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A reliability-based methodology for resilient spare parts planning and control

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Abstract: Geo-political conflicts, financial crises, natural disasters, pandemics, human operational errors, and other disruptive events can affect supply chain integrity with unpredictable consequences. In addition, intermittent demand patterns and strict service requirements enhance the complexity of Spare Parts Supply Chains (SPSCs). SPSC resilience has become a significant challenge in today's increasingly competitive business environment.

This study presents a reliability-based methodology with a customer-oriented perspective to support industrial companies in spare parts planning and control. This original approach provides resilience to SPSCs by defining a statistical variable to study supply chain variabilities and externalities, aiding stockout risk control, and suggesting spare parts management plans. The application of the proposed methodology in a case study of a packaging machine company is illustrated.

Keywords: Spare parts supply chain, spare parts management, reliability, resilience.

1. INTRODUCTION AND LITERATURE REVIEW

Spare parts management and after-sales service represent the main source of revenue for modern manufacturing companies (Cohen et al., 2006). However, supply chain disruptions can affect the firms' integrity, exposing the normal flow of goods and materials to operational and financial risks (Zhang et al., 2018). Examples of disruptive events include geo-political conflicts, financial crises, natural disasters, pandemics, human operational errors, strikes, and labor disputes (Alvarenga et al., 2023). Such disruptions might adversely affect supply chains with limited access to raw materials, increased production costs, reduced revenues, supply delays, and loss of reputation (Dolgui et al., 2018). In particular, managing the Spare Parts Supply Chain (SPSC) can be a complex endeavor (Bacchetti & Saccani, 2012). SPSCs are typically characterized by a large variety of components (Cohen et al., 2006), an intermittent demand pattern (Boylan & Syntetos, 2010), and a high risk of stock obsolescence (Cohen et al., 2006). In addition, SPSCs require higher service levels than other supply chains, as the effects of stockouts may be financially remarkable (Huiskonen, 2001).

Spare parts unavailability can result in (i) lost revenues (e.g., longer production downtime), (ii) customer dissatisfaction and possible associated claims (e.g., in airlines and public transportation), and (iii) public safety hazards (e.g., military settings and power plants) (Driessen et al., 2015). Moreover, the availability of spare parts plays a pivotal role in dissuading customers from seeking alternative solutions. This issue poses a critical concern for original component manufacturers, as activities such as reverse-engineering, self-repair, and the acquisition of non-original 3D-printed spare parts can lead to reductions in repair times, labor costs, storage expenses, material utilization, and transportation (van Oudheusden et al., 2023). Therefore, finding an effective and resilient way for SPSC planning and control has become a major challenge in today's increasingly competitive business environment (Sirri et al., 2023). Establishing a spare parts management system is essential to ensure effective control over stockout risks, maintain high on-time delivery rates to meet customer demands, and support spare parts inventory management.

Literature on spare parts mainly concerns the classification of Stock Keeping Units (SKUs), demand forecasting, and spare parts inventory management and control. Spare parts management has been extensively studied, especially concerning maintenance planning and control activities. Miranda et al. (2019) proposed a simulation-based modeling methodology to support the decision-making process of SPSCs and maintenance operations in manufacturing systems. Zhu et al. (2020) developed a dynamic inventory control method based on a simple forecasting mechanism applied to the maintenance plan. Fan et al. (2023) implemented a joint optimization of maintenance and spare parts inventory considering a stochastic lead time behavior in a gas pipeline system. Other studies focused on cost-based approaches aiming at SPSC cost minimization (Battini et al., 2014; Rinaldi et al., 2022). Battini et al. (2014) considered transportation costs, supplier location, and freight vehicle utilization ratio to build an EOQ model. Rinaldi et al. (2022) proposed a simulation model to manage spare parts inventory level in an engineering-to-order company, including order emission and inventory costs. Although many authors have applied reliability theory to spare parts management, reliability-based approaches are mainly limited to predicting failure events. Kovacs et al. (2021) developed a Weibull-based smart maintenance tool to predict remaining service life and support spare parts inventory management. İfraz et al. (2023) introduced different regression and machine learning methods to forecast spare parts demand in an urban transport bus fleet, considering the time between failures and the number of breakdowns.

