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Repairing smarter: Opportunistic maintenance for a closed-loop supply chain with spare parts dependency

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Abstract

Adopting a closed-loop supply chain enhances spare part provisioning through repair, remanufacturing, and recycling. However, poor maintenance of components can have severe consequences. Unlike traditional opportunistic maintenance methods that assume regular inspections or precise degradation monitoring, we propose a model that leverages historical repair data to replace worn components preventively. It considers the real-world workflow where parts are often restored only to a functional level. We study maintenance strategies for repeatedly repaired multi-component systems by applying preventive operations only during corrective repairs. Our model considers component ages, failure time distributions, and structural and economic dependencies, favoring collective over individual replacements for cost efficiency. Stochastic dependencies are mapped using Nataf transformation for component subsets, and a genetic algorithm identifies optimal maintenance strategies to reduce long-term operational costs by balancing maintenance against potential failure penalties. We demonstrate the effectiveness of our approach with a case study on MRI power supply machines, showing that preventive actions can cut early life failures by up to 50% and extend useful life by over a year. Sensitivity analysis reveals that logistic costs, interest rates, and planning horizons influence decisions. Opportunistic maintenance can reduce logistic costs and increase the lifetime of spare parts after repair. Integrating stochastic dependency is computationally efficient for industrial systems and can help predict failures more accurately.

Keywords: multi-component spare parts; opportunistic maintenance; reliability; stochastic dependence; Nataf transformation.

1. Introduction

Maintenance is a crucial element in asset life cycle management, as it directly affects the reliability and availability of assets and represents a significant portion of life cycle costs (Zhu et al., 2021). For instance, operations and maintenance costs for offshore wind farms can account
5 for up to a quarter of total life cycle costs (Papadopoulos et al., 2021; Irawan et al., 2017). To address these challenges, various maintenance strategies have been developed to optimize repair processes, minimize system downtime, and reduce maintenance expenses. For an overview of different maintenance strategies, refer to De Jonge and Scarf (2020) and Syan and Ramsobag (2019). A critical prerequisite for implementing any maintenance strategy is the availability of spare
10 parts. The unavailability of necessary spare parts can significantly delay maintenance activities,

leading to substantial financial losses (Hu et al., 2018; Zhang et al., 2022, 2021). Therefore, establishing and operating an effective supply chain of spare parts while minimizing operational costs is a critical operations management problem for companies.

A common industry solution is the closed-loop supply chain (CLSC) strategy, where failed spare parts, called Line Replaceable Units (LRUs), are recovered, repaired, and reintegrated into the supply chain. This process reduces the need for new parts, cutting operational costs and enhancing supply chain circularity. CLSCs have garnered substantial attention in recent decades in both academic and business circles (Diallo et al., 2017). Research in this area has primarily focused on strategic and tactical decisions such as supply chain network design (Moini et al., 2023; Govindan et al., 2017), remanufacturing production planning and inventory control policies (Qin et al., 2021), coordination mechanisms (Zhao and Zhu, 2017), channel management (Tombido and Baihaqi, 2022), and so on. However, much of this research assumes that repaired parts are as reliable as new ones (Zhang et al., 2021). This assumption often fails in practice due to aging components and potential repair-induced damage. For example, Figure 1 below shows real-world statistics of the average lifetime of a spare part vs. the number of repairs (data from our industrial partner). The lifetime after repair keeps decreasing as the number of repairs increases. Failing to account for these factors can lead to increased returns, reduced warranty profits, higher logistics costs, and potential loss of clients.

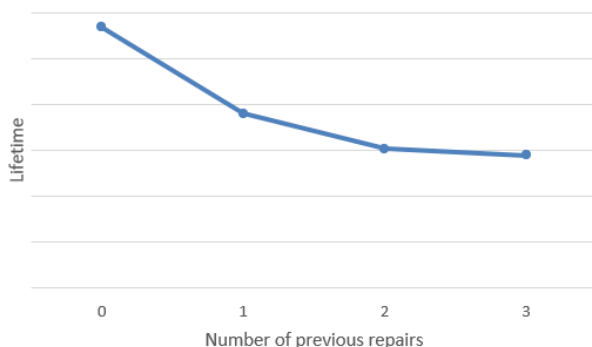


Figure 1: Average lifetime evolution after repair

As emphasized by Mirzahosseini and Piplani (2011), improving repair efficiency should take precedence over simply adjusting basestock levels in CLSC systems. One effective approach to enhancing repair efficiency is deploying preventive maintenance techniques, which can anticipate component failures before they occur. In this context, our paper proposes an **opportunistic maintenance (OM)** model designed to minimize long-term costs while maintaining the reliability of repaired spare parts. Unlike remanufacturing, which restores products to a like-new state, repairs address specific faults, leading to varying degrees of components' degradation. Thus, each component may require a tailored maintenance strategy.

Traditional OM models rely on either time-based criteria (Zhu et al., 2021; Mena et al., 2021) or condition-based assessments (Pinciroli et al., 2023; Zhu et al., 2019). However, both methods suffer from practical limitations. Time-based maintenance assumes the availability of known preventive maintenance windows. In contrast, condition-based maintenance assumes the capabil-

ity to accurately monitor degradation through sensors or regular inspections, allowing for timely interventions. In the context of spare parts repair, continuous monitoring of every component's degradation is economically unfeasible, and the only practical opportunity for preventive maintenance typically arises when a part fails and is returned for repair, making timely interventions
45 challenging.

Given these constraints, our proposed OM model leverages repair events as opportunities for preventive maintenance of aging but working components. This model evaluates each opportunity to determine which components require replacement, considering their varying degrees of wear and tear. These decisions can range from replacing a few key components to recommending the use
50 of an entirely new spare part. By carefully balancing maintenance costs with the reliability of repaired components, this model aims to reduce long-term operational costs within the CLSC.

Notably, when dealing with multi-component systems, considering component dependencies is essential for effective maintenance strategies. Olde Keizer et al. (2017) identify four key types of dependencies: economic, structural, stochastic, and resource. They also distinguish structural
55 dependencies between technical aspects, where one component's maintenance necessitates servicing others, and performance aspects related to system configuration. Economic and performance-based structural dependencies are the most studied due to their direct impact on OM performance (Rebaiaia and Ait-Kadi, 2022; Wang et al., 2019; Salari and Makis, 2020). However, technical dependencies receive less attention. For instance, Dinh et al. (2022) propose an OM strategy using a
60 directed acyclic graph (DAG) to model disassembly impacts. Our work builds on this by addressing technical structural dependencies to optimize repair times and minimize the negative effects of disassembly. Furthermore, research that integrates multiple dependencies remains limited. For example, Xu et al. (2024) develop a **condition-based maintenance (CBM)** model that addresses stochastic, economic, and resource dependencies, while Sun et al. (2021) incorporate economic,
65 stochastic, and disassembly impacts. Our paper advances this research by proposing an OM model that jointly considers structural dependencies from technical and performance perspectives, alongside stochastic and economic dependencies.

Stochastic dependencies, in particular, present significant computational challenges. Existing methods that utilize time-based data and maintenance records, such as Monte Carlo simulations
70 (Son et al., 2016; Ahmad et al., 2022) and copula-based approaches (Lin et al., 2021; Navarro and Durante, 2017), are often limited to small systems due to their computational intensity. To overcome these limitations, we propose a dimension reduction method that analytically approximates the joint distribution of dependent component lifetimes more efficiently. This approach employs a Nataf transformation to map correlated random variables from non-normal spaces to the standard
75 normal space, enabling the practical application of stochastic dependencies in larger, more complex systems.

