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Development of Capability for Integrated Smart Production-Spare Part Warehouse System for SMEs in Fast-Moving Consumer Goods sector

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Abstract

To maximize productivity of SMEs in Fast-Moving-Consumer-Goods sector (SMEs-FMCG), reducing machinery's downtime due to spare-parts unavailability is crucial. Data-integration is essential for smart-production capability-development, by enabling real-time optimization to increase productivity. Since data-integration solutions are costly while SMEs-FMCG have slim-profit margin, SMEs-FMCG have not adopted Data-integration in spare-parts warehousing. This study proposes an affordable approach for spare-parts inventory costs minimization while maximizing their availability for maintenance using real data. A Linear-Programming-Model was formulated/integrated with Warehouse-Management-Systems software to optimize number of spare-parts orders alongside order-quantity. This was applied to a baked-goods manufacturer, minimizing downtimes due to spare-parts unavailability and inventory cost.

1. Introduction

Maintenance is needed to be carried out properly to ensure the productivity of the machines is always at its peak. Maintenance strategies can be classified into two major types, predictive maintenance and reactive maintenance.

Industry 4.0 refers to digitalization, automation, and interconnected technologies [1]. The application rate of such technologies is different in different countries, due to the way the industry in that country functions. Although Australia is a developed country, the machinery manufacturing industry is not a large industry [2]. Hence, most of the machines and their spare parts are imported from other countries. This causes an issue since companies need to consider different factors such as the run time, lead time, holding costs, etc. Many companies still don't use industry 4.0 technologies, especially for spare parts warehouse to manage their inventory levels required for maintenance. Although, frameworks have been proposed for implementing smart technologies in spare parts warehouses

[3], the proposed concepts have yet to be adopted by industry as they require advanced systems to be installed or being expensive and need complex implementation processes.

FMCG goods manufacturers have a slim profit margin on their products [4], which discourages them from implementing elaborate/costly solutions. Inventory management optimization of spare parts required in maintenance is the main objective of this study. This study aims to develop an affordable framework within the spare parts warehouse that can be integrated with industry 4.0 technologies. In a manufacturing system, spare parts inventory is kept assuring smooth operation of the machinery used. This paper focuses on optimization of spare parts inventory for smooth operation of machinery used.

2. Literature review

First the relevant literature in the context of integrating industry 4.0 technologies to spare part warehousing are critically reviewed. Then, the research gaps are discussed.

This review paper [5] looked at how different industry 4.0 technologies relate to sustainable warehousing. They found that there is a positive correlation between application of industry 4.0 in warehousing and economic, environmental and social sustainability. This paper reviewed existing approaches to manage inventory of components that can be repaired/reused [6] .This paper reviewed the existing approaches for spare part management by considering various types of costs, networks, inventory policies, maintenance strategies, but not specific to FMCG [7]. Both papers concluded that optimization was the most used approach for spare parts inventory management.

This paper [8] investigated different types of maintenance in which the spare parts are used and the reasons why companies face issues with the availability of spare parts when needed. The paper pointed out a need for a system that integrates the suppliers and company for improving their communication to reducing the lack of spare parts.

This paper formulated a machine learning algorithm for spare parts warehouse management [9], but did not account for variability in demand while required high levels of expertise for implementation which makes it difficult to be implemented in SMEs with limited access to programming skills.

This paper investigated application of optimization for spare parts management on two logistics models: single-location and multi-echelon [10].Yet, it did not provide any optimization model and only discussed the possibility of its application.

This paper classified spare parts based on quantity, demand variance, and rate of movement [11] and discussed the 'dead stock' concept. Yet, it did not provide a framework to apply that in real-world and did not consider fluctuation in demand in FMCG industry. This paper looked at a product life cycle [12], focusing on spare parts acquisition before or after a product's life ends. The paper compared different models to determine order quantities and periods for the spare parts that are going to be discontinued and concluded that a heuristic model is optimal to solve such problems compared to a decision tree.

This paper looked at ordering policies for rotatable spares used in maintenance procedures [13] and proposed a model that allowed ordering the related spares at the same time to prevent longer lead times. The paper did not consider the variability of demand, usage of machines, and shipping cost. This study [14] investigated on a fuzzy neural network-based decision support system to manage automobile spares inventory in a warehouse. A machine learning algorithm was developed but can be only useful to large scale warehousing, since the fuzzy models require substantial input's number. Also, applicability of that approach was not investigated when addressing the variable requirements of a spare parts inventory of an FMCG industry.