Uncertainty affects spare parts in several stages of the supply chain. Disruptive events and variabilities in supply lead time

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and customer demand require the entire SPSC to be resilient. From a business perspective, customer satisfaction plays a major role in creating a competitive advantage in capital-intensive industries (Selçuk & Agrali, 2013). Thus, using reliability-based approaches for stockout control and risk assessment has become essential for spare parts companies to guarantee high service requirements. Literature on spare parts offers limited insight into this issue (Bacchetti & Saccani, 2012). This paper aims to cover this literature gap by addressing how the variability in order quantity and supply lead time impact the SPSC. The proposed methodology provides a solid basis for a resilient and reliability-based approach to spare parts management and control. It encompasses the entire SPSC, from the part suppliers and manufacturers to the final users, applies standard statistical tools on supply lead times and spare parts demand, and suggests effective spare parts inventory management rules.

The remainder of the paper is organized as follows. Section 2 introduces the methodology and describes the proposed structure. Section 3 presents a case study of a packaging machine company. In conclusion, section 4 reports the results discussion and some directions for further research.

2. METHODOLOGY

Figure 1 introduces the proposed reliability-based methodology designed to empower decision-makers to manage and control SPSC. Such a methodology identifies three main layers of analysis (the vertical sections in Figure 1): Supply (i), Service (ii), and Demand (iii). Each layer refers to a specific actor of the SPSC. The "Stakeholder" section reports the actors corresponding to each layer, while the "Role in SPSC" section displays their function within the SPSC. The Service Layer identifies the company responsible for producing machines and spare parts (the SP Company). Other than internal manufacturing, the SP Company could also rely on external suppliers (the SP Suppliers), identified by the Supply Layer in Figure 1. The customers of the SP Company (the SP Customers) correspond to the machine users and refer to the Demand Layer. Their demand for spare parts drives the material flow along the entire SPSC, involving all three layers.

The proposed methodology offers a data-driven approach and requires SP Company a substantial data collection from all the stakeholders involved. The "Data" section in Figure 1 reports some of the most crucial information required. The study of historical data from spare parts production and sales represents the fundamental pillar of the entire methodology. For this reason, the SP Company needs to collect the whole history of internal production, purchase, and sales orders. While the purchase orders refer to external manufacturing and have the corresponding production orders in the Supply Layer, the sales orders find their counterpart in the SP Customers' purchase orders in the Demand Layer. The number and geographic location of SP Suppliers and Customers represent other relevant information. The characteristics of the SP Suppliers manufacturing process (e.g., the Economic Order Quantity, EOQ) and the SP Customers demand details (e.g., service level requirements and maintenance plan) are parts of this data collection. Regarding the Service Layer, access to SP Company inventory levels and demand forecasts are also required. The proposed data-driven approach is based on the availability of historical lead times for internal and external production (the manufacturing LT) and SP Suppliers delivery (the shipment LT). Finally, the proposed methodology needs visibility over some SPSC costs in order to perform a complete economic assessment. These economic contributions may include the production, material handling, and delivery costs of the SP Suppliers (i.e., manufacturing and logistics costs), the manufacturing, inventory, and stockout costs of the SP Company, and the SP Customers costs for maintenance and production loss due to downtimes.

Despite SPSC data availability, some crucial issues may arise. The "Critical issues" section in Figure 1 reports some concerns for SPSC management. Uncertainty in production and logistics affects SPSC, causing variability in both internal and external manufacturing and shipment lead times. SP Customer demand variability is also critical, as the frequency and quantity of customer orders directly impact the SP Company ability to plan and control inventory. The necessity of SP Customers to maintain machinery and replace components generates the demand for spare parts. Insight into their maintenance plans can unveil recurring demand patterns. Other externalities may affect the entire SPSC with unpredictable changes.