Overall, taking a holistic and long-term approach to spare part maintenance can help orga-

nizations balance cost savings, quality, and environmental sustainability. By carefully considering factors such as product phase, component dependencies, and component ages, organizations
80 can design maintenance strategies to optimize system lifespan and performance while minimizing waste and environmental impact. This work extends the research of Boujarif et al. (2023) by integrating stochastic dependencies and offering a comprehensive analysis of their impact on CLSC efficiency. We propose an opportunistic replacement model that accounts for component ages, remaining useful life, and various dependency types, evaluated through case studies using data from
85 *GE HealthCare (GEHC)* Magnetic Resonance Imaging (MRI) machines. Our contribution to the CLSC models is to develop an opportunistic maintenance model for CLSC, as OM is used more often in practice but rarely studied in the CLSC literature. More specifically, the contributions of this paper include:

- Developing an OM model tailored to the closed-loop supply chain for spare parts, leveraging
90 maintenance records collected during repairs;
- Integrating multiple dependencies—economic, structural (technical and performance), and stochastic—within the maintenance model for a comprehensive analysis;
- Improving the existing method to evaluate repairable spare parts reliability under stochastic dependency using clustering techniques to group dependent components based on their
95 correlation coefficient and a Nataf transformation to build joint distributions.

Implementing these methods on GE HealthCare data showcases their accuracy in modeling repairable part reliability under dependency, with significant improvements in failure prediction, maintenance strategies, and overall system efficiency. This improved accuracy was evident in the substantial gains in reliability post-implementation, with some parts showing up to an increase
100 in reliability of 25%. Moreover, the opportunistic maintenance strategy extends the remaining useful life of parts, in some cases, by more than a year. Economically, the model demonstrates remarkable efficacy, achieving cost reductions of more than 5% due to lowered failure risks and a 42% overall reduction in early life failure total costs. These improvements are coupled with a notable decrease in CO_2 emissions, contributing to environmental sustainability.

An important insight from our study is the role of stochastic dependency in improving the
105 prediction accuracy of failures and enhancing the benefits of component changes. However, our findings indicate that a model without dependency consideration can still yield reasonably good results, especially for parts with a single critical failure component. Both models effectively predict early failures, and sometimes, disregarding dependencies may be more advantageous. These
110 insights emphasize the need to tailor maintenance strategies to the system’s specific characteristics, including component lifetimes and dependencies. Our approach offers a balanced solution for improving multi-component systems’ operational efficiency, reliability, cost-effectiveness, and sustainability.

The rest of the paper is organized as follows. Section 2 presents the state-of-the-art, and the
115 model formulation is described in Section 3. In Section 4, we describe the approach to modeling

stochastic dependency. We provide a study case based on real data with the description of the genetic algorithm operators and the optimization technique in Section 5. We discuss the results in Section 6. Section 7 discusses the developed strategy and derives managerial insights, and Section 8 summarizes the potential avenues for enhancing the model’s effectiveness and applicability. Finally, Section 9 concludes the paper and highlights future research.

2. Literature review

As shown in Section 1, the three main contributions of this paper lie in CLSC, opportunistic maintenance and reliability modeling considering dependencies. In what follows, we briefly review these three streams of research and then position the paper’s contributions within the existing literature.

2.1. Closed-loop supply chain

Research on closed-loop supply chains provides the theoretical foundation for discussions on circular economy, focusing on recovery options like repairing, recycling, and remanufacturing to reduce material needs, energy use, and waste, thereby enhancing profitability (Agrawal et al., 2019). Reviews by Liu et al. (2019) and Kerin and Pham (2020) cover advancements in remanufacturing, while Selviaridis and Wynstra (2015) explore performance-based contracting and the interaction between manufacturers and clients concerning repairable spares.

Most CLSC studies concentrate on strategic and tactical decisions such as network design and inventory policies, aiming to maximize profits and minimize environmental impact (Souza, 2013). For example, Zhang et al. (2021) analyze the pricing of remanufactured products, assuming they match the quality of new ones, while Tahirov et al. (2016) compare different production and remanufacturing models in CLSC. Moini et al. (2023) integrate inventory management with network design decisions, incorporating economic, environmental, and social sustainability dimensions using Life Cycle Assessment (LCA) techniques. Their model considers repair capacity, expertise, and demand uncertainty, employing a stochastic approach for more reliable decision-making. Additionally, Kim et al. (2018) propose a mathematical framework that incorporates a budget of uncertainty to address the variability in recycled materials and processes, ultimately leading to a more effective CLSC operation plan. This framework also considers the repair and production of spare parts, along with the strategic location of supplier production and repair centers.

However, most CLSC literature assumes repaired parts are as good as new, with few studies addressing the actual quality of repaired spares. Notable exceptions include Kim et al. (2007), who integrate reliability considerations into after-sales service management, calling for further research on long-term product reliability versus inventory decisions. Jin and Tian (2012) respond by combining reliability design with inventory optimization. Mirzahosseini and Piplani (2011) model a CLSC system that emphasizes improving component reliability and repair efficiency over adjusting basestock levels. Despite these efforts, quantitative models investigating the quality and

reliability of repaired items in CLSC are scarce (Diallo et al., 2017). Qin et al. (2021) optimize repairable spare parts provisioning in a multiregional market, considering failure rates but neglecting the degradation effect after each repair. In this paper, we intend to fill this gap by developing a quantitative, opportunistic optimization model to consider the reliability of the repaired spare parts and investigate its impact on CLSC.

2.2. Opportunistic maintenance

Opportunistic maintenance policy is a preventive strategy where functional components are replaced during downtime alongside any failed ones. Ab-Samat and Kamaruddin (2014) review OM strategies up to 2014, while Olde Keizer et al. (2017) focus on CBM with opportunistic replacement before 2017. Diallo et al. (2017) examine maintenance strategies for second-hand products up to 2017, highlighting the lack of opportunistic strategies in this area. We briefly review recent related works and then position the paper’s contributions within the existing literature.

The literature generally classifies OM works into time-based and condition-based approaches. Time-based maintenance schedules actions based on fixed thresholds like component age, irrespective of actual condition. For example, Wang et al. (2021) and Sun et al. (2021) propose an age-based opportunistic maintenance model for a two-unit series system. Zhu et al. (2021) formulate the problem as a two-stage stochastic linear integer model and develop a progressive-hedging-based heuristic algorithm to handle and solve large-scale problems. Mena et al. (2021) develop a mixed-integer linear program to optimize group maintenance within predefined time windows. In contrast, CBM relies on real-time data, allowing maintenance to be scheduled based on the actual condition of components. This approach is becoming more popular due to its efficiency (Pinciroli et al., 2023). For instance, Chateauneuf et al. (2018) and Zhu et al. (2019) adopt the risk-based measure to compare the risks of replacements or not. In contrast, recent studies by Nguyen et al. (2019) delve into integrating predictive maintenance techniques with real-time monitoring systems, offering a more proactive approach to maintenance scheduling and reducing the reliance on reactive measures.

