A digital twin for spare parts supply chain planning and control

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Abstract: Geopolitical crises, raw materials shortage, the COVID-19 outbreak, and social and economic disruptions have significantly and unpredictably affected the supply chains' performance. Managing a wide variety of products, as well as the relationships with different suppliers and customers spread worldwide, have become more challenging, especially for companies operating with global and extremely complex supply chains. With its high service level requirements, the spare parts supply chain has been one of the most affected. This paper aims to introduce a digital twin system to support spare parts planning and control through a cost- and reliability-based model design. The proposed model minimizes the overall supply chain cost, including holding cost, power consumption for material handling, stock-out risk, and sale loss probability. This model aids decision-makers in managing spare parts inventory and controlling customers' service level under uncertainty. The digital twin is applied to a case study of an Italian automatic packaging machine company to support decision-makers on spare parts decisions.

Keywords: spare parts, visual digital twin, performance, Weibull

I. INTRODUCTION AND STATE OF THE ART

Many industries depend on the availability of high-value capital assets to provide their services or to manufacture their products. Spare part management is vital to many capital-intensive businesses, directly impacting the availability of high-value capital assets, essential to the operational processes [1]. Therefore, one factor determining the criticality of a spare part is the lead time of supply [2], which can be deeply affected by severe supply chain disruptions such as political conflicts, natural disasters, economic crises, and the COVID-19 pandemic [3,4]. Large supply lead time can result in:

1. lost revenues (e.g., stand-still of machines in a production environment);
2. customer dissatisfaction and possible associated claims (e.g., in airlines and public transportation);
3. public safety hazard (e.g., military settings and power plants).

Concerning different actors, the spare parts supply chain (SPSC) comprises different needs. Final customers want to respect their maintenance plans to avoid production loss, while suppliers and manufacturers pursue reducing the total supply chain cost for spare parts management. The challenge for a comprehensive and effective tool for SPSC management is the union of these two perspectives. Such an instrument aims to satisfy the spare parts demand, guaranteeing on-time deliveries, maintaining a high customer service level, suggesting a spare parts inventory management plan, and reducing the total supply chain cost. Therefore, finding the optimal setting for spare parts planning and control has become a major goal in order to simultaneously reduce costs and improve customer service in today's increasingly competitive business environment.

The literature presents several approaches to assess spare parts planning and control. [5] proposed a simple forecasting mechanism in order to estimate the spare part demand using the maintenance plan. Their models are applied to a real-world aircraft case study, producing cost savings if compared to traditional methods. Albeit the model application shows cost reduction, the information needed to feed such models makes this theory unfeasible for capillary SPSC. [6] proposed an innovative EOQ model linked to the material lot size analyzed from the beginning to the end of the order life. In particular, internal and external transportation costs, supplier location, and the different freight vehicle utilization ratio are considered in order to provide an easy-to-use methodology. [7] proposed a simulation-based modeling methodology to support the decision-making process related to the SPSC and maintenance operations in manufacturing systems. The use of a digital twin for SPSC performance evaluation is not widely covered in the literature, as shown by [8].

The literature relating to digital twin design currently offers limited insights into the approach required for their design. It often focuses on a relatively small physical entity [9], e.g., a manufacturing cell, rather than an entire factory or site. In order to cover this literature gap, the presented paper aims to introduce a digital twin (DT) to support spare parts planning and control in complex production systems subjected to corrective and preventive maintenance actions. The proposed DT adopts an original cost-based and reliability-based model that helps decision-makers identify the best inventory level per each stock-keeping unit. The proposed solution minimizes the total supply chain cost, including handling, logistics, and stock-out contributions.

The presented DT deals with the spare parts production and purchasing process, its lead time variability (i.e., "supply level"), and the sale-to-customer process (i.e., "demand level"). The statistical analysis of both purchasing orders and customers' orders of spare parts is devoted to quantifying the expected probability of some critical occurrences corresponding to logistics and operational events, such as the stock-out, the shipment delay, and the loss of customer orders.

The reliability-based model embedded in the DT combines statistical analyses on order quantity and supply lead time with reorder cycle theory, as shown in [10]. In such a theory, different variabilities are taken into account:

1. purchasing and production variability ("supply level");
2. demand variability in time and quantity ("demand level").