This paper investigated the application of digital twin in the supply chain but did not provide a specific solution to warehousing. As a case study, the effects of customization on spare part business in the metal industry was discussed [15].

This paper proposed the application of digital twin for warehouse management by application of value stream analysis but did not focus on spare part management [16].

This paper explores [17] how spare part availability and lead time from supplier's impact machine uptime. The paper relies on assumptions such as identical machines running in parallel, an infinite repair capacity, and a one-to-one replenishment for spare parts. It concludes the need for a model accounting for multiple machines, critical spare parts, and suppliers.

Some works investigated application of RFID or IoT in warehousing, but that is out of the scope of this paper [18].

A major shortcoming in existing works is that it is assumed that every component was from a different supplier and every order only consisted of one component. The studies did not give enough attention to lead time, downtime cost, assuming that holding cost was primary cost for inventory management. In most of the existing works, the model proposed have not based on a rolling demand and instead were based on historical demand. The existing models also require high level technological expertise which might not be suitable for SMEs.

3. Research Scope

With COVID-19 pandemic, outlook of companies on Industry 4.0 has changed [19] as there were a lot of issues, such as lack of inventory, increased shortage for perishables [20]. The effects on the manufacturing industry could have been abated using Industry 4.0 technologies. In Australia, most machines used by manufacturing companies are bought from third party dealers which introduces a network of third-party dealers that connect users with OEM's. Hence, most companies in Australia utilize a two-echelon network, consisting of a central depot and multiple warehouses, for their raw materials and spare parts as most of the inventory utilized in the manufacturing process is imported from overseas [20]. This leads to large lead times for vital spare parts or keeping excess inventories, which leads to poor warehouse management.

This work [21] focused on FMCG manufacturing and improving spare parts inventory for an SME. This work utilized a case of a small-scale Baked goods Australian manufacturer to investigate application/implementation a Linear Programming (LP) to form an inventory optimization tool that works with real data, as a realization of industry 4.0. The proposed tool can also be integrated with digital twin technology proposed earlier for the spare parts warehouse. The proposed approach is explained with a real case study to ease the explanation, yet it allows demonstrating its applicability in real industrial settings. The proposed approach is generic and can be applied in other industrial settings. In the study we work with MEX software to use warehousing data and create a model to optimize the order frequency, quantity, and inventory levels. LP uses data from Warehouse Management Systems (WMS) to give an optimal solution for number of orders and the number of parts ordered.

4. Methodology

In SMEs, most of the maintenance is reactive and orders for spare parts are usually being placed as rush orders, leading to high delivery costs, which might exceed the cost of part itself, and lead to downtime and profit loss.

4.1. Integration of software platform

Most warehouses use software for their inventory update. In the case study, the manufacturer uses MEX software to track the location and quantities of spare parts available. Every new

part that would arrive or be taken off the shelf, would need to be updated in the system. The MEX software did not have predictive extensions to consider the average run time of machines and provide a predictive order schedule. In this research, we proposed applying industry 4.0 technologies such as smart warehousing and digital twin. Yet, the company pointed at the cost and complex application process to be barriers for application of such technologies, like many SMEs. To overcome this challenge, this research suggested integration of excel as the repository shared in cloud that could use the data extracted from a warehousing software (e.g., MEX) to provide an optimized order schedule based on real data obtained from the warehousing software. This ensures that spare parts required are on site before they are required, which would save on downtime costs, call out costs, delivery cost (by ensuring economic order quantity is fulfilled), and so on.

4.2. Architecture

4.2.1. Process flow and Machines runtime

This research proposes a high-level system optimization approach. To identify the areas within the production process flow that could be improved using industry 4.0 technologies, it is suggested to start by mapping out the process flow. Fig. 1 shows the process flow for the case study.
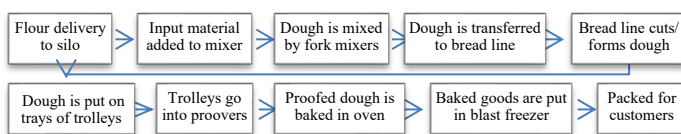

Fig. 1 The process flow of case study

To develop the optimization model of the spare parts used in machines, we suggest measuring the run time of each step of the production process, per machine per cycle.