Disruptive events such as geo-political conflicts, financial crises, natural disasters, and pandemics represent critical and unpredictable issues for SPSC, concerning all the stakeholders involved and their processes. For instance, problems in raw materials sourcing can generate material shortages, supply delays, inventory stockouts, and production losses in customer plants.

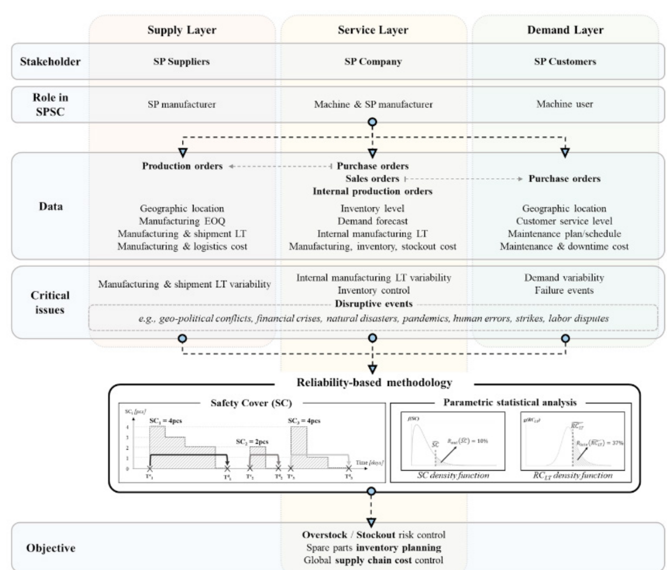

Figure 1. Reliability-based methodology for spare parts management.

This paper presents a reliability-based methodology to control SPSC, addressing the critical issues identified for the three layers of analysis. In Figure 1, the visual section named "Reliability-based methodology" introduces the proposed Safety Cover (SC) statistical variable. The parametric statistical analysis is part of the proposed methodology. A probability plot analysis provides the SP Company with two representative parametric density functions for SC and replenishment cycle lead time (RC_{LT}), $f(SC)$ and $g(RC_{LT})$ respectively. $f(SC)$ aids the SP Company in selecting a SC target level (i.e., $\widehat{SC}$ in Figure 1) that aligns with the desired customer service level. On the other hand, $g(RC_{LT})$ produces the parametric risk of a late supply delivery.

The "Objective" section of Figure 1 summarizes the main goals of the proposed methodology for the SP Company: overstock and stockout risk control, spare parts inventory planning, and global supply chain cost control.

2.1 Safety Cover and statistical analysis

Spare parts management poses some challenges, notably due to the significant variability in supply lead times and replenishment cycles (RCs). A RC begins in correspondence with the emission of a production or purchase order (PPO) and concludes when delivered to the SP Company, ready for the final shipment to the SP Customer. The RC_{LT} corresponding to a specific component is the time needed for its supply. However, the unpredictable nature of supply lead time poses a direct obstacle to the SP Company ability to guarantee timely deliveries to SP Customers.

Effective control over spare parts procurement and inventory must mitigate stockout risk during unpredictable RC_{LTs}. For this purpose, spare parts historical PPOs are analyzed with SP Customer historical sales orders (SOs) to combine the three layers of analysis reported in Figure 1. The resulting data-driven approach contributes to the definition of the statistical variable SC that encompasses the variability in RC_{LT} (1), sales frequency (2), and demand quantity (3). SC represents the minimal quantity of inventory to keep in stock in correspondence with the emission of a PPO (i.e., the beginning of a RC) to avoid stockout during the unpredictable supply lead time.