Various dependency types are considered in OM literature when grouping maintenance operations. Olde Keizer et al. (2017) identify four main types: structural (static relationship between components), stochastic (degradation of one component affecting others), economic (cost benefits from combined maintenance), and resource (involving shared maintenance resources like spare parts or workers) (Yan et al., 2020; Wang and Zhu, 2021; Zhang et al., 2021, 2022). Recent studies introduce geographical dependencies addressing maintenance efficiency in dispersed systems (Nguyen et al., 2019; Zhu et al., 2024).

Among these dependencies, economic and performance structural dependency are most frequently studied due to their direct impact on OM performance (Xu et al., 2024). Research by Ma et al. (2018), Wang et al. (2019), and Salari and Makis (2020) explore CBM models that account for shared setup costs in grouped operations. Nguyen et al. (2022) develop a value decom-

position network algorithm to optimize the maintenance of series parallel system considering the
190 imperfect maintenance quality. Yang et al. (2022) build a deep reinforcement learning model to
optimize the condition opportunistic maintenance for redundant systems with arbitrary structures.
However, few address technical structural dependencies. For instance, Dinh et al. (2022) propose
an OM strategy using a directed acyclic graph (DAG) to represent disassembling impacts in a
six-component system.

195 Studies on stochastic dependencies include Wang et al. (2022), who examine OM in a "2-out
of-3" structure using Frank Copula, and Xu et al. (2021), who use a Markov decision process with
Monte Carlo simulation to model dependencies in a K-out-of-N. Zhou et al. (2022) use a multi-
agent reinforcement learning model to analyze the impact of economic, performance structural,
and stochastic dependency on a system with 12 components. However, research that considers
200 interactions among multiple dependencies remains limited. For example, Xu et al. (2024) formulate
a CBM model addressing stochastic, economic, and resource dependencies, while Sun et al. (2021)
examine economic, stochastic, and disassembly impacts, incorporating fixed costs for disassembly.

As seen from the reviewed literature, maintenance is considered either as scheduled or as
condition-based maintenance in existing OM models. However, such assumptions do not always
205 hold for CLSC. Scheduled maintenance is difficult to implement because it is hard to access the
parts once it leaves the repair center. Condition-based maintenance is hard to implement because,
economically, it is often unfeasible to monitor every component's degradation continuously. In
practice, for a spare part in a CLSC, the only practical opportunity for preventive maintenance in
a repair context is when the spare part fails and is returned to the repair shop. Therefore, in this
210 paper, we develop an OM model for CLSC that considers spare part failure as an opportunity for
preventive maintenance.

In the studies of maintenance policies, various dependencies have been considered. However,
existing opportunistic maintenance studies primarily focus on economic and performance-based
structural dependencies, with limited exploration of technical structural aspects. Further, these
215 dependencies are rarely considered in CLSC maintenance models. In this paper, we develop an
opportunistic maintenance model for CLSC that integrates economical, structural from technical
and performance aspects and stochastic dependency.

2.3. Multi-component system reliability considering dependencies

Assessing the reliability of complex systems comprising dependencies is one of the critical chal-
220 lenges to the reliability community. The degradation of individual components significantly affects
associated components, influencing the overall system transition from higher to lower performance
levels. Researchers often employ stochastic models that utilize a set of probability distributions
to describe failure rates of individual components and their interdependencies. One common ap-
proach is using fault tree analysis (FTA), a graphical method representing the system as a series
225 of events and their dependencies. The top event in the tree represents the system failure, and the

branches represent the different paths that can lead to this event. Wang et al. (2013) use FTA to structurally represent multi-component systems and describe the probabilistic behavior under common cause failure. Kabir (2017) notes that FTA suffers from various shortcomings, requiring much manual effort. Research has focused on simplifying dependability analysis by looking at how
230 to synthesize dependability information from system models automatically.

Another approach is the Markov model. These models represent the system as a set of states and the transitions between them. The states correspond to the different operational and failure modes, and the transitions represent how the system can change from one state to another. Ahmad et al. (2022) implement the Markov chain Monte Carlo algorithm to obtain a Bayesian estimation of
235 the system reliability model. Son et al. (2016) propose a systematic approach to Markov modeling for analyzing the dependability of complex fault-tolerant systems. However, Simpson and Kelly (2002) argue that Markov modeling is not correctly applied to repairable redundant systems, as the process ceases to be a Markov process. Zhang et al. (2019) use a Markov model to evaluate the reliability of a modular multilevel converter. They acknowledge that the large number of
240 sub-modules in the converter causes reliability evaluation to be challenging.

Other researchers use historical failure data and marginal distribution for components to compute system reliability as a joint distribution of component survival functions. Copula functions model the joint distribution of random variables by capturing their dependence structure without making assumptions about their marginal distributions. Navarro and Durante (2017) propose an approach for assessing the reliability of coherent systems with dependent components
245 using copula-based representations for residual lifetimes. Lin et al. (2021) develop a copula-based Bayesian reliability analysis method for parallel systems with dependent components, where the component failure probability and frequency are modeled separately. Other papers consider a specific copula-based approach to map the correlated variable with independent ones called the Nataf transformation. Nataf transformation is a method used in statistical analysis to transform a set of
250 correlated variables into equivalent independent variables. It simplifies the analysis by reducing the correlation between the variables. Xiao (2014) analyze the properties of the correlation coefficient in the Nataf transformation and propose a new method to evaluate it using a series expansion. Lin et al. (2020) present a probabilistic power flow (PPF) approach for high-dimensional correlated
255 uncertainty sources in operation based on the Nataf transformation. The method can model the uncertainties of power system parameters with continuous and discrete probability distributions and consider their correlations.

The literature presents multiple approaches to evaluate the reliability of multi-component systems under dependency. Some of these approaches require manual effort, while others are computationally expensive. To take advantage of the replacement records during previous repairs, we
260 decide in this paper to use the correlation coefficient to map the relationship between components failures. We developed a simplification methodology to apply Nataf transformation to evaluate

the reliability of the spare parts under stochastic dependency.

3. Modeling and problem formulation

265 We consider a CLSC of spare parts where the failed units in the field are directly replaced with a spare part from the CLSC inventory. The failed units are then shipped back to the repair center for refurbishment. Once repaired, these units re-enter the supply chain, ready to replace future failures in the field. The unit is repaired by replacing the failed components. In this paper, we assume that a spare part is always available in the CLSC whenever a repair is needed. This
270 assumption is justified by the presence of a central distribution center that manages inventory levels across various regional centers to meet client demands. This central hub is also responsible for sourcing spare parts from new suppliers and repair centers.

When a failed unit arrives at the repair center, it presents an opportunity to replace functional but aging components preventively, reducing the likelihood of future failures for spare parts within
275 the CLSC. In this paper, we develop an opportunistic maintenance optimization model to minimize the long-run operational costs of the CLSC while maintaining the reliability of the repaired spare parts to an acceptable level. For clarity, in this paper, the terms "spare part," "LRU," and "system" refer to the entire unit being maintained, while "component" refers to the individual elements within these units.

280 In the opportunistic maintenance optimization model, a maintenance opportunity occurs whenever a unit fails in the field and is returned to the repair center. Two choices exist for each functional component: replace it preventively when another component fails or use it without preventive replacement. Under the second decision, the item will either fail before the other components and lead to a system failure or survive until another fails. We can see that the optimization problem is
285 dynamic because each failure occasion creates a decision point. However, as soon as a replacement is made, one life cycle for a component is ended, and a new one starts with an identical time-to-failure distribution. The process continues until we finally dispose of the unit. Thus, unlike in the literature, where the opportunity for preventive replacement is undefined, we consider a one-time window to decide whether to replace the non-failed components.