For case study, the machines' run time was measured, as each machine was set up with specific production parameters. Table 1 shows the production parameters including the number of machines, their cycle times, and run times based on monthly demand (the values were obtained from shopfloor). Packing process time includes the time taken by box machine to erect boxes and wrapping machine to wrap the products individually.

Cycle time is the amount of time it takes to fill 4 trolleys (1440 units) with the dough before being proofed or baked.

Table 1 Machine parameters and run-time based on monthly demand

Machine	Number	Cycle time (minutes)	Run time in months
Mixers	5	20	0.9
Bread Line	3	10	0.7
Proovers	7	30	0.8
Ovens	9	20	0.6
Blast freezers	5	15	0.7
Packing lines	3	10	0.7

Run time per cycle (in hours) = 1.75 hours/cycle
One cycle = 1440 units, forecasted monthly demand = 14 million units, equates to 9722.2 cycles
Monthly run time of machines (MRTM) is calculated as:

$$MRTM = \frac{cycle\ time\ *\ forecasted\ monthly\ demand}{(60*24*30)*(number\ of\ machines)}$$

To calculate the machines' monthly running time, the average monthly demand was used. The maintenance budget was being decided monthly and the total cost of the warehouse would be determined at the end of each month. The higher end of the forecast was considered which was 14 million units in a month. Even with such a high demand, the machines would not need run continuously if the machines don't experience any breakdown. However, since there would be some breakdown and downtimes, the machines would be running around the clock to fulfil the demand almost in most days. This shows the importance of spare parts' inventory optimization.

4.2.2. Critical Processes and Maintenance Analysis

This research suggests identifying critical processes in the next step, which can be done by analyzing the failure rates of the processes and calculating the maximum output of machines in each process. For the case study, the machines' outputs are given in Fig. 2. Proofers were the bottleneck in the process as they would break down often and create back logs, Also, proving the dough was the lengthiest process, identified after process flow analysis and calculating the runtimes. The ovens were the second most problematic step, since the baking process is the second longest process. Because it is required to be done in the middle of the process flow, this would lead to major backlog especially considering that the burners and ovens were not being serviced regularly and were being run at temperatures higher than the recommended. Moreover, proofer would break down quite often as they were quite old and since only reactive maintenance was performed, the proofers would periodically be out of service waiting for parts.
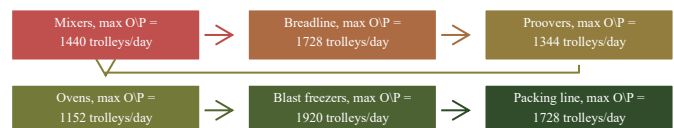
Fig .2 Maximum output of each step of the process

By investigating failure/maintenance data, the problematic parts in machines were identified, which even the OEM manufacturer did not detail the replacement time for parts, as it is generally assumed that the machines were only used at a recommended setting which is not necessarily the case as every company has its own working method. This again shows the importance of proper spare parts inventory management.

Further, data was collected and included in MEX software about the parts that would need to be replaced and their replacement intervals to develop a long term, and sustainable, strategy (black box strategy) for the maintenance department.

4.3. Optimization model

Industry 4.0 promotes using real-time data to achieve an adaptive approach for performance optimization. Since, different parts were needed to be replaced at different times, this research continuously exported output from MEX software to the shared cloud-excel file. An 'if' function was embedded

in the excel, to get correct value for runtime of a part, given in (1), to assure continuous production.

Run time of machine:

$If (parts ordered in previous period$
$\geq\ number\ of\ components, 0\ , run\ time)$

Run time of the parts since replacement (RTij) =   (1)
  $RT\ of\ machine\ +\ forecasted\ RT\ for\ next\ period$

ni = number of parts per machine

Inventory on hand (Iij) = ni- $parts\ ordered\ in\ last\ period$

Number of parts required (Nij):
  $If (RT\ from\ previous\ order > 0\ , Iij\ , (ni\ -\ Iij)$

$MTTFij\ =\ MTTF\ for\ cpart\ i\ by\ supplier\ j$
$Nij\ =\ Number\ of\ units\ of\ part\ i\ required\ to\ be$
$replaced\ on\ a\ machine\ ordered\ from\ supplier\ j$