This study suggests some empirical, statistical, and reliability-based analyses to support supply chain performance assessment through a set of KPIs and the representation by a visual dashboard. Considering the entire supply chain of spare parts (i.e., from the supplier/manufacturer to the end user), and using cost-based and reliability-based models, the presented DT stands out from the other works mentioned in the literature.

The remainder of the paper is organized as follows. Section II introduces the DT and describes the proposed model structure and the levels of analysis. Section III presents an application to a case study of an Italian packaging machine company. Finally, section IV reports the conclusions and some directions for further research.

II. Methods and Materials

Figure 1 illustrates the data-driven approach and the conceptual framework that hosts the proposed model and DT for spare parts planning and control.

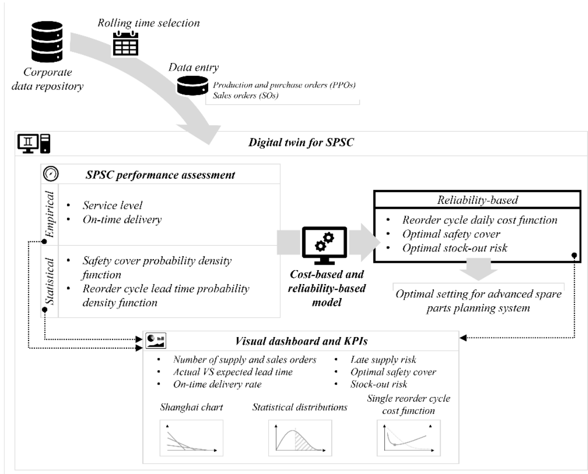

Figure 1. DT schema and data-driven approach

The corporate data repository gathers information from several data sources, including both supply and demand perspectives. A time window selection provides the data entry for the DT. However, the time window width varies the number of production and purchase orders (PPOs), sales orders (SOs), and stock-keeping units involved, affecting data entry dimension and results effectiveness.

The proposed DT allows the SPSC performance analysis by adopting empirical, statistical, and reliability-based approaches. The study of customer service levels and on-time delivery rates (empirical approach) enables the analysis of how the SPSC responds to the unpredictability of customers' demand and supply/purchasing lead time. The statistical approach accounts for the control of late deliveries and stock-out risks. It is based on the actual reorder cycle lead time (RC_{LT}) statistical distribution and the introduction of a specific statistical variable named safety cover (SC).

A cost-based and reliability-based model combines the empirical and statistical approaches into a reliability-based analysis. The model exploits both SC and RC_{LT} to generate a reorder cycle daily cost function whose minimization produces the optimal

SC value for each component and the expected stock-out risk.

As a result, the combination of these approaches supports the optimal setting for an advanced spare parts planning system.

Finally, charts, KPIs, and results from empirical, statistical, and reliability-based analyses are collected into a visual dashboard that helps decision-makers control SPSC performance. An in-depth illustration of each approach is reported below.

A. Empirical approach

The empirical study of actual SO quantities, lead times, and the comparison with their expected values support the company in targeting the most problematic components and supply chains. Also, analyzing actual PPO quantities, lead times, and expected values enhances the visibility of supply chain uncertainties.

B. Statistical approach

The study of actual RC_{LT} statistical distribution supports a statistical approach for spare parts management and deepens supply chain variability comprehension. In particular, RC_{LT} statistical distribution analysis provides the risk of observing a supply lead time higher than expected for each supplier and component. However, the statistical variable SC is designed to combine the supply and demand levels, conveying the variability of PPO lead time, SO lead time, and SO quantity. Thus, SC considers the minimal quantity of inventory to keep in stock in correspondence with the emission of a PPO to avoid stock-out during the supply lead time. Therefore, as shown in Figure 2, the SC related to a specific reorder cycle represents the sum of the SO quantities that occurred during its lead time. For instance, during the first RC_{LT}, two SOs appeared (SO_1 and SO_2) with a demand of one and three pieces, respectively. Keeping four pieces in stock at the PPO emission (T^e_1) would have prevented stock-out with the lowest possible starting inventory.