The SC related to a specific RC is the total demand quantity during its supply lead time. Figure 2 illustrates an example of SC evaluation for a component with three replenishments: RC_1, RC_2, and RC_3. During RC_1 from T_1^e to T_1^d three sales occurred (SO_1, SO_2, and SO_3), with a demand of one, one, and two pieces, respectively. Thus, the SC value related to RC_1 equals the total demand of the three SOs (SC_1 = four pieces). An illustration of the inventory level is reported in the second part of Figure 2. SOs affect spare parts inventory by decreasing the available storage quantity. Keeping four pieces in stock in T_1^e would have prevented stockout during RC_1. Regarding RC_2 and RC_3, the resulting SC value corresponds to two and four pieces, respectively.

Extending the SC measurement to each component and historical replenishment cycle allows the application of statistical analyses to support decision-makers in controlling the performance of the entire supply chain. In particular, the probability plot analysis gives practitioners effective statistical methods to develop reliability evaluation models (Manzini et al., 2010). Applying the probability plot to SC and historical RC_{LTs} means identifying the parametric statistical distribution that best fits actual values. The resulting density functions provide a parametric way to address the SPSC variability and make inferences about supply lead time and demand patterns. These statistical analyses allow decision-makers to identify the stockout risk associated with a specific inventory level, supporting spare parts management with a reliability-based approach.

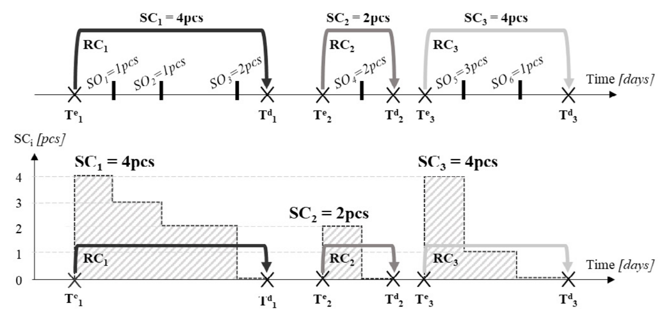

Figure 2. Example of Safety Cover evaluation. (T^e_i: *i-th* PPO emission date; T^d_i: *i-th* PPO delivery date; SO_j: *j-th* sales order quantity; RC_i: *i-th* replenishment cycle; SC_i: required Safety Cover for RC_i).

2.2 Stockout risk control and inventory management

To ensure customer satisfaction, spare parts companies establish specific targets for customer service level. These targets are determined by considering various factors, including market competitiveness, profit margins, sourcing strategies, customer location, demand volume, and marketing policies. A common service-level target selection procedure is defining the maximum acceptable stockout risk for each component and SP Customer combination. The previously introduced SC variable is the way to control the stockout risk by the statistical analysis of historical SC observations. The resulting SC inverse distribution function directly translates the chosen maximum acceptable stockout risk into the corresponding SC target value (i.e., $\widehat{SC}$). This value represents the inventory level maintained at the beginning of every RC to provide the desired customer service level. The SC corresponds to the Reorder Point (RoP) in a continuous inventory system.

This novel approach would enable customer-oriented spare parts inventory management, triggering replenishments and PPO emissions and supporting the SP Company stockout risk control. The suggested RoP would differ from the one proposed by applying the traditional EOQ model combined with the safety stock (SS) determination. In addition, while the proposed methodology employs probability plot analysis to identify the best-fitting SC parametric function, the conventional SS assumes a normal distribution for SP Customer demand.

2.3 Global supply chain cost function

Lead time variability generates early/late supply deliveries producing a significant economic impact on SPSC. Regarding early deliveries, the SP Company must contend with the cost of overstocks, as the received materials need to be stored before being dispatched to the SP Customer. This cost represents the additional holding and material handling cost. It includes structural costs (i.e., rental fees, maintenance, insurance, general equipment, supervisory, and depreciation), energy costs due to energy consumption, and labor costs for handling and logistics operations. On the other hand, when the available spare parts quantity is insufficient to satisfy SP Customer demand, a late supply delivery may cause a stockout event, producing sales delays, customer dissatisfaction, and stockout costs. This economic contribution considers the devaluation for profit delays, the cost of emergency shipments, and the loss of revenues due to downtimes at the SP Customer's plants. Service level reductions and stockout events also affect the SP Company revenue, increasing the risk of losing sales and customers.