290 Three types of dependencies are considered in the optimization model:

- Economic dependence means that the cost of maintaining several components together differs from the sum of their individual maintenance costs. It can be further classified into positive and negative economic dependence, depending on the impact on the total maintenance expense. We consider only the positive effects by assuming that the joint replacement of
295 several components is cheaper than the maintenance of components separately.
- Stochastic dependence occurs when one component's condition affects others' lifetime distribution. For instance, the failure of a component may induce a one-time damage effect on surrounding components, accelerating their degradation or even causing immediate failure.

This phenomenon is often observed in electronic devices, where a short circuit in one part can negatively impact others.

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- Structural dependence means that components structurally form a connected set such that the maintenance of one part requires the disassembly of others. A disassembly sequence exists between elements in the system, necessitating the dismantling of all preceding components in this sequence to reach a particular element for maintenance (Dinh et al., 2020). The disassembly operation may affect maintenance duration and introduce additional degradation to the disassembled components. This impact arises because disassembly often involves shocks or stresses that can increase the degradation levels of the affected components. For instance, Dinh et al. (2020) studied the impact of shock-induced disassembly on the degradation level of components. Although we do not model this effect mathematically in our current work, minimizing disassembly time by prioritizing components that are already dismantled for replacement can reduce this additional degradation.

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Given the practical challenges of continuous monitoring within a closed-loop supply chain, our model relies on maintenance logs as the primary data source, a common practice in sectors where continuous data collection is restricted due to economic or confidentiality reasons. These logs typically, as presented in Table 3 in Section 5.1, provide the ID of the repaired unit, the repair operation, and a binary state indicating the replacement of each component during the repair. This data allows us to model an aspect of stochastic dependency by prioritizing replacing components that frequently fail together. Although our approach does not assume a unidirectional dependency, it aims to model stochastic dependencies pragmatically by identifying patterns where certain failures are commonly linked, thereby supporting maintenance decisions that enhance system reliability and reduce potential downtimes.

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The objective of this opportunistic maintenance optimization model is, then, to select a set of components to be replaced preventively during each maintenance opportunity, so as to minimize the long-term operational costs over the planning horizon of T years while achieving minimal waste of residual lifetime. A minimum required reliability level is considered as an additional quality constraint.

325

To formally define the optimization model, let us introduce the following notation:

- $\zeta = [1, 2, 3, \dots, n]$: set of components in the spare part,
- $Cost_c$: price of component c ,
- Mul_c : the average lifetime of component c ,
- $RV_c = \frac{cost_c}{Mul_c}$: residual value per unit time of component c ,
- LC : labor cost per unit of time,

330

- $Cost_0$: logistic cost for each repair (shipping cost to replace the LRU with a new one at the client site),
- 335 • τ_c : disassembling time for component c ,
- a_c : age of component c ,
- $R_c(t)$: reliability function of component c ,
- $f_c(t)$: probability density function of failure time for component c ,
- $R_{sys}(t; a_1, a_2, \dots, a_n) = h(R_1(t; a_1), \dots, R_n(t; a_n))$: reliability function of the spare part as a
- 340 function of reliability of its components,
- $f_{sys}(t; a_1, a_2, \dots, a_n)$: probability density function of system lifetime,
- T : planning horizon,
- r : interest rate,
- $D = (D_{ij})_{\zeta X \zeta}$: disassembly matrix for the system,
- 345 • s_c : state of component c ,
- $s_c = \begin{cases} 1, & \text{if component } c \text{ is in a failed state,} \\ 0, & \text{otherwise,} \end{cases}$
- $T_{warranty}$: period during which we consider all the failures as early failures,
- R_{min} : minimum required reliability after repair.

One of the characteristics of spare parts reparation is that the components may have different

350 ages with a significant variance; the fragile ones usually would have shorter lifetimes, while the robust items would have relatively larger lifetimes. Therefore, estimating the unit reliability is not straightforward. We propose to express the unit reliability R_{sys} as a function of component reliability and age. For example, for multi-independent units in series, the reliability of the part can be expressed as $R_{sys}(t) = \prod_{c \in \zeta} R_c(t; a_c)$.

355

We then formulate the optimization problem as follows.

Decision variables: we define the binary decision variable x_c for each component c , with

$$x_c = \begin{cases} 1, & \text{if component } c \text{ is replaced preventively,} \\ 0, & \text{otherwise.} \end{cases}$$

Constraints: In this model, it is assumed that a failed component can always be detected and

360 replaced correctively. If $s_c = 1$, then the component c should not be considered for preventive maintenance as it has been correctively replaced. As a result, we have

$$x_c + s_c \leq 1, \forall c \in \zeta. \quad (1)$$

Furthermore, one of the model objectives is to maximize the reliability of the spare part after repair. The warranty period plays a crucial role in product support, as it defines the duration during which the manufacturer is obligated to repair or replace defective parts. This period directly impacts customer satisfaction, brand reputation, and the financial liability of the manufacturer. Ensuring that repaired spare parts function reliably throughout the warranty period is essential for optimizing costs and maintaining customer trust. Today, most products come with warranty contracts driven by competition, industry standards, and customer expectations (Luo and Wu, 2018). Manufacturers often view warranty costs as overhead and face pressure to control these expenses. For instance, Wang et al. (2020) examine the impact of customer delays on preventive maintenance policy optimization and associated warranty costs. Additionally, Zheng and Zhou (2021) compare three preventive maintenance policies for products sold with a free repair warranty, analyzing the conditions under which each policy proves most cost-effective.

$$\frac{R_{sys}(T_{warranty}; a_1(1 - (x_1 + s_1)), \dots, a_n(1 - (x_n + s_n)))}{R_{sys}(0; a_1(1 - (x_1 + s_1)), \dots, a_n(1 - (x_n + s_n)))} \geq R_{min}. \quad (2)$$

The chance constraint in Eq.(2) ensures that the reliability of the spare part after repair meets or exceeds the minimum required reliability R_{min} during the warranty period, thus maximizing the likelihood that the spare part will not fail within this critical timeframe. The ratio written in the equation represents the conditional probability of the unit surviving the warranty period, given its survival probability immediately after repair at ($t = 0$). This is crucial because not all components are new after repair. The term $a_i(1 - (x_i + s_i))$ models the age reduction for component i either due to failure or preventive replacement.

Objective function: An optimal solution minimizes the total cost of maintenance, denoted by TC , which consists of four parts, as shown in Eq. (3).

$$\mathbf{min} \quad TC = C_r + C_w + C_f + C_L, \quad (3)$$

Where C_r represents the total costs due to replacement, including corrective and preventive replacements, and can be calculated as

$$C_r = \sum_{c \in \zeta} (x_c + s_c) \cdot Cost_c. \quad (4)$$

The second term, C_w , is a penalty cost penalizing the unused remaining life of the components to be replaced preventively. It is given by

$$C_w = \sum_{c \in \zeta} x_c \cdot \frac{RV_c}{R_{sys}(0; a_1(1 - s_1), \dots, a_n(1 - s_n))} \cdot \int_0^{+\infty} t f_c(t; a_c) dt. \quad (5)$$

The residual value per unit time of a component, denoted by RV_c , monetizes the useful life of a

component based on its purchase price and its mean time to failure. Suppose the mean residual
 390 life of a component is MRL . The penalty cost for preventively replace is calculated as $RV_c \cdot MRL_c$.
 Eq. (5) gives the loss value of the selected items since a portion of their life is lost for opportunistic
 activity. Note that the mean residual life is calculated given the condition that at $t = 0$, the failed
 components are replaced correctively, and the system is working after the corrective replacement.
 This assumption is justified, as post-repair testing is routinely performed to verify the effectiveness
 395 of the repair. Consequently, the mean residual life calculation assumes the system is fully functional
 following any necessary corrective actions, offering a realistic foundation for informed preventive
 maintenance decisions.

