementing those strategies (i.e., SC and PdM) in practice. This is because production disruption caused by machine downtimes has been reported as a significant factor in factory maintenance and it can be easily quantified, hence the importance of investigating the impact of this factor in more details. Also, the present study was concentrated on the technical integration of SC, inventory management and PdM, and the data capture process was limited in distilling price or investment-related information. Nevertheless, incorporating monetary information into the simulation can be one of the key future research areas, which together with machine downtime reduction would better inform corporate decision-making on the integration of SC and PdM.

3.3. Simulation

The flexibility of the selected approach enabled us to develop a variety of plausible scenarios (figure 4) that may not currently exist and prevented any incurring costs of physically implementing them for experiments. Simulation can offer a distinct advantage for decision making by exploiting capabilities, insights, and information of all SC members and extend the scope of study to a wider extent (Van Der Zee and Van Der Vorst, 2005).

In Scenario 1, a factory can have one or multiple machine clusters for production. When any component fails at a given time, the associated machine and cluster would stop running, until the part is completely replaced with a spare one. As a result, the maintenance strategy in this scenario is unplanned and reactive, which can lead to longer downtime in production line due to shortage in the inventory and increased lead time. Once the maintenance team has identified the failed part, an order would be placed to the factory's suppliers by the procurement team to get a replacement. As those suppliers can be diversely distributed in geography, the lead time for an order to be fulfilled can be as short as one day or as long as one week. As a result, the downtime of the whole factory can be unpredictably long, causing high monetary losses.

Scenario 2, in contrast, replaces the factory's existing suppliers with Company C's centralised system (Vendor Inventory Management) to provide spare parts. The maintenance strategy remains intact as in Scenario 1, but the average downtime of the factory can be shortened because the lead time of replacement and order fulfilment is considerably shorter with the new on-site vending technology. The order handling time would also be shorter since the maintenance team only needs to liaise with one rather than many suppliers. Scenario 3 is another version of Scenario 1, where the SC system is unchanged, but the maintenance strategy has been upgraded to be predictive. The integrated system now screens each part and checks if it has passed certain days of operation. If that is the case, then at a certain likelihood the part can be identified to be failing soon and a maintenance alert is raised, thereby triggering a replacement order for the SC and inventory system. This is a continuous stochastic process, and it can model the wearing-out and expiring behaviour of machine parts in reliability engineering study to some extent. However, it is noteworthy that this is an abstraction of Company D's PdM algorithm, but it has the key capability of preventing unplanned part failures. Scenario 4 is the final integrated solution in which both Company C's SC and inventory system and Company D's PdM are leveraged to further drive down machine downtime.