A global supply chain cost function is defined to comprise these contributions. Given a continuous spare parts inventory planning system and a reorder point level RoP, this is the global supply chain cost function:

$$C_{global}(RoP) = C_{over}(RoP) + C_{out}(RoP) + C_{inv}(RoP) + C_{emission}(Rop) \tag{1}$$

where $C_{over}(RoP)$ is the expected overstock cost, $C_{out}(RoP)$ the expected stockout cost, $C_{inv}(RoP)$ the inventory cost, and $C_{emission}(Rop)$ the PPO emission cost.

As far as the SP Company adopts $\widehat{SC}$ as the RoP, all the contributions depend on $\widehat{SC}$. High inventory levels reduce the risk of stockout. However, higher inventory means greater inventory costs, also reducing the number of replenishments and the related emission cost. Therefore, the definition of an acceptable trade-off between these contributions is required.

3. CASE STUDY AND RESULTS

This section presents the application of the proposed reliability-based methodology to a SP Company operating worldwide in the packaging machine industry.

Figure 3 shows the historical SC and RC_{LT} observations for two selected components over three years. Component A counts 28 replenishments and 247 SOs, for an amount of 604 pieces demanded by the SP Customers. On the other hand, the historical number of replenishments for Component B is 23, with a total SP Customer demand of 182 pieces divided into 119 SOs. Hence, the provided dataset results in 23 and 18 SC observations for components A and B, respectively.

In Figure 3, the scatterplots report the historical observations of the two components. Each dot on the graph, e.g., $P_1(23; 65)$, represents a single SC observation and the corresponding RC_{LT}. Each plot also includes the parametric density functions $f(SC)$ and $g(RC_{LT})$ generated by the statistical analysis. In particular, the SC observations of Component A best fit with a Gamma distribution ($k = 1.08$; $\theta = 24.34$), while the parametric density function that best represents the historical RC_{LT} values is a Log-logistic distribution ($\mu = 3.15$; $\sigma = 0.37$). Regarding Component B, the probability plot analysis suggests a 2-parameter Weibull distribution for both SC ($\lambda = 11.01$; $\kappa = 1.53$) and RC_{LT} ($\lambda = 46.71$; $\kappa = 2.47$).