$Monthly\ Holding\ Cost\ (HC) = Ws\ *\ Wc$ (2)
= warehouse space utilised by part (Ws)
$*$ warehouse cost per unit space per month (Wc)
$Rtij = RT\ of\ part\ i\ on\ machine\ j\ since\ replaced$
$Dtc\ =\ Downtime\ cost\ per\ hour$
$Ltij\ =\ Lead\ time\ of\ part\ i\ from\ supplier\ J$
$Eoqj\ =\ Economic\ order\ quantity\ from\ supplier\ j$
$MTTRij\ =\ MT\ to\ replace\ part\ i\ by\ supplier\ j$
$Dj\ =\ Delivery\ cost\ from\ supplier\ j$
  $Cij\ =\ Cost\ of\ part\ i\ supplied\ by\ supplier\ j$

Decision variables:
$Qij\ =\ Number\ of\ units\ of\ parts\ i\ needed\ to\ be$
$ordered\ from\ supplier\ of\ machine\ j$
$Xj\ =\ Number\ of\ placed\ orders\ in\ a\ time\ period$

Objective function b: Min$\sum(Xj * Dj) + \sum(Qij * Cij)$ (3)

Constraints:

Equation (4) shows the number of units of a part required in a period.

$((RTij + Ltij + MTTRij)\ /\ MTTFij) * Nij\ <\ Qij$ (4)

Equation (5) shows ordering and holding cost of part should not exceed cost of not having it on hand as there are parts that, if they are not on hand, do not lead to downtime for machine.

$(Xij * Dij) + (Ws * Wc * avg. Ltij)$ (5)
$< \big((Avg. Ltij + Avg. MTTRij)\ * 31 * 24) * (Dtc)\big) + Dij$

Equation (6) shows the total number of received parts in period T should be more than the number of parts required in period.

$(Xj * Zj)\ >\ \sum(Qij)$ (6)

4.3.1. Input data of spare parts

Table 2 and Table 3 show sample data extracted from MEX software required for the optimization model developed for case study, consisting of lead time (LT), Delivery Cost (DC), and Meantime to replace the part (MTTR). Taxes and delivery costs were included in the part's cost. Downtime (DT) cost was 5 dollars per hour per machine as each time a machine would be out of service, it would cause backlogs, leading to staff working overtime to meet the demand. Hence, not only was the machine not being used, but causing overtime pay increases and causing other machines to be overused.

A key benefit of the proposed approach is that, here excel is used as the platform to make the model an accessible tool that

can be used by SMEs when adapting to industry 4.0 paradigm, which is lacking in many sophisticated approaches in the literature. Holding cost was calculated based on space required to store parts and space cost.

The cost of space was roughly 3 dollars/month/sqft. Every part on the shelf was put into a box and placed in a 1 sqft area.

Table 2 Maintenance data related to parts

Part Name	Stock on Hand	Cost/unit
Oven window door gasket	4	62.84
Oven control flange V50-52	6	12
Oven table thrust bearing	0	1571.42
Oven motor timing belts XPZ	6	71.11

Table 3 Maintenance data related to machines maintenance

Machine	Frequency	LT	MTTR	Tasks
Proover	1 Months	2	1.25	> Replace (RP) heating element, check/clean nozzles/solenoid valves
Proover	3 Months	2	1	> RP solenoid valves and fans, clean the drains and fan covers
Proover	5 Years	2	3	> RP sensors and nozzle stems, clean the condensors.
Oven	4 Weeks	3	0.5	> RP drive belts, clean under the turn table, grease bearings
Oven	2 Weeks	3	1	> RP solenoid valves, internal temperature sensor, check table bearing.
Oven	1 Months	3	1	>RP table bearing, check motor/service the burner.