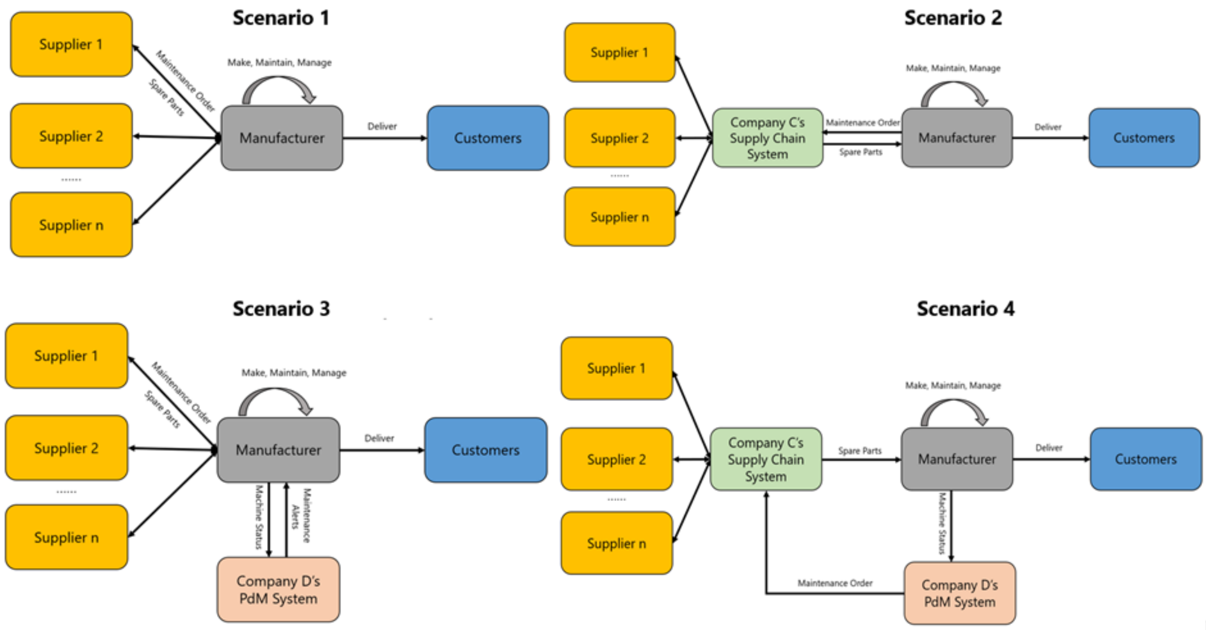


Figure 4- four simulated scenarios of discrete-continuous spare parts SC and maintenance processes

3.4. Part Failure Simulation

The other driver of the simulations is the failure of spare parts in production systems. When simulating the failure of a part, two main design considerations were at stake. The first was that failures are to some extent stochastic without taking into account the external factors, such as natural disasters. This was satisfied as we focused on simulating the ‘natural’ decay of parts and in this setting the process can be assumed to be randomly distributed. Our second point of consideration when simulating part failures was that they have certain heterogeneity. Some parts are short-living and can fail within a shorter period of time compared to more enduring parts. Since it is challenging to accurately characterise the average lifetime of each individual part in a factory, we took the approach to randomise how long on average a part can work effectively before failing. Given these considerations, we proposed to simulate the heterogenous failure distribution of spare parts using the Weibull distributions with varying parameters. The Weibull distribution, with two unknown parameters, is a sufficiently useful life distribution model that can simulate the complex non-constant hazard ratio of spare parts in the real-world. The probability density function (PDF) of the model is as follows:

$$f(\eta,\beta,t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

where η and β are the scale and shape parameters to be set respectively, and t is time. The reliability of a part in this model is expressed as the following:

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

When $\beta = 1$, the model is reduced to the exponential distribution that essentially assumes that the failure hazard rate of each spare part is constant throughout its life span, which is very unlikely as most spare parts wear out in manufacturing and hence can become more prone to failures through aging. As a result, we chose to set β above 1 for our simulations. In this case, the scale parameter η of the model can be related to the so-called mean-time-to-failure (MTTF) of spare parts $\bar{T}$ via the following functional form:

$$\bar{T} = \eta\Gamma(\frac{1}{\beta} + 1)$$

in which $\Gamma(\cdot)$ is the Gamma function.

Figure 5 shows two example cases, one with the parameters β=1.2 and $\eta = 300$, and the other with β=1.6 and $\eta = 500$. In the first case, it can be seen that the probability of a part failing when it reaches its 80 days is 20%, with the reliability is set at 80%. Once 220 days have passed and the part is still functioning, it will fail at a 50-50 chance in the next moment. If the part has survived for more than 1000 days, it is almost surely to fail with a near 0 reliability. However, if we increase the scale parameter to 500 days as in the second case on the bottom of Figure 5, a part can survive longer. In fact, the reliability is around 20% even though 660 days have elapsed. Only after 1400 days will a part almost definitely fail if it has not yet. In both cases, the hazard ratio of each spare part is constantly increasing, which agrees with empirical observations that parts wear out during manufacturing processes and as a result become increasingly less reliable. A higher shape parameter as shown on the bottom of Figure 6 means that the parts will be simulated to wear out more quickly compared with a smaller shape parameter. This is convenient particularly for simulating heterogenous scenarios.