Given a historical horizon time, applying the probability plot to the observed values of SC per each component and reorder cycle gives decision-makers effective statistical tools to control the risk of stock-out [11]. The density function adopted to conduct the statistical analyses of RC_{LT} and SC historical values is the 2-parameter Weibull distribution. The Weibull distribution scale (λ) and shape (k) parameters convey a feature behavior, setting the position, skewness, and shape of its probability density function. A k value lower than 1 means a random behavior expressed by an exponential distribution, whereas higher values represent log-normal distributions.

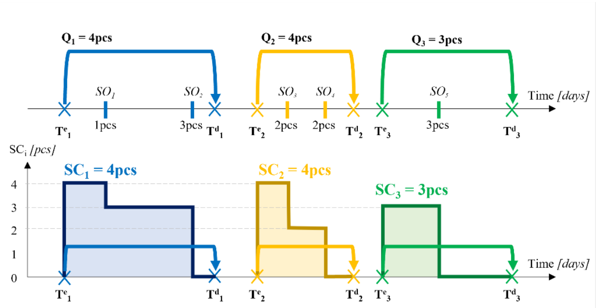

Figure 2. Safety cover representation; (Legend: Q_i: customer demand in period *i*; T^e_i: *i-th* PPO emission date; T^d_i: *i-th* PPO delivery date; SO_j: *j-th* sales order; SC_i: required safety cover for *i-th* PPO.)

The study of SC statistical distribution responds to the unpredictability of both lead time and demand, producing the risk of stock-out at any inventory level. Therefore, RC_{LT} and SC statistical distribution feed the proposed cost-based model, introducing the DT reliability-based approach.

C. Reliability-based approach

The proposed empirical and statistical analyses provide the basis for the cost-based and reliability-based model. For this purpose, early supply probability and stock-out risk must be expressed in economic terms. For what concerns early deliveries, an additional inventory cost is generated as the received material needs to be kept in stock before moving to the customer. This cost represents the daily costs incurred by the company for additional warehousing and material handling, including:

1. Structure cost (i.e., rental fee, depreciation, maintenance, general equipment, insurance, and supervisory cost);
2. Energy cost (i.e., energy and gas consumption cost);
3. Labor cost (i.e., handling and logistics cost).

Rather, stock-outs result in sales delays, generating a service level reduction. The generated delay can be quantified by defining a stock-out unit cost as the combination of the following contributions:

1. daily depreciation of a profit delay;
2. daily cost for a sales order loss;
3. daily cost for a customer loss.

The cost-based and reliability-based model defines a reorder cycle daily cost function by combining the above costs with the probability of early and late supply deliveries provided by the RC_{LT} statistical distribution. On-time supply delivery has a different impact on the total supply chain cost, as an early delivery produces additional inventory costs, while a late delivery generates stock-out costs. However, the magnitude of these costs depends on the SC value, as a greater inventory level reduces the size and the risk of stock-out, despite an increase in inventory cost.

Since SC represents a decision variable for the spare parts company, the model conveys a parametric approach to the DT, producing the expected daily supply chain cost for the single spare parts at different values of SC. Therefore, this cost comprises the following three contributions:

1. C_1, the average stock-out cost in case of a late supply delivery;
2. C_2, the average additional inventory cost due to an early supply delivery;
3. C_3, the inventory cost related to the perfectly on-time supply delivery.

As a result, the model identifies the minimum expected cost per component, providing the corresponding SC value and stock-out risk. Hence, the DT suggests decision-makers with the best inventory level to maintain in stock when emitting a PPO, balancing customers' needs and supply chain costs.

D. Visual dashboard and KPIs

A visual dashboard is proposed to help the SPSC performance assessment, supporting spare parts planning and control. In addition to the reorder cycle daily cost function and stock-out risk, a visual representation of SC and RC_{LT} is illustrated in a diagram named Shangahi chart (Figure 3). The graph comprises two sections.

1. An empirical section provides a chart for the SC-RC_{LT} pairs observed in the selected historical horizon time. This representation helps highlight the geopolitical, social, and economic contingencies affecting SPSC, allowing a dynamic analysis through a rolling time selection. For instance, Figure 3 reports the effects of raw material availability issues on a specific spare part. While the oldest observations (displayed with a lighter color in the chart) tend to present short supply lead times, the most recent ones (represented with a darker color) are affected in the production of spare parts by delays, showing a shift to the right on the x-axis. In addition, a contemporary growth in customer demand leads to superior SC values, increasing management complexity.
2. The statistical section of the graph comprises the SC and RC_{LT} probability density function distribution, f(SC) and g(RC_{LT}) respectively. Selecting a specific SC value for f(SC) (e.g., $\widetilde{SC}$) identifies the stock-out risk as the right-hand-side red area below the curve. Similarly, g(RC_{LT}) provides the risk of a late supply delivery at any RC_{LT} (e.g., $\widetilde{RC}_{LT}$).