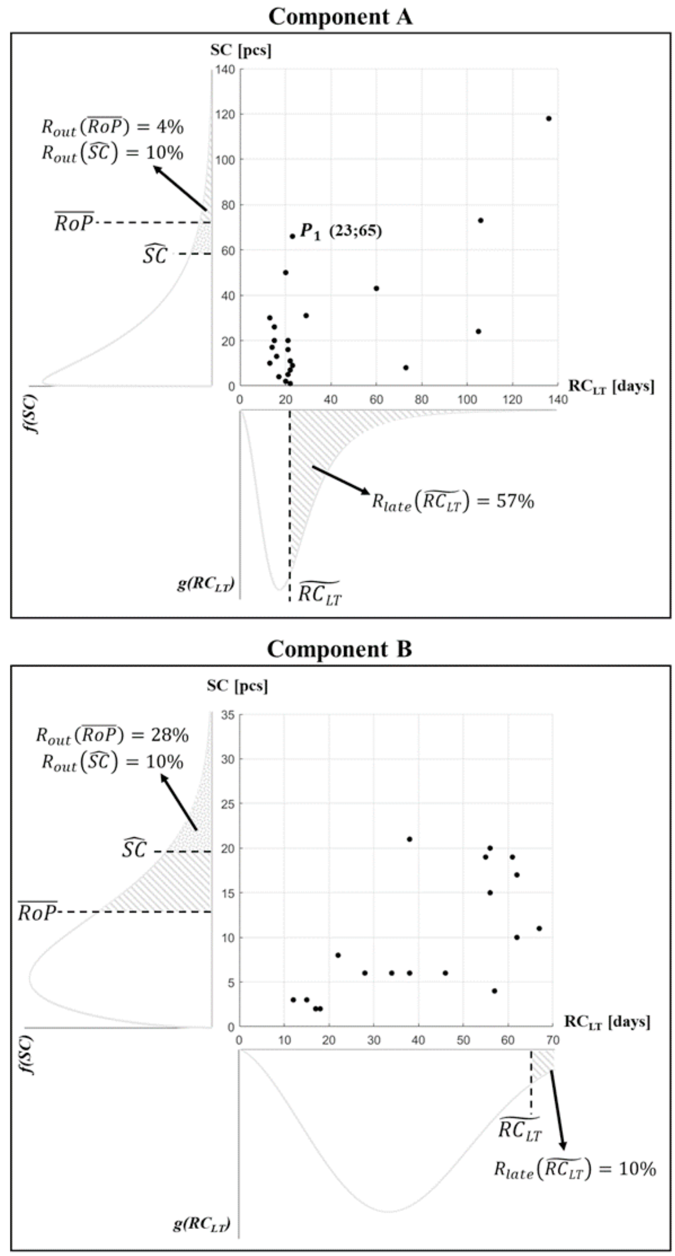

Figure 3. SC and RC_{LT} historical observations for Components A and B with the respective parametric density functions $f(SC)$ and $g(RC_{LT})$. ($\widehat{SC}$: target value for Safety Cover; $\overline{RoP}$: average reorder point; $R_{out}(RoP)$: stockout risk; $\widetilde{RC_{LT}}$: nominal lead time for replenishment; $R_{late}(\widetilde{RC_{LT}})$: late delivery risk).

For both the selected components, the SP Company sets a target service level of 90%, ensuring a maximum stockout risk, $R_{out}(\widehat{SC})$, equal to 10%. Given this target level, the SC inverse distribution function provides the corresponding SC value, named $\widehat{SC}$ in Figure 3.

The $\widehat{SC}$ values corresponding to a 10% stockout risk are equal to 59 and 19 pieces for Components A and B, respectively. The SP Company could implement these values as the new RoPs in a continuous spare parts inventory control system. Considering the supply lead time adopted by the SP Company planning system ($\widetilde{RC_{LT}}$ in Figure 3), $g(RC_{LT})$ provides the corresponding risk for a late supply delivery (i.e.,

$R_{late}(\widetilde{RC_{LT}})$). For Component A, the SP Company assumes $\widetilde{RC_{LT}}$ equal to 21 days. The expected risk for a late supply delivery is 57%. On the other hand, the $\widetilde{RC_{LT}}$ of Component B is equal to 65 days and corresponds to $R_{late}(\widetilde{RC_{LT}})$ equal to 10%. Both the estimated risks are reported in Figure 3 with the corresponding parametric density function.

Table 1. Economic comparison of the SC Scenario with the AS-IS Scenario.

	Component A	Component B
$C_{over}(RoP)$	- 23.6%	+ 81.7%
$C_{out}(RoP)$	+ 80.7%	- 69.3%
$C_{inv}(RoP)$	- 19.8%	+ 46.2%
$C_{emission}(RoP)$	+ 24.7%	- 31.6%
$C_{global}(RoP)$	+ 23.7%	- 31.5%

Table 1 compares the application of the suggested $\widehat{SC}$ values as the RoP in a continuous inventory control system (SC Scenario) with the actual system adopted by the SP Company (AS-IS Scenario). The inventory levels measured during the three years of analysis of the AS-IS Scenario reveal a historical average RoP (named $\overline{RoP}$) equal to 74 and 13 units for Component A and Component B, respectively. Figure 3 reports these values on the respective $f(SC)$.