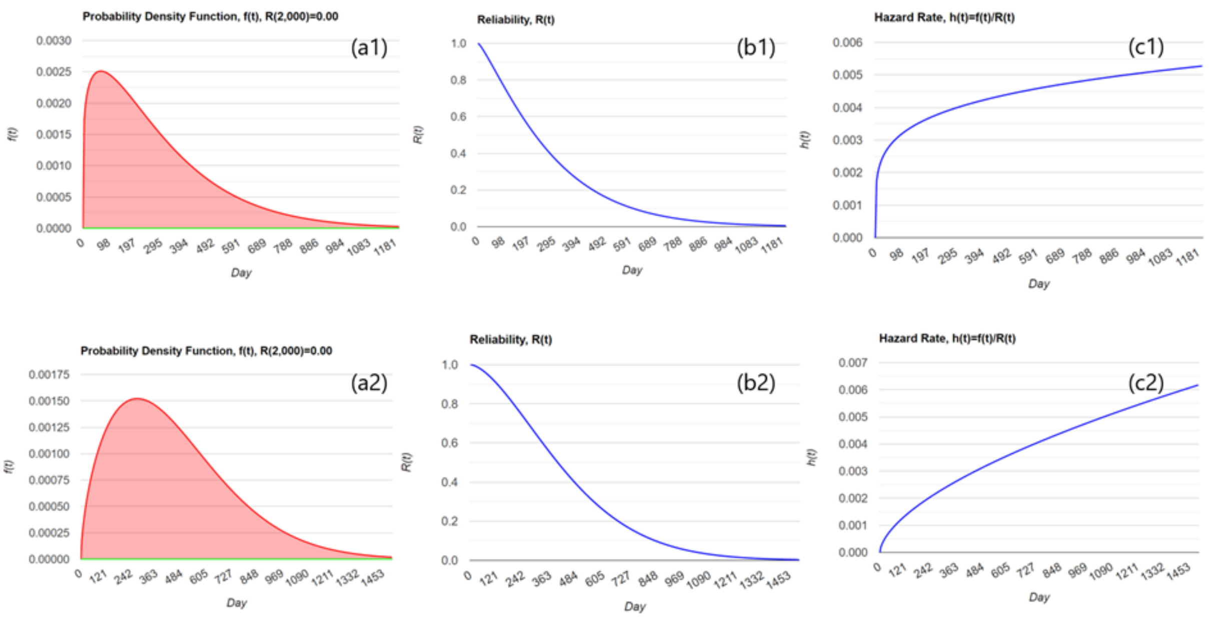


Figure 5- Weibull distribution for simulating the failure of spare parts against time. Top row: β=1.2, η=300. Bottom row: β=1.6, η=500

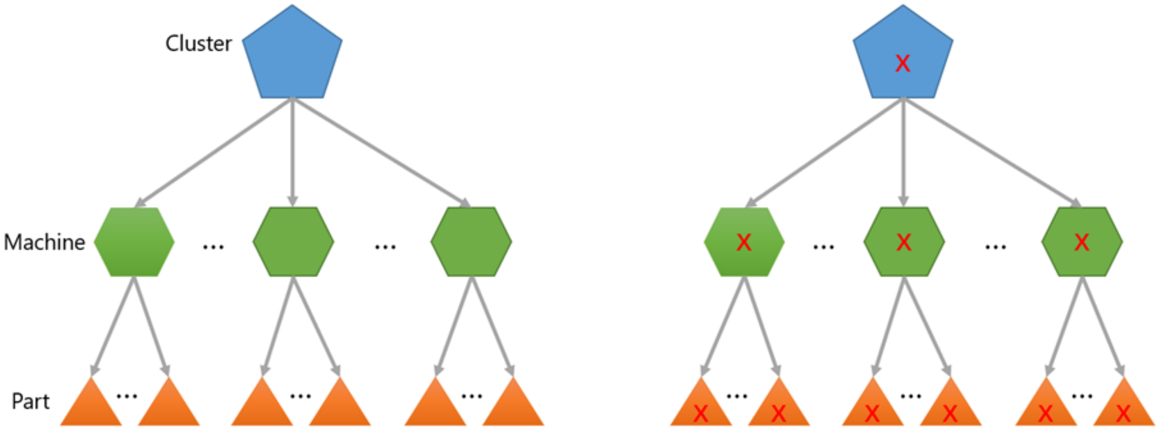


Figure 6- (left) a single cluster of machines; (right) the failure of any part causes the machine that contains this part to fail, which in turn shutdowns the whole cluster of machines that co-depend on each other's functioning

3.5. Machine Layout

As shown in Figure 7, after abstracting away irrelevant details, we model a factory as the hierarchical composition of three key entities: machine clusters, machines, and spare parts. The top layer of hierarchy corresponds to machine clusters where under each is a collection of machines that depend on and cooperate with each other to accomplish the belonging cluster's production job. Further down the hierarchy, each machine consists of multiple spare parts. These parts vary in nature and functionality, and they work closely with each other to let the machine function properly. The flexibility of such hierarchical modelling allows us to simulate distinct types of factories.