The third term, C_f , represents the expected cost due to the failure of the repaired spare parts
 during the planning horizon. It is assumed that a spare part enters the CLSC and is immediately
 400 installed in the field once repaired. When the repaired spare part fails, a logistic cost $Cost_0$ must
 be counted. This cost includes shipping the LRU to the client site, system downtime, and onsite
 maintenance activities for replacing the failed unit. However, since this cost often occurs in the
 future, its *present value* is calculated to evaluate its value at the planning time.

The Present Value Method compares all future payments over a certain time to the present
 405 time. The present value, say PV , is the amount of money that should be deposited into the bank
 now at a certain interest rate r to pay for an outlay C after $\Delta.T$ years. It is computed as follows.

$$PV = C \cdot (1 + r)^{-\Delta T}. \quad (6)$$

During the planning horizon $t \leq T$, the conditional probability of failure after reparation can
 be expressed as,

$$P(T_{sys} < t) = \frac{F_{sys}(t; a_1(1 - (x_1 + s_1)), \dots, a_n(1 - (x_n + s_n)))}{R_{sys}(0; a_1(1 - (x_1 + s_1)), \dots, a_n(1 - (x_n + s_n)))}. \quad (7)$$

410 For the replaced components (either correctively or opportunistically, *i.e.*, $x_c + s_c = 1$), their age
 would be restored to zero, while the age of the other components remains the same. So for a small
 variation of time, this probability can be expressed using an approximated probability density
 function (*pdf*) of the system f_{sys} , so the present value of the logistic cost is $Cost_0 \cdot (1 + r)^{-t}$. Thus,
 the total present value of the expected cost of failure during the planning horizon, C_f , can be
 415 expressed as

$$C_f = \frac{Cost_0}{R_{sys}(0; a_1(1 - (x_1 + s_1)), \dots, a_n(1 - (x_n + s_n)))} \int_0^T \frac{f_{sys}(t; a_1(1 - (x_1 + s_1)), \dots, a_n(1 - (x_n + s_n)))}{(1 + r)^t} dt. \quad (8)$$

We can note that economic dependence is intricately modeled through the interaction between
 C_r and C_f as detailed in equation (3). The replacement cost C_r optimizes the cost-effectiveness

of joint component replacements, in clear contrast to separate maintenance strategies. In separate maintenance—where certain components are replaced during a scheduled event and others are deferred until future failure—overall costs are typically higher due to increased logistics expenses and prolonged downtime, as quantified in Eq. (8). By prioritizing joint replacements, the model strategically reduces both the direct costs of replacements and the consequential expenses associated with future failures. This approach reduces the risk of imminent failures and strongly supports joint replacement strategies when component failure risk is high, enhancing economic efficiency and lowering long-term operational costs.

The last cost term in Eq. (3), C_L , represents the labor costs incurred during the maintenance process of the spare part. In this paper, we assume that the labor costs are proportional to the total time needed to disassemble the spare parts and replace the needed components. Structural dependency plays an important role when evaluating C_L , as replacing some components might require disassembling others based on their interrelated structural arrangements. We use an approach developed by (Dinh et al., 2020) to calculate the total maintenance time for a component group. Based on the structure connection between components, the disassembly matrix D is constructed. The elements of the matrix are binary coefficients. The parameter $D_{i,j} = 1$ if component j must be disassembled to reach component i for maintenance. The cumulative disassembling time of a component c , denoted by τ_c^D , can be defined as the sum of disassembling times for all the components on the path of disassembly. It is given by

$$\tau_c^D = \sum_{k \in \zeta} \tau_k \cdot D_{c,k}. \quad (9)$$

For a group of components, there may be some intersections between the disassembly path of different items. As a result, the disassembly duration of the intersection nodes must be counted only once, even if it appears on several ones. Eq. (10) provides the replaced components' total disassembly time, denoted by τ_{group} .

$$\tau_{group} = \sum_{c \in \zeta} (s_c + x_c) \cdot \tau_c^D - \sum_{c \in \zeta} \tau_c^D \cdot \max\left(\sum_{k \in \zeta} (s_k + x_k) \cdot D_{k,c} - 1, 0\right), \quad (10)$$

where the first term represents the total disassembly duration of all replaced components when replaced separately; the second term is the time saving due to intersections among the disassembly paths. Note that $\sum_{k \in \zeta} (s_k + x_k) \cdot D_{k,c}$ represents the total number of components in the replaced group that have component c on their disassembly path. If there is no intersection, the second part in Eq. (10) equals zero. Therefore, the total labor cost is the total reparation time times the labor cost per time unit, *i.e.*,

$$C_L = 2 \cdot LC \cdot \tau_{group}. \quad (11)$$

Note that to replace a component, the old one must first be removed, and a new one installed.

That is why it is necessary to increase the maintenance costs in Eq. (11) by a factor of 2.

4. System reliability modeling considering stochastic dependency

450 Computing the joint distribution of component lifetimes is critical to consider the stochastic dependency in optimization models. As reviewed in Section 2, existing system reliability models that consider stochastic dependencies like Monte Carlo simulation (Son et al., 2016; Ahmad et al., 2022) and copulas (Lin et al., 2021; Navarro and Durante, 2017) share a common shortcoming: they are computationally expensive and may not be feasible for high-dimensional problems. Faced
455 with this challenge, we propose a dimension reduction method to compute the joint distribution of dependent component lifetimes in Section 4.1. Then, the joint distribution of the dependent clusters are calculated by a Nataf transformation (Section 4.2).

4.1. Components clustering

To derive the dependent clusters, we first calculate the covariance coefficients among each pair
460 of components from their historical repair data. We construct a distance matrix $H = (h_{i,j})$ between components based on the correlation coefficients among them $R = (\rho_{i,j})$; ($h_{i,j} = 1 - |\rho_{i,j}| \forall i, j$). It is easy to verify that by defining distances like this, the stronger the dependencies among a pair of components, the smaller the distance between them. The components are, then, clustered based on the distance matrix using Agglomerative Hierarchical Clustering algorithm (Sasirekha and Baby,
465 2013). This technique is the most common type of hierarchical clustering used to group objects in clusters based on their similarity. **The algorithm begins by considering each object as its own individual cluster. It then iteratively merges pairs of clusters until a single cluster encompassing all objects is formed.** The result is a tree-based representation of the objects. To select the best clustering configuration, the distance δ between groups is varied from 0 to 1 by a step of 0.1 to
470 extract all distinct grouping possibilities. Then, we construct the reliability distribution for every cluster in each configuration.