5. Application, Results, and Discussion

The developed optimization model was applied to the proofers and ovens, which rely on every part functioning properly to get the best result. To run sample tests to validate the proposed model, 'i' was considered to be any part from the proofer or oven and 'j' was to indicate which machine that part belongs to. 'N' refers to the number. The constraint equations used in the model are as follows:

Quantity constraint:

Taking the proofer heating element (HE) as an example:

$\frac{(RT\_HE) + (LT\_HE\ from\ supplier) + (MTTR\_HE)}{MTTF}$ *

$(N\ of\ HEs\ in\ a\ proover)\ <\ (N\ of\ HEs\ to\ be\ ordered)$

$=\left(\frac{0.83+0.46+0.00034}{1}\right) * (8) \leq\ (Qhp)\rightarrow (10) <= (10)$

Qhp is the number of heating elements needed to be ordered from the proofer supplier. The equation considers the total time to get the part from supplier's warehouse to install and run it in machine to avoid downtime. This is repeated for proofer solenoid valve, fans, sensor, oven belts, solenoid valves, sensors and bearings, separately as shown in Table 4.

Order constraint:

Taking the proofers as an example:

$(N\ of\ placed\ orders\ for\ proover\ supplier\ *\ order\ DC)$
  $+ (monthly\ HC\ *\ avg\ LT)$

$$< \left(DT \text{ cost} * (avg\ LT + avg\ RP * 31 * 24) \right) \\ + delivery\ cost$$

$$=(Xp * 160) + \left(3 * avg(0.46 + 0.46 + 0.46 + 0.46) \right) \leq$$
$$(5 * ((avg(0.46 + 0.46 + 0.46 + 0.46) + avg(0.00034 + \\ 0.00034 + 0.00034 + 0.0013)) * 31 * 24)+160=358<=1877$$

Quantity constraints:
Taking the proofers as an example:

$$(N\ of\ \text{placed }orders\ in\ period \\ * EoQ\ of\ orders\ from\ supplier) \\ < N\ of\ parts\ required\ in\ a\ period$$

$$=(Xp * 7) \geq (Qhp + Qsp + Qfp + Qs'p) = 16 >= 16$$

Where Xp is the maximum number of orders to be placed from proofer supplier in a period, Qh is the number of heating elements required, Qsp is the number of solenoid valves required, Qfp is the number of proofer fans required and $Qs'p$ is the number of proofer embedded sensors needed in the period. The above equation considers the number of parts needed in a period and their associated cost, ensuring the maximum number of orders placed accounts for the total number of parts required for the period and the costs associated with keeping them as inventory. The equation also assumes that even if the part is ordered early and kept on hand till the working part fails, it still makes sense to order the parts.

Table 4 Number of parts to be ordered and maximum number of orders

Component	N of units to order	Supplier	Max N of orders
Proover heating element (Qap)	10	N of orders for proovers- Xp	2
Proover solenoid valve (Qbp)	1	N of orders for ovens- Xo	1
Proover fans (Qcp)	3		
Proover sensors (Qdp)	1		
Oven belts (Qao)	5		
Oven solenoid valves (Qbo)	1		
Oven sensors (Qco)	0		
Oven bearings (Qdo)	0		

Table 4 shows the results regarding the number of parts required during the next month and the optimal number of orders within which makes financially makes sense. The model returns the number of parts ordered, and the maximum number of orders placed by a certain supplier.The proposed model embodies a dynamic and adaptive perspective, meaning that by updating the demand, the run time of machines will be updated and accordingly the spare parts will be needed in future. This adaptive approach embodies a key concept of industry 4.0. The model also works on a weekly basis to suggest how many parts need to be ordered in a week. For initial implementation, the forecasting was done on monthly demand as it allows a comparison with the preexisting model being used by the company. Although the number of machines included in the model does not account for all machine in process flow but the model can be easily extended to include more machines, different parts, suppliers, etc.

5.1. Results

The results show that within a one-month period, by using the proposed approach the company would not only be ordering parts that are required immediately but also ordering small quantities of the parts, such as the proofer fans or oven solenoid valves, that would be required later to ensure that by the time there is a need for the parts, they are already in hand. For example, the model suggests that in the next period it is needed to order 10 units of heating elements, 1 unit of solenoid valves, 3 units of fans and 1 unit of proofer sensors. The results suggest it is needed to place a maximum of 2 orders in the month. With regards to ovens, the model suggests placing one order which consists of 5 units of belts and 1 unit of solenoid valves. Some parts will be kept in inventory for a while but that is still worth the cost when considering all the cost and lost profit due to the machine's breakdown and unavailability of spare parts. This cost tradeoff analysis is addressed in the model as one of the constraint equations considering the time that specific components would be held in inventory and the cost that would incur to do so. In this case study, the inventory holding cost is trumped by the cost of not having the part on hand. In this way we would also be prepared for unexpected breakdowns as well as expected replacement.