In actual implementations, when simulating a whole factory, the key control logics are:

1) machine clusters operate independently unless all clusters are down.

2) all machines within the cluster must have finished their tasks and returned successful status before simulation can step further.

3)each spare part will be assigned with a time to normal functioning of machine and part sourcing, replenishment and fitting in the event of failure and with limited time of maintenance team. Scenarios 3 and 4 are applied here (figures 5 and 6).

4. Findings

4.1. Results from the participant observations and expert panel discussions

It was observed that Company B had more flexibility comparing to Company A in their production planning and control including the use of different machines in the event of machine failure and sourcing their spare parts from different vendors. It was also observed that the approaches towards high variety, low volume and high value spare parts inventory management are relatively different comparing to consumable parts which are more homogeneous and high volume.

The process mapping analysis in Companies A and B (Figure 2) highlighted the major obstacles to be investigated before integration happens (table III). The expert panel discussion with Company C exposed that they are the major spare part provider for Company A (5000 units) managing the inventory through vendor inventory management (vending machines on the shop floor) and statistical analysis of the real time data saving Company A with over £1m between 2012 and 2021. The major obstacles for Companies C and D to be considered before the integration are provided in Table III.

Table III appears here

The identified factors were categorised to be used for the second stage of the analysis, which is presented in figure 7. We classified the identified influential factors as the result of data collection and analysis in the first stage. These factors were grouped into four categories, namely: i) technology/machinery, ii) strategy/system, iii) finance; and iv) organisational culture. The above clusters are aligned with the categorisation put forward by socio-technical approach and can be involved in designing business models for this integration and experimental simulation of this study as the following stage since both SC and manufacturing robots/equipment encompass technology (machines), human input, and a level of interaction between them. Therefore, that classification can be exploited in system design and locate the interdependencies between the four categories. The identified parameters from practice provided in table III and figure 5 were used for the second stage that was experimental simulation.

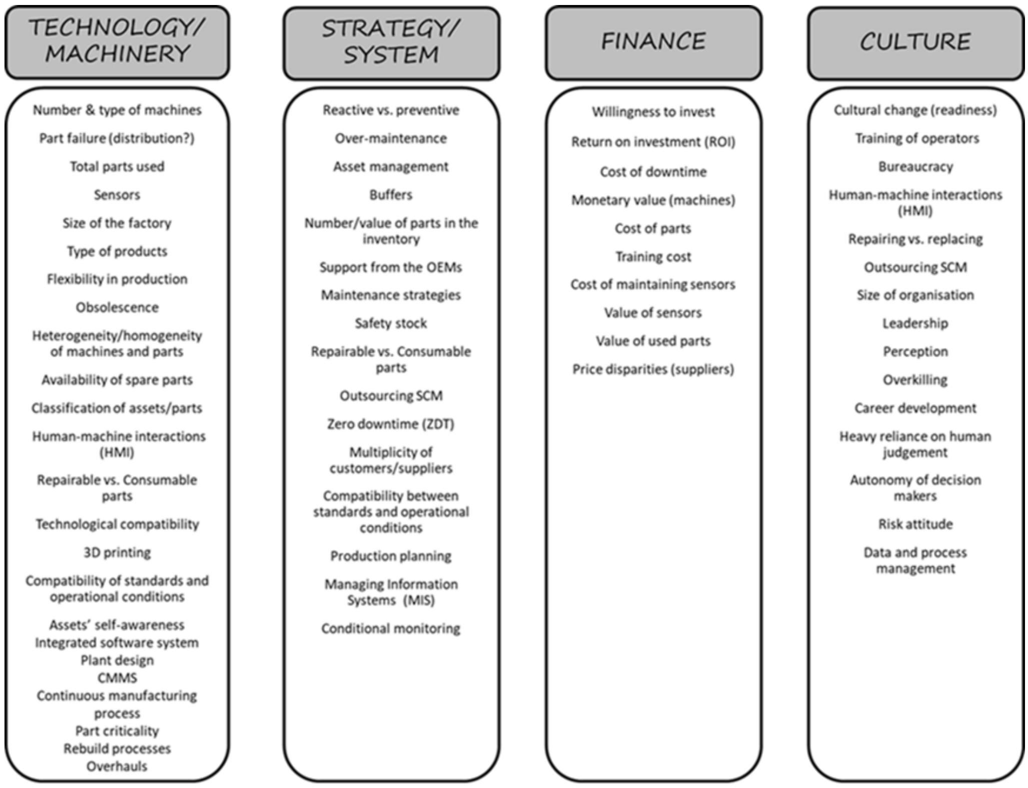


Figure 7 – Categorised factors involved in digital integration of spare part inventory management and PdM