We assume each cluster **functions as an independent super-component, with the failure of any component within a cluster resulting in the failure of the entire cluster. Component failures within each cluster are interdependent. Based on these assumptions, we reconstruct the replacement
475 history for each group and calculate the super-component's revised time-to-failure.** The reliability function is then estimated by fitting the best distribution model. The system reliability is then constructed under the independence assumption as follows for a series system, where Ξ is the set of formed clusters:

$$R_{sys}^*(t) = \prod_{g \in \Xi} R_g(t; a_g). \quad (12)$$

We evaluate the likelihood and the number of components by groups to select the best config-
480 uration. The objective is to choose the threshold δ that minimizes the number of components by group and maximizes the likelihood of system time-to-failure distribution. Similar to the *Akaike*

information criterion (AIC) metric, we create an index to evaluate the best solution. For a statistical model of some data with a number k of estimated parameters and a maximized value L of the likelihood function, the usual AIC value is the following $AIC = 2k - 2\ln(L)$. The objective of AIC is to minimize the number of parameters k while maximizing the likelihood. In our case, we consider k as the maximum number of components per group.

4.2. Nataf transformation

After selecting the best grouping configuration using the approach explained in Section 4.1, a Nataf transformation is used to compute the joint distribution for each formed group of components. For a group of component g in a series system, the survival function $R_g(t)$ can be expressed as follows.

$$\begin{aligned}
 R_g(t) &= P(\min_{c \in g}(X_c) \geq t) \\
 &= P\left(\bigcap_{c \in g} X_c \geq t\right) \\
 &= 1 - P\left(\bigcup_{c \in g} X_c \leq t\right) \\
 &= 1 - \sum_{c \in g} F_c(t) + \sum_{1 \leq c_1 \leq c_2 \leq n_g} P(X_{c_1}, X_{c_2} \leq t) + \dots + (-1)^k \sum_{1 \leq c_1 \leq c_2 \leq \dots \leq c_k \leq n_g} P(X_{c_1}, X_{c_2}, \dots, X_{c_k} \leq t) \\
 &= 1 + \sum_{1 \leq k \leq n_g} (-1)^k \sum_{1 \leq c_1 \leq c_2 \leq \dots \leq c_k \leq n_g} P(X_{c_1}, X_{c_2}, \dots, X_{c_k} \leq t).
 \end{aligned} \tag{13}$$

Nataf transformation was proposed by Liu and Der Kiureghian (Liu and Der Kiureghian, 1986) to model correlated random variables. Given the marginal probability density functions for a vector of random variables, Nataf transformations map variables from any non-normal space to the standard normal space and vice versa. It can be decomposed into three parts as follows (Lebrun and Dutfoy, 2009).

$$u = T_N(X) = T_3 \circ T_2 \circ T_1(X) \tag{14}$$

where :

$$T_1 : X \rightarrow W = [F_{x_1}(x_1), \dots, F_{x_n}(x_n)]^T,$$

$$T_2 : W \rightarrow Z = [\Phi^{-1}(w_1), \dots, \Phi^{-1}(w_n)]^T,$$

$$T_3 : Z \rightarrow U = L^{-1}Z,$$

where $\Phi^{-1}(\cdot)$ is the inverse CDF of the standard normal vector Z , F_{x_i} is the CDF of the component x_i , and L represents the lower triangular matrix obtained from the Cholesky decomposition of $R_Z = (\rho_{i,j}^Z)$ the correlation matrix of the standard normal vector Z . The joint probability of the random vector X is then formulated as

$$P(X \leq t) = P(X_1, X_2, \dots, X_n \leq t) = \Phi_{R_Z}(\Phi^{-1}(F_{x_1}(t)), \Phi^{-1}(F_{x_2}(t)), \dots, \Phi^{-1}(F_{x_n}(t))). \tag{15}$$

The major obstacle to Nataf transformation is to evaluate the equivalent correlation matrix in the standard normal space. More specifically, it requires to calculate $(\rho_{i,j}^Z)(i \geq j)$ for each entry $(\rho_{i,j}^X)$ of R_X the correlation matrix of the random vector X . According to (Lebrun and Dutfoy, 2009), we can write $\rho_{i,j}^X$ as a function of $\rho_{i,j}^Z$ as follow

$$\rho_{i,j}^X = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left(\frac{x_i - \mu_i}{\sigma_i}\right) \left(\frac{x_j - \mu_j}{\sigma_j}\right) \cdot \phi_2(z_i, z_j, \rho_{i,j}^Z) dz_i dz_j, \quad (16)$$

505 where μ_i, σ_i are the mean and the covariance of random variable x_i . We use linear search (Xiao, 2014) to evaluate the new correlation matrix as detailed in Algorithm 1.

Algorithm 1 Linear algorithm search

```

if  $\rho_{i,j}^X \geq 0$  then
     $a \leftarrow \rho_{i,j}^X$ 
     $b \leftarrow 1$ 
else
     $a \leftarrow -1$ 
     $b \leftarrow \rho_{i,j}^X$ 
end if
Initialize search interval  $\rho_{i,j}^Z \in [a, b]$ 
Fix the error  $\Delta$ 
while  $b - a \geq \Delta$  &  $\rho_{i,j}^{X*} \neq \rho_{i,j}^X$  do
     $\rho_{i,j}^{Z*} \leftarrow \frac{b-a}{2}$ 
    Evaluate  $\rho_{i,j}^{X*}$  using Eq.(16)
    if  $\rho_{i,j}^{X*} > \rho_{i,j}^X$  then
         $b \leftarrow \rho_{i,j}^{Z*}$ 
    else
         $a \leftarrow \rho_{i,j}^{Z*}$ 
    end if
end while
 $\rho_{i,j}^Z \leftarrow \rho_{i,j}^{Z*}$ 

```

5. Industrial case study

We illustrate in this section an application of the developed model based on an actual industrial case from our industrial partner GE HealthCare. First, we present the historical data and the approach to extract the reliability functions in Section 5.1. Then, we explain the solution technique used to solve the optimization problem (Section 5.2).

5.1. System description and data collection

GEHC is one of the global leaders in sales and services of medical systems, notably those of medical imaging, with 4 million systems installed in more than 160 countries. Because of the criticality of its products (medical devices) and the technological characteristics of its components, GE HealthCare offers a maintenance service to its customers. The service's main objective is to ensure its products' reliability (reducing the failure rate) while reducing unavailability simultaneously. As the spare parts are expensive and disposal of the failed parts creates circularity problems, a CLSC is implemented in GEHC.

520 In this study, we implement the developed OM optimization model on the power supply of MRI machines and investigate its strategic impact on the efficiency of the CLSC. The spare part under consideration is composed of 11 components connected in series. Figure 2 illustrates the physical structure and disassembling order of these components provided by our industrial partner, while Table 1 details the real disassembly times required for each component. In Figure 2, "(0)" represents the cover of the spare part. For example, components 4, 5, and 7 must be disassembled before component 10 can be replaced. Table 2 also provides the purchase prices for new components and their mean useful lifetimes (Mul) in unit time (u.t.).