The orders placed for spare parts of slicers was a case that particularly stood out as the orders were placed less than a week apart, as the parts that failed were ordered in the first week and the very next week another part failed which was due for replacement soon. This specific order instance is an example emphasising the necessity for this research.

The proposed model is internally developed with simplification while still can satisfy the company's needs and gives an acceptable accurate reading for the maintenance requirements of the company. As mentioned, highly sophisticated approaches, cost, lack of skill, and inaccessibility to specific software platforms have been the main drawbacks of the existing approaches which hinder the SMEs from adapting to industry 4.0 paradigm. The actual downtime and breakdown of machines was gathered within the last few months, also included the reason for the downtime. The data shows that the company has an unusual number of breakdowns monthly. This research analyzed the number of orders placed previously and the result show that most of the orders were rush orders, because the parts were not being in stock when they were required.

In the month of April, due to the breakdown of machines, the company faced a backlog and increased production costs due to needing more production staff to mitigate the effects of the failure of certain machines.

As shown in Fig. 3, the proposed model suggests ordering more parts in each order, leading to a decrease in total delivery costs. Fig. 4 compares the suggested values by the proposed model for the number of orders, the number of parts in an order and the amount of monthly paying delivery fees, with the suggested values for same variables using the preexisting model used by the company. This research investigated the downtime of machines in April with its associated cost, compared to the downtime that would incur if using the proposed model, shown in Table 5.
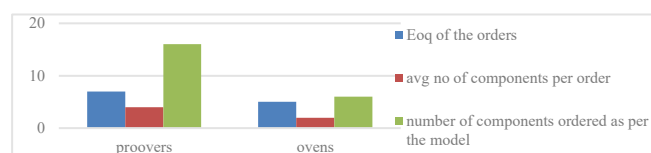
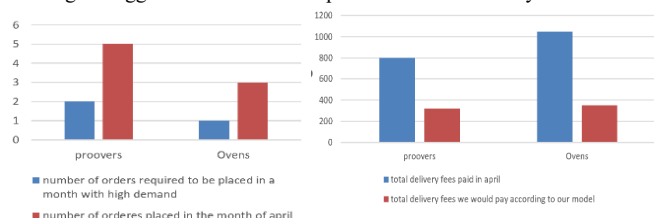Fig .3 Suggested number of components in each order by the model

Fig .4 a) Comparison of number of orders b) Comparison on delivery cost

To not being biased in favor of the proposed model, the comparison assumed an optimistic downtime cost for machines, yet the data still suggests that over a year the company would roughly spend 7,200 dollars on proofer breakdowns and 17,280 dollars on oven breakdowns, if the company were to continue using the existing strategy. There will be penalties involved with any backlogs. Also, when there are backlogs the other machines would be running for longer periods of time to compensate for the machine that is out of service, which would then lead to possibly more breakdowns and downtime like an endless cycle.

The proposed model can be integrated into MEX software with ease, which not only increases the value of the proposed approach to but also be the next step to improve maintenance and warehousing software's such as MEX.

Table 5 Comparison between the cost of downtime

	DT	DT cost	DT, by model	DT cost, by model
Proovers	5 days	600 AUD	0 day	1.27 AUD
ovens	12 days	1440 AUD	0 day	5.10 AUD

6. Conclusion

As was demonstrated in this research, the spare parts warehouse management adoption to industry 4.0 does not need to be a very expensive endeavor involving complex, hard to navigate and expensive systems. It can be achieved by integration of available software affordable to an SMEs as an excel model. The proposed approach can be integrated with smart technologies to automatically get real-time data. For example, weight sensors on the warehouse shelves can be used to update the inventory levels directly, either way the constraints and the rest of the equations can remain unchanged while such integration allows to have real-time communication with the warehouse. A digital twin can expand the scope of this work and include fault modelling. The robustness of the proposed approach is demonstrated through its integration with real data and generating valid results accordingly. There are quite a few papers that suggest integration of motion sensors, but such approaches do not account for high costs for SMEs. Overall, this research proposed an approach to overcome such gap and its effectiveness was compared to the current systems being used in managing the spare parts warehouse and even stands up to the other systems proposed by papers in the past.