4.2. Results from the experimental simulation

The period of simulation was set at 5 years. Table IV provides information on the factories' configuration and size while Table V demonstrates the downtimes. Overall, the results in table V show that Scenario 2 consistently outperforms Scenario 1, regardless of factory size with average 21% reduction in downtime. Quantitatively better than Scenario 2, Scenario 3 improves over Scenario 1 by average 33% which represents a great reduction of unplanned downtimes due to adopting PdM. It is evident from the results that the combination of SC and PdM, i.e. Scenario 4, creates a compound effect on the performance of factories of varying sizes with average machine downtime reduction by 50%. It means that the proposed integration could on average save a great amount of the unplanned downtime across factories. In terms of economic gains, for factories with 1600 machines, the results show that the annual downtime cost in Scenario 1 would be around £68.64m. After integrating our proposed system, the cost is expected to be driven down to £53.28m, representing a saving of £15.36m.

Table IV appears here

Table V appears here

Firstly, as shown in Table V, factory size has a profound effect on the simulated production downtime. This shows that the average downtime is decreasing with an increasing factory size, which is consistent with what we can observe in the real world as larger factories tend to be more resilient in inventory and production management and as a result suffer less from machine failures in terms of downtime.

Secondly, as Figure 8 depicts, Scenario 2 consistently outperforms Scenario 1, regardless of factory size. Thirdly, it is evident from the results that the combination of inventory management and PdM, namely Scenario 4, creates a compound effect on the performance of factories of varying sizes. Comparing to the average reduction of 19.19% and 30.46% from the traditional system to Scenario 2 and 3 respectively, 44.31% is even greater and it means that the proposed integrated system can on average eliminate up to half of the unplanned downtimes across factories. The relationship between machine downtime reduction and factory size (i.e., number of assets) tends to be nonlinear. This can be explained as when a factory becomes larger, the amortised downtime over each machine is lower in comparison with a much smaller factory, which makes it harder to reduce the average downtime further even by deploying advanced technologies. In other words, a positive yet non-linear relationship between the scale of service activities and profitability can exist in a way that early levels of servitisation lead to a steep rise in profitability. A period of relative decline may be observed before the positive relationship between the scale of services and profitability returns (Kastalli and Van Looy, 2013). However, this does not take into the fact that with a larger factory the impact of breakdown events generally might have a more severe consequence for the production. As stated in Section 3.2, our simulation is focused on machine downtime without considering production details or price-related information due to the lack of historical data. Nevertheless, our results can substantiate the benefit of implementing such digitally integrated PdM and SCM.