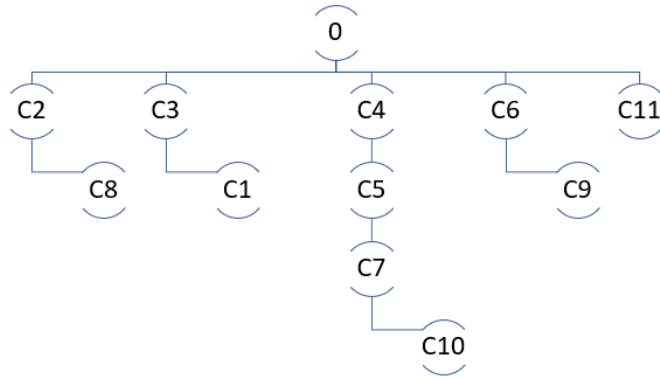


Figure 2: System's structure

Table 1: Components' dismantling time

Component	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Disassembling time (u.t)	3	1	1.5	0.2	2	4.5	9	4.5	1	1	1

Table 2: Costs parameters

Component	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Component cost (U.C)	22	24	6	43	140	2	34	23	6	9	8
Mul (u.t)	71k	22k	54k	44k	1.5k	16k	68k	183k	37k	58k	24k

GEHC's spare parts supply chain is so particular because its efficiency mainly depends on the quality of its repaired parts. The repair center annually provides around one thousand repaired power supplies to maintain thousands of MRI systems. Besides, depending on forecasted demand and stock levels, one part can be reallocated multiple times to different warehouses worldwide before being installed on a system, which makes gathering parts' lifetime data challenging. Different information systems and databases are used to store maintenance and logistic data. We developed an algorithm to extract repair information and lifetime data for each LRU.

535 We have collected 13,200 operating time and maintenance records for 7,514 spare parts. 3,490 LRUs were repaired multiple times. We consider the operating time of the functioning parts to be censored. We randomly selected 260 LRUs that were repaired multiple times with different ages and multiple failed components. We apply the optimization model on the selected parts for a planning horizon of 730 *Unit of time (u.t)*. The remaining records are used to build system reliability functions. Table 3 represents an example of the data format. Column **ID** and **Repair**

Number are the part’s serial number and repair record. The functioning parts are marked with value 1 in column **Censored**. Column **Time to failure** represents the observed time to event before each repair. The remaining columns represent the failed components. A value equal to 1 for a component C_i represents its failure.

Table 3: Example of data format

ID	Repair Number	Censored	Time to failure	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
1	0	0	1260	0	0	0	1	1	0	0	0	0	0	0
1	1	0	1319	0	0	0	0	1	0	0	0	0	0	0
1	2	1	969	0	0	0	0	0	0	0	0	0	0	0
2	0	0	2159	0	0	0	0	1	0	0	0	0	0	0
2	1	1	1410	0	0	0	0	0	0	0	0	0	0	0
3	0	0	1675	0	0	0	0	0	0	1	0	0	0	0
3	1	0	1873	0	0	0	0	1	0	0	0	0	0	0
3	2	1	2628	0	0	0	0	0	0	0	0	0	0	0

5.2. Solution approach

Our objective is to minimize the overall maintenance costs (3)—including replacement, waste, labor, and expected failure costs—while ensuring that the system meets a minimum reliability after the repair. It can be shown that the complexity of this optimization model is equivalent to a Multi-Dimensional Knapsack Problem (MDKP), a well-recognized NP-hard challenge that involves selecting items to maximize value without exceeding specific capacity limits (Puchinger et al., 2010). Therefore, our optimization is also NP-hard.

To demonstrate its equivalence to an MDKP, we note that the maintenance actions in our model correspond to items in an MDKP, where minimizing costs aligns with an MDKP’s objective of maximizing negative costs or minimizing positive costs. The reliability constraint in our problem mirrors the capacity constraints of the MDKP, ensuring system reliability meets or exceeds a certain level after maintenance. Since the opportunistic maintenance optimization model is NP-hard, we develop heuristic and approximation methods, like genetic algorithms, to find near-optimal solutions, given the impracticality of exact solutions for large instances.

Furthermore, we incorporate a model that estimates lifetime distributions from data presented in Table 3 while considering stochastic dependencies as explained in Section 4. The challenge is compounded by the need to calculate conditional reliability to evaluate failure costs (8), which hampers the simplification of the objective function. Considering the binary choices for each component and the exponential number of possible solutions, we employ a binary genetic algorithm to achieve a near-optimal strategy, acknowledging the problem’s NP-hard nature and the complexities involved.

Genetic algorithms (GAs) are a metaheuristic optimization technique well-suited for tackling problems with numerous local optima or non-convex landscapes. They excel at efficiently searching large solution spaces to identify global optima, without requiring the gradient of the objective function, and are easily adaptable to parallel computing architectures. The steps for solving the opportunistic replacement model are detailed in Algorithm 2.

We represent the genes as binary variables and consider a GA with 40 generations and a population of 8 chromosomes. We reduce the search space by fixing the failed components variables x_c to 1 to satisfy Constraint (1) because they should not be replaced opportunistically. We set the fitness value for solutions that do not meet system reliability constraint after repair (2) to equal a very large number. The classic genetic algorithm chooses a single fixed mutation rate for all solutions, regardless of their fitness values. As a result, mutations can disturb good and bad chromosomes equally. We use the adaptive technique with two fixed probabilities $p_{max} = 1$ for the low-quality solutions and $p_{min} = 0.4$ for the good ones. The bad solutions have a fitness value less than the population's average, while the high-quality chromosomes have a higher value. We terminate the algorithm evolution if the fitness does not change for 10 consecutive generations; after that, we reset the population and rerun the GA. After 4 times of execution, we select the best solution provided. Since the first objective is to decide whether to repair or scrap the parts, the first genetic algorithm is initialized using the corrective solution and the one that suggests consuming all the components. For the other GA, we initialize the population with the two best solutions and the two worst solutions. In our case, the fitness function is computationally expensive because of the integral calculations. In order to minimize execution time, we save the evaluated individuals' scores so they can easily be extracted if the solution has already been evaluated in previous iterations.

For the model parameters, We consider logistic cost equal to 750 *Unit of Cost (u.c)* and an interest rate of 15%. To evaluate the model, we define two metrics:

- The net benefit, denoted by NB , is the difference between the cost TC_0 of the corrective solution ($x_c = 0, forc \in \zeta$) and the best solution found by the GA:

$$NB = TC_0 - TC_{best}. \quad (17)$$

- The benefit ratio, denoted by $NB\%$, is the saved ratio of the total corrective cost:

$$NB\% = 100 \cdot \frac{NB}{TC_0}. \quad (18)$$

6. Numerical Experiments

This section provides the results of our opportunistic strategy on the test subset. As explained in Section 5.1, we selected 260 spare parts that were repaired multiple times to test the performance of opportunistic maintenance. First, we present the performance of the clustering method described in Section 4 to model dependency in Section 6.1. Then, we describe the efficiency of the solution approach in Section 6.2. Finally, we present the opportunistic maintenance effect on parts reliability in Section 6.3.

using the Pearson method (Li et al., 2012). Figure 3 shows the obtained correlation matrix. By visually examining the results, it can be seen that there are different grouping possibilities. We can either group $C1$, $C2$, with $C3$ and $C7$ with $C10$ or focus on grouping only $C1$ with $C3$ and consider the remaining components independent. The grouping algorithm presented in Section 4.1 is then used to determine the best grouping strategy by maximizing the likelihood and minimizing the number of components per group. The results of the grouping algorithm are given in Table 4, where thresholds and groups provide the minimum correlation level selected and the formed groups, respectively; **N_super_comp** and **Max_comp_group** are the number of formed groups and the maximum number of components per group. It can be seen from Table 4 that the best threshold for grouping components is 0.6 because it maximizes the log-likelihood and minimizes the number of components per group. It can be verified that by grouping like this, the result's marginal distributions can satisfy the positive definite constraint needed for applying Nataf transformation.