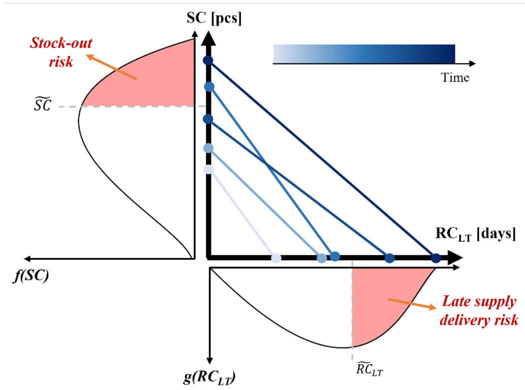

Figure 3. Example of a Shanghai chart

The proposed dashboard also includes a numerical section, providing a wide set of empirical, statistical, and reliability-based KPIs, e.g., the observed number of PPOs and SOs, the actual and expected lead times, the SC and RC_{LT} Weibull parameters, the average RC_{LT}, the risk of a late supply, the on-time delivery rate, the minimum reorder cycle daily cost, the optimal SC suggested by the cost- and reliability-based model, and the related stock-out risk.

III. Case Study and Results

This section presents the DT application to a case study of an Italian automatic packaging machine company that operates with a global network of suppliers, serving more than 100 countries. Since the large number and variety of machines sold and spread worldwide, spare parts management represents a crucial business for the company, counting over 300,000 different components and more than 32,000 PPOs and 195,000 SOs per year.

Figure 4 outlines the DT visual dashboard generated for a single component. The selected time window refers to the supply and sales data from January 2020 to February 2023. The spare part is produced by a single manufacturer and supplied to customers in 15 different countries worldwide for a total of 97 pieces demanded in three years. This data set comprises 13 purchasing orders and 40 SOs for the