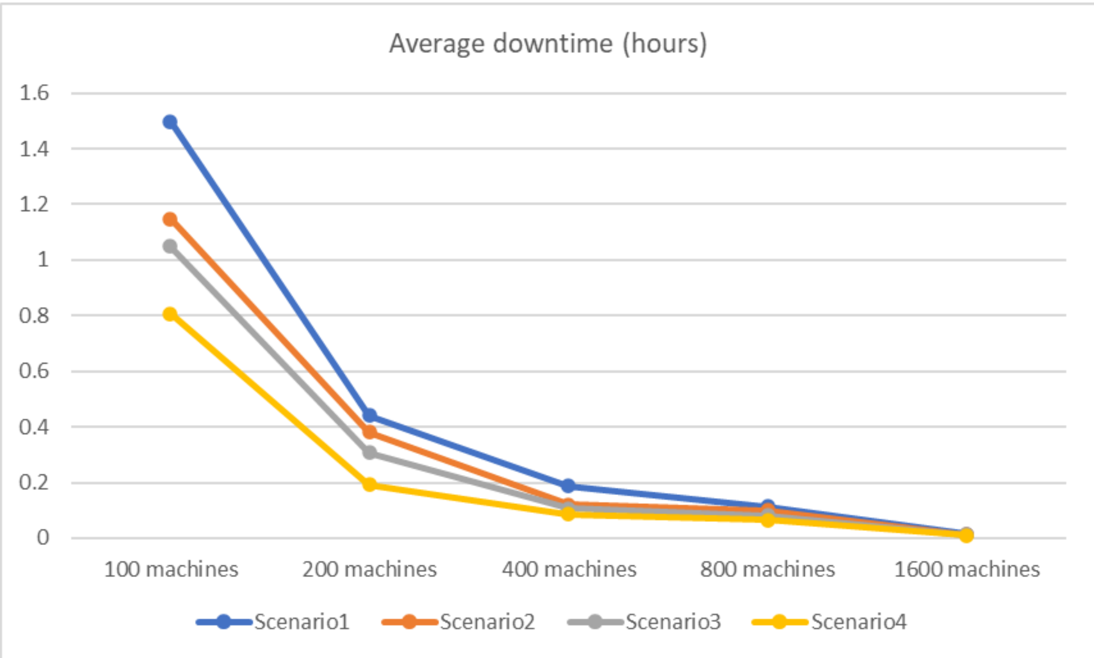


Figure 8- average machine downtime with respect to factory size (i.e., number of machines)

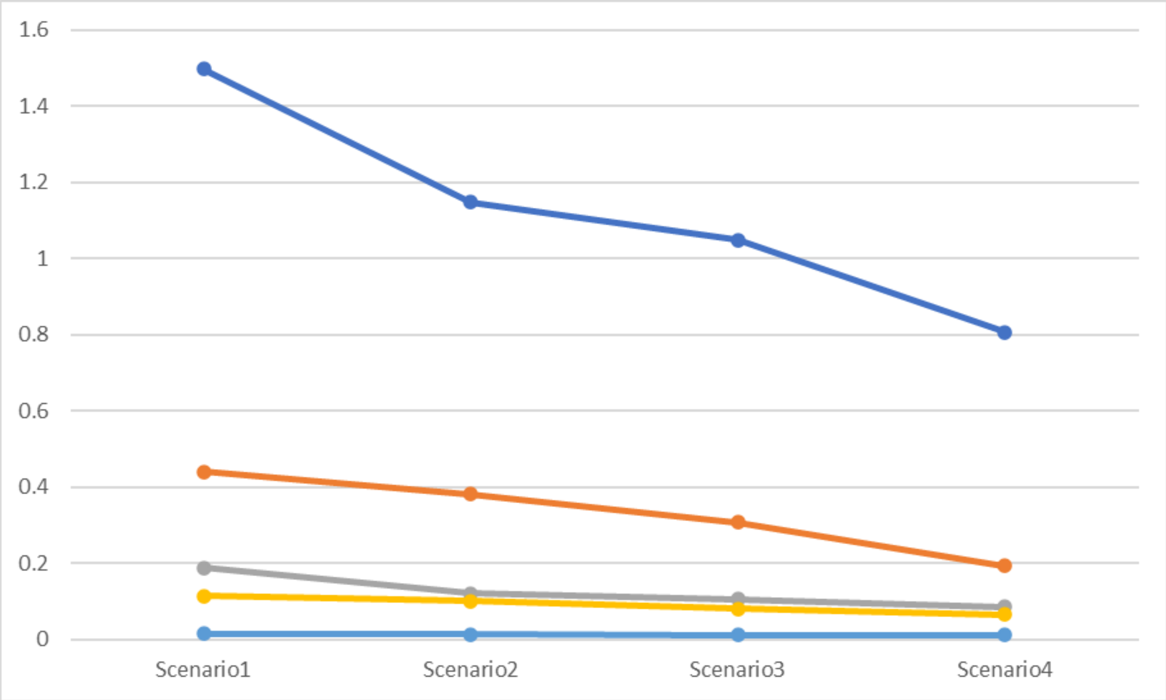


Figure 9- average machine downtime with respect to different scenarios

5. Discussions

5.1. Practical implications

The findings in the previous section revealed the practical implications such as obstacles and economic benefits for the digital integration of spare parts inventory management with PdM. Scenario 4 appeared as a feasible and most effective solution to address one of the key manufacturing objectives in relation to PdM, inventory management and SC, which is avoiding the unplanned machine downtimes due to shortage of spare parts (Bousdekis et al., 2019). The present study also reflects the suitability and necessity of a multi method approach for investigating the readiness of organisations across the ASC to embrace the proposed digital transformation. It also supports the principles behind the OC (Shee and Miah, 2021; Münch et al., 2022) where digital integration of spare parts inventory management with PdM is associated with both external and internal ASC factors.