References

[1] Imran Ali, Ahmad Arslan, Zaheer Khan, Shlomo Yedidia Tarba. The role of Industry 4.0 technologies in mitigating supply chain disruption: empirical evidence from the Australian food processing Industry. IEEE Transactions on Engineering Management, 2021.

[2] ibisworld.com, 01 August 2023. [Online]. Available: https://www.ibisworld.com/au/industry/machine-tool-parts-manufacturing/278/#TableOfContents.

[3] Samuel Marino. Delivering smart warehousing in Australia Delivering smart warehousing in Australia. in International Conference on Electronic Business (ICEB). 2023.

[4] statistics, 2023. [Online]. Available: https://www.abs.gov.au/statistics/industry/industry-overview/australian-industry/latest-release#cite-window1.

[5] lmran Ali, H.M Phan. Industry 4.0 technologies and sustainable warehousing: a systematic literature review and future research agenda. The International Journal of Logistics Management. 33 (2). 2022. p. 644-662.

[6] Jr V. Daniel Guide, Rajesh Srivastava. Repairable inventory theory: Models and applications. In European Journal of Operational Research. European Journal of Operational Research, 102(1), 1997. p. 1-20.

[7] Shuai Zhang, Kai Huang, Yufei Yuan. Spare parts inventory management: A literature review. Sustainability, 13 (5). 2021. p. 1–23.

[8] W. J. Kennedy, J. Wayne Patterson, Lawrence D. Fredendall. An overview of recent literature on spare parts inventories. In Int. J. Production Economics, 76 (2), 2002. pp. 201-215.

[9] Qiwei Hu, Salem Chakhar, Sajid Siraj, Ashraf Labib. Spare parts classification in industrial manufacturing using the dominance-based rough set approach. European Journal of Operational Research. 262 (3), 2017. p. 1136–1163.

[10] Robertus Johannes Ida Basten, Geert-Jan van Houtum. System-oriented inventory models for spare parts. Surveys in Operations Research and Management Science. 19(1), p. 34–55.

[11] Rahul Mor, Arvind Bhardwaj, Vishal Kharka, Manjeet Kharub. Spare parts inventory management in warehouse: a lean approach. International Journal of Industrial Engineering & Production Research. 32(2). 2021.p. 4.

[12] Karl Inderfurth, Kampan Mukherjee. Decision support for spare parts acquisition in post product life cycle. Central European Journal of Operations Research.16. 2008. p. 17-42.

[13] U. C. Moharana, Sarada Prasad Sarmah. Determination of optimal order-up to level quantities for dependent spare parts using data mining. Computers and Industrial Engineering. Computers and Industrial Engineering. 95. 2016. p. 27–40.

[14] S. G. Li, X. Kuo. The inventory management system for automobile spare parts in a central warehouse. Expert Systems with Applications. 34(2). 2008. p. 1144-1153.

[15] Pratik Maheshwari, Sachin Kamble, Satish Kumar, Amine Belhadi, Shivam Gupta. Digital twin-based warehouse management system: a theoretical toolbox for future research and applications. The International Journal of Logistics Management, (ahead-of-print). 2023.

[16] S. Abdoli. Digital twin and Value Stream Mapping of Warehousing in Era of Industry 4.0. ESSN: 2701-6277. 2023. p. 823-832.

[17] Schultz* CR. Spare parts inventory and cycle time reduction. International Journal of Production Research. 2004.42(4):p.759-76.

[18] Walaa Hamdy, Noha Mostafa, Hesham Elawady. Towards a Smart Warehouse Management System History of Science View project Towards a Smart Warehouse Management System. In Proceedings of the international conference on industrial engineering and operations management, 2018. p. 2555-2563.

[19] J. Schulz. Future Shocks: Automation. American Behavioral Scientist. 2023. p. 8.

[20] Shruti Agrawal, Anbesh Jamwal, Sumit Gupta. Effect of COVID-19 on the Indian Economy and Supply Chain. Preprints, 2020.

[21] V. Daniel R. Guide Jr, Rajesh Srivastava. Repairable inventory theory: Models and applications. Repairable inventory theory: Models and applications.102(1). 1997. p. 1-20.