In particular, considering Component A, the SC Scenario suggests a RoP level lower than $\overline{RoP}$, entailing a 19.8% reduction of the SP Company inventory cost. However, the new RoP level is associated with a 10% stockout risk, while the AS-IS Scenario reveals a lower value (5.6%). As a result, the SC Scenario reports a higher cost for stockout (+80.7%) and a lower cost for overstock (-23.6%). Due to the lower RoP level, the SC Scenario requires more replenishments for the SP Company, increasing the order emission cost by 24.7%. Overall, the SC Scenario of Component A shows a 23.7% rise in the $C_{global}(RoP)$ if compared to the AS-IS Scenario.

Regarding Component B, the SC Scenario suggests a higher RoP level, leading to increased inventory (+46.2%) and overstock (+81.7%) costs. However, the stockout risk is higher in the AS-IS Scenario (28% vs 10%). Therefore, the adoption of the $\widehat{SC}$ value as the RoP level determines a 69.3% reduction of the stockout cost. The higher RoP suggested by the SC Scenario also allows a 31.6% decrease in emission cost, requiring fewer replenishments. Finally, the $C_{global}(RoP)$ for Component B is lower in the SC Scenario, with a 31.5% save.

Concerning customer service level, evaluating other target values of stockout risk would affect the SP Company inventory control system with significant changes in the frequency of replenishment and inventory levels. Table 2 analyzes the RoP definition at different stockout risk values. It includes the number of replenishments (R_{num}) and the variation of $C_{global}(RoP)$ compared to the AS-IS Scenario. Considering four target values of stockout risk from 5% to 20%, Table 2 highlights the importance of a tailored approach to identify the best parameterization of the inventory planning system. Also, the different results obtained for the selected components demonstrate that there is no absolute value of risk to be assumed as the target for the whole portfolio of spare parts.

Table 2. Effects of RoP definition at different values of stockout risk; ($R_{out}(RoP)$: stockout risk; RoP: reorder point; R_{num}: number of replenishments; $\Delta C_{global}(RoP)$: variation of the global supply chain cost compared to the AS-IS Scenario).

	$R_{out}(RoP)$	RoP	R_{num}	$\Delta C_{global}(RoP)$
Component A	5%	77	8	- 3.2%
	10%	59	11	+ 23.7%
	15%	49	13	+ 48.5 %
	20%	42	15	+ 73.5%
Component B	5%	23	8	- 42.2%
	10%	19	10	- 31.5%
	15%	17	11	- 22.2%
	20%	15	12	- 13.5%

4. DISCUSSIONS AND CONCLUSIONS

The complexity of spare parts supply chains (SPSCs) requires tailored approaches to effectively plan and control the spare parts management and best satisfy customer demand. Guaranteeing spare parts availability is crucial to meet customer service requirements and provide high service levels. Many critical issues affect the SPSC, making spare parts management a real challenge for spare parts (SP) Companies. Variability in production and supply lead time, failure occurrence, and disruptive events like geo-political crises, pandemics, and natural disasters may have unpredictable consequences on the SPSC processes.

This study introduces a novelty approach to support resilient spare parts management, aiding SP Companies in production and logistic planning and control. A statistical variable named Safety Cover is defined to provide SP Companies with a reliability-based methodology to measure and control stockout risk and inventory levels. This study also considers some economic implications for SPSCs by including overstock and stockout costs in a global supply chain cost function.

The focus on stockout control requires SP Companies to define the target service level for each combination of components and customers. However, the efficacy of a certain target value is inherently contingent, and it is not generalizable to the entire spare parts portfolio. Consequently, future research should investigate the application of analytical and statistical models to identify the optimal stockout risk for each component.

The economic implication of stockout and unpredictable lead times warrant further investigations, particularly regarding the impact of the individual contributions within the global supply chain cost function. A sensitivity analysis can be a valuable tool in this investigation.

Moreover, the application of the presented methodology to different case studies is required to demonstrate its generalizability across other supply chain systems.

Finally, further research on comparing the proposed methodology based on Safety Cover with existing inventory planning models is required, addressing both the economic perspective and customer satisfaction.

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