The significance of SC digitalisation for inventory management has been already raised by several research scholars (e.g., Holmström et al., 2019; Kovács et al., 2020; Queiroz et al., 2021; Farajpour et al., 2022; Eslami et al., 2023) and has been manifested by our study. However, the scope of the present study was narrowed down to the UK car manufacturing sector which has recently faced profound challenges due to SC disruptions (Ambrogio et al., 2022). Dynamic, uncertain and volatile environment of ASC in recent years, especially the shortage of semiconductors, represents ED (Dubey et al., 2020; Shan et al., 2021) that is an indication of the influence of organisational and external factors on a digital and integrated PdM and inventory management. The internal and external influences on this integration provided a ground for this study to identify the obstacles in the way of digitalising ASC (Victer, 2020; Shee and Miah, 2021; and Münch et al., 2022) that requires to be a collaborative SC. The essence of SC collaboration through digitalisation of any SC and inventory management was highlighted by our findings where the best-case scenario (i.e., Scenario 4) promotes a more viable integration and collaboration among the participatory parties across an ASC (Bortolotti et al., 2015). Digitalisation and data transition across ASC can foster cyber-physical capabilities (Victer, 2020) including data and information analytics through enhancing asset categorisation, sensing capabilities, data acquisition, and condition monitoring.

Furthermore, the proposed solution proves to be effective for upgrading SC performance management criteria, particularly for SC resilience and risk propagation as important operations objectives (Balakrishnan and Ramanathan, 2021; Qader et al., 2022). The main risk factor that was studied in this research is indeed the inefficient spare parts and ineffective inventory management for manufacturing assets. That shortage can lead to machine downtimes and disrupted production. In broader terms, the economic gains (i.e., manufacturing and SC cost reduction) will drive organisations of various sizes across the ASC to embrace interconnectivity facilitated by digitalisation of their machinery spare part SC and inventory management systems. Unexpected breakdowns and shortage of spare parts are not unique to the automotive industries and would produce the same consequences (i.e., increased downtimes and production costs) in various sectors (Aransyah et al., 2020). This means, our study has unique significant economic value for the manufacturers by turning their attention more towards hidden SC costs associated to the spare parts as a decisive indicator for the overall SC cost with comprising of 20-50% of the overall procurement cost (Wallin Blair et al. (2020). Accordingly, the findings of this research can provide insights for other industrial firms than just automakers. Great deal of Environmental, Social and Governance (ESG) enhancements is another managerial implication and appears to have a potential to contribute towards OC and needs further exploration and analysis.

Apart from the obstacles that surfaced during the observations and can impede the proliferation of a digitalised SC, there are other deterrents discussed in the literature and can complement our preliminary results. Cyber and data security is among the primary concerns for organisations when considering digitalisation of their processes and interconnecting their assets (Holmström et al., 2019; Farajpour et al., 2022). Initial investment for embedding infrastructural capabilities (Queiroz et al., 2021; Farajpour et al., 2022; Tortorella et al., 2024) and training staff (Aransyah et al., 2020; Zangiacomi et al., 2020; Deepu and Ravi, 2023) may also discourage industrial firms to adopt SC digitalisation. Uncertainties around ROI is another inhibiting factor (Gupta et al., 2022). While digitalised operations will generate a broader array of maintenance- and logistics-related data sets, data ownership in interfirm production systems (e.g., servitisation of processing assets) and concerns over commercial/confidential data usage (or leaks) need to be meticulously addressed (Olsen and Tomlin, 2020).

A strong positive correlation was found between factory size (or in other words number of manufacturing machines) and profitability of the proposed solution. This can be explained in terms of economies of scale (i.e., fixed costs distributed over more units). Economies of scale can also be achieved when an independent service provider (Company D) is serving multiple customers, while a single manufacturer needs to invest in service resources and capabilities for a relatively smaller number of machines (Kastalli and Van Looy, 2013). Economies of scope, in contrast, may not necessarily realise as heterogeneity of machines and their spare parts can increase costs.