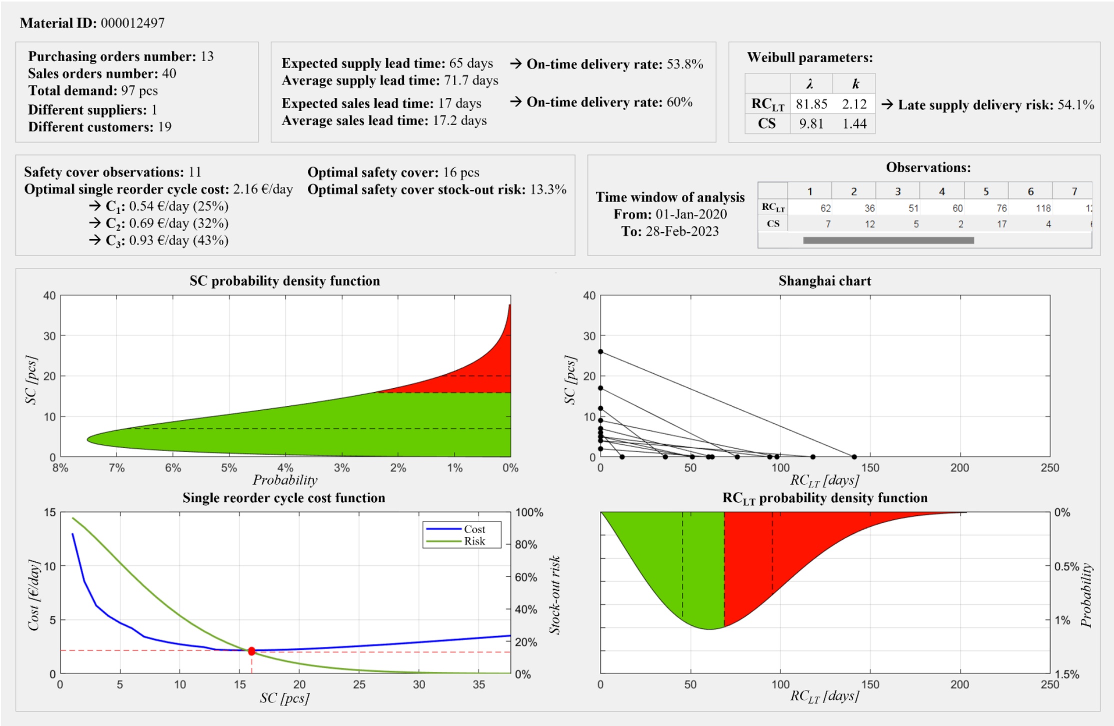

Figure 4. Visual dashboard produced for a single SKU

component, providing 11 SC-RC_{LT} pairs visually illustrated by the Shanghai graph in the top-right section of Figure 4.

The visual section of the dashboard also displays the SC and RC_{LT} probability density functions. Their Weibull distributions report a shape parameter of 1.44 and 2.12 respectively, conveying a log-normal trend. Therefore, given an expected supply lead time of 65 days, the estimated risk of late delivery is 54.1%. The company succeeded in customers' deliveries in 17.2 days on average, showing a 60% on-time delivery rate.

The dashboard also reports the graph for the reorder cycle daily cost function and its corresponding expected stock-out risk, identifying 16 pieces as the optimal SC, with a 13.3% stock-out risk. The total supply chain cost minimization results in 2.16 €/day, with stock-out costs (i.e., C_1) accounting for 25% and additional inventory costs (i.e., C_2) for 32%. However, while the total supply chain cost is not subjected to a significant variation with growing levels of SC, the corresponding stock-out risk witnesses a relevant reduction. An increase of five product units over the optimal SC value reduces the stock-out risk to 5% and generates an additional cost of about 7% (0.15 €/day).

Given a generic spare part, the optimal SC represents the inventory level corresponding to the reorder level in a reorder point inventory system or the reorder quantity in a push-based inventory system (e.g., the Material Requirement Planning).

The proposed DT and cost-based model support decision-makers in statistically controlling the expected risk and cost generated within the supply chain.

IV. Discussions and Conclusions

The complexity and importance of SPSCs require tailored tools in order to evaluate their performance and control their behavior. For this purpose, the paper introduces a DT to support spare parts planning and control in complex production systems subjected to corrective and preventive maintenance actions. An application is presented in Section III, providing a visual dashboard and several KPIs to account for SPSC performance from supply and demand perspectives.

A historical data rolling time analysis can outline the effects of geopolitical crises, raw materials shortage, the COVID-19 outbreak, and social and economic disruptions. An example is reported in Figure 5, where the supply on-time delivery rate and the optimal SC proposed by the model are compared in a three-month rolling analysis.

The supply on-time delivery rate decreases from 73.3% (i.e., T1, January 2017 – February 2020) to 53.8% (i.e., T13, January 2020 – February 2023), showing significant reductions in correspondence with the Russia-Ukraine conflict outbreak (i.e., observation T8). The corresponding optimal SC proposed by the model presents an increasing trend (+78%) due to the higher uncertainties affecting the supply chain.

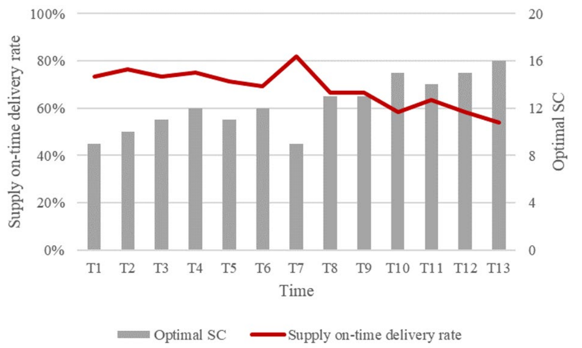

Figure 5. Rolling time analysis result

The proposed DT provides a data-driven and reliability-based approach to support spare parts management for each product individually. Further developments are required to define a more general spare part planning, looking at the whole set of components as a single entity and providing a wider view of the company. The perspectives embedded into the model can also be expanded to include the production cost at the manufacturer’s site and the stand-still of customers’ machines.

V. References

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