5.2. Theoretical contributions

A key challenge to the SC recovery endeavours is limited availability of data and information sharing which would further degrade a firm’s resilience in recovering from SC disruptions (Jain et al., 2022). Although the importance and utility of a digital integration between PdM and spare part inventory management has been stressed in the academic literature, lack of empirical evidence would hinder the development and adoption of that innovation (e.g., Calatayud et al., 2019; Carvalho et al., 2019; Kovács et al., 2020; and Dubey et al., 2020). To shorten this gap and provide contemporary evidence, this research centred on lack of accurate forecasting for machine failures, a centralised on-demand inventory management system and financial gains of timely planning for spare part replenishment (Zhu et al., 2022; and Balakrishnan and Ramanathan, 2021). This research is a preliminary attempt to identify the most impactful organisational and process-related factors in spare parts inventory and demand management.

Our multi-faceted findings are also in favour of diffusion of socio-technical system theory into inventory management in car manufacturing industries (Dubey et al., 2020; Hobscheidt et al., 2020; Balakrishnan and Ramanathan, 2021) by recognising the significant role of organisational culture alongside the technical aspects such as IT infrastructure, part criticality, and technological compatibility. In that manner, the emergent themes reflected a classification for greater and broader aspects of obstacles, and this can bridge previous studies about technical aspects such as data management (Aivaliotis et al., 2021) and those conducted around organisational change management during an SC transformation (Zimmermann et al., 2020).

The inter-organisational interfaces cantered around digitalised SC opens up new avenues for theory elaboration (Holmström et al., 2019). Digitalisation, where cyber-physical and production-control systems are intertwined, enables real-time data access, empowering organisations to screen fluctuations in demand and resource availability, and to pinpoint bottlenecks and process variability in an unprecedented way. This provides opportunities to revisit firm boundaries and DC within the SC and can be further examined through the lens of OC theory. DC build, integrate and reconfigure OCs in rapidly changing environments (Eslami et al., 2021).

5.3. Limitations

A noteworthy limitation of this research is lack of historical data to validate our simulation and quantify the actual impact of the concerned SC transformation and other organisational KPIs which could be followed by an in-depth analysis of a wider range of benefits than just cost savings. Further analyses to statistically test the perceived impacts of the specified obstacles on the SC and machine performance in addition to (mutual) interactions of these obstacles as a part of a transition to this digital integration could provide complementary insights. Another limitation relates to the scope of this research. Although we adopted a socio-technical lens to appraise the proposed solution, most of the barriers that were identified fall under the organisational and technical categories. Since this research was at the feasibility phase and focused on a few case studies, we were unable to gather real-world data and simulate an operating PdM system. Instead, we estimated the failure rates in a stochastic manner and focused on the impact of such process on machine downtime intervals.

6. Conclusions and future research

Lack of machinery spare parts and long lead times pose a threat to the maintenance and productivity of manufacturing assets in the automotive sector. Shifting to data connectivity and homogenisation through a digital PdM integration with spare part inventory management was suggested and demonstrated the potential to enhance the efficiency of spare parts SC mainly through improved forecasting accuracy, reduced machine downtimes, and augmented OCs (i.e., maintenance practices). This would lead to increased SC and organisational resilience and ultimately yield more ROI. On the other hand, the simulation results advocate that MTTF and factory size are critical heterogeneity indicators that can impact this integration. Addressing these obstacles or challenges would facilitate integrating PdM with disruptive technologies such as AI/ML thereby upgrading it into prescriptive maintenance linked to a digital spare part inventory management to optimise the ordering system. The RQ1 was addressed through identification of internal and external practical obstacles and challenges towards the proposed digital transformation (please see figure 7). The economic benefits of this transformation such as substantial cost reduction in machinery and maintenance were most reflected in scenario 4 where integration of a centralised SC system and PdM can yield the highest benefits.

Implementation of such a digital innovation requires significant attention to data analytics, information management system, ordering process improvement, infrastructure enhancement and cultural transformation. Our study offers fresh insights for the current maintenance systems, ordering spare parts and inventory management across ASC with broader applications, such as integration of I4.0 technologies with spare part inventory management. The enhanced ordering system in this context refers to a less cumbersome and complex ordering system with less SC cost.

Considering the possible heterogeneity of the ASC and the volatilities in the external market, a further exploratory study of the market together with probabilistic analysis of inherent uncertainties, can complement the present study and provide additional evidence base for decision makers. Implementation research including action research or case study following the identified obstacles and financial incentivisation (e.g. significant cost reduction and machine downtime) can be designed to evaluate the circular economy and environmental benefits (e.g. CO2 emission reduction and resource efficiency) for the proposed solution. The main KPI in this research was machine downtime, which lays at operational level, but future research can be expanded to comprise variables at tactical and strategic levels.

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