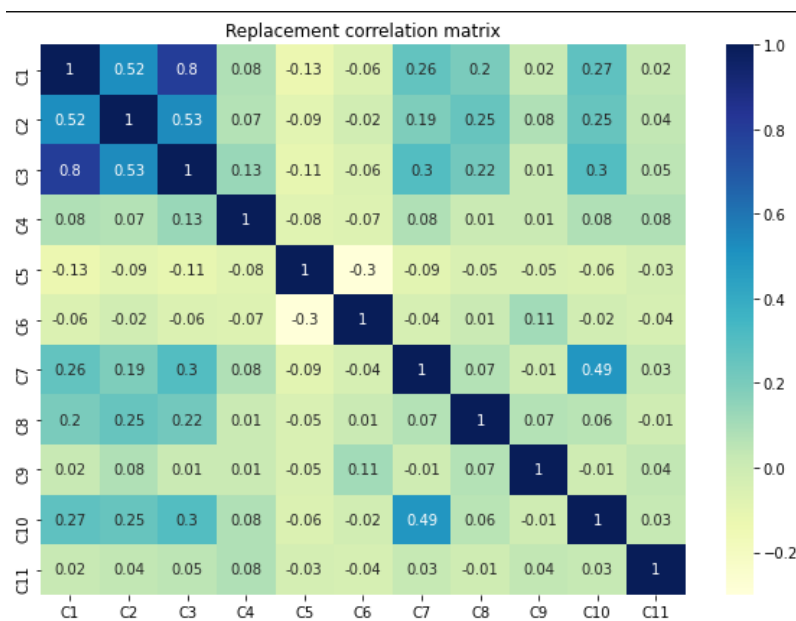


Figure 3: Correlation matrix

Table 4: Grouping components results

Threshold	Groups	N_super_comp	Max_comp_group	Positive definite	AIC	Loglikelihood
0.6	(C1,C3)	10	2	1	10571.19	-10567.19
0.1	(C1,C2,C3,C7,C10)	7	5	0	10578.31	-10568.31
[0.4,0.5]	(C1,C3); (C7,C10)	9	2	1	10583.59	-10579.59
[0.2,0.3]	(C1,C2,C3);(C7,C10)	8	3	0	10591.78	-10585.78
[0.7,0.9]	(C1);(C2);(C3);(C4);(C5);(C6);(C7);(C8);(C9);(C10);(C11)	11	1	1	10593.28	-10593.28
0	(C1,C2,C3,C4,C7,C10); (C5,C8,C11); (C6,C9)	3	6	0	26482.69	-26470.69

The system reliability is then calculated based on Eq. (13) considering the stochastic dependencies and the component clusters. Figure 4 presents the result and a comparison to the empirical estimates directly from data. As we can see, the computed system lifetime distribution from the proposed model fits the empirical data quite well.

6.2. Genetic algorithm performance

The solution method presented in Section 5.2 is based on running 4 GAs with a small generation number, a small population size, and with memory to save the previously visited solutions. We evaluate the quality of our approach by first comparing it to the exact approach (consisting of an

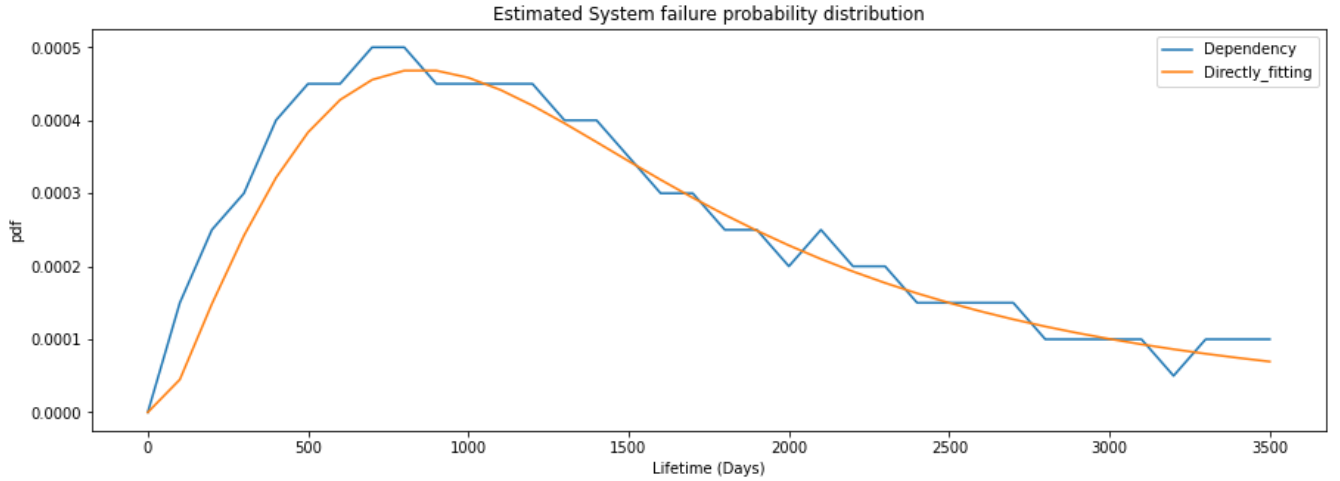


Figure 4: Modeling failure distribution under dependency

625 exhaustive search) and, subsequently, to a conventional single GA configured with a more extensive search consisting of 100 generations and 8 chromosomes, incorporating a termination criterion after 40 generations without further improvement. Figure 5 showcases the comparative analyses of our solution’s efficacy against the exact search method.

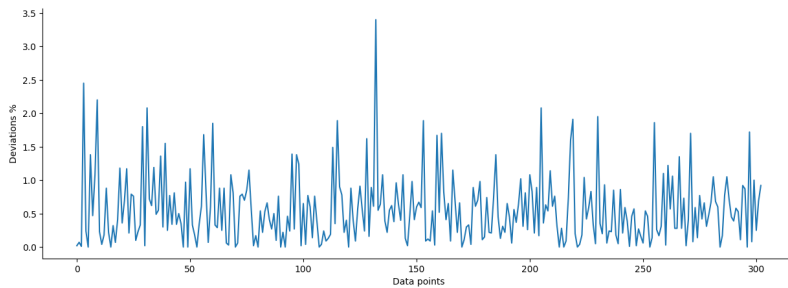


Figure 5: Deviation from optimum solution

In the comparative analysis, we examine the deviation of the GA solutions from the optimum solutions identified by the exact approach. The results show good performance of the heuristic. 630 The GA deviation typically does not exceed 3.5%, and in about 70% of the cases, it provides the optimal solution. This success is partly due to the evaluation of trivial solutions and the strategy to reset evaluation points to avoid local optima, as explained below.

Usually, setting a relatively high mutation probability and a large number of generations helps 635 the GA better explore the solution space and converge to good-quality solutions. However, because of the quality Constraint (2), we set a huge penalty as a cost for solutions that do not satisfy the constraint. As a result, the traditional GA may converge to a local optimum despite the high mutation probability. This may lead to an early saturation of the model and a termination with poor-quality solutions. Moreover, by initializing the generation with the corrective solution in our 640 approach, we make sure that we guarantee that the obtained one will always be better than the corrective one.

Another drawback of setting a high maximum generation number is the computation time. In our case, increasing the number of generations is time-consuming since evaluating the objective function (3) is computationally expensive. As a result, we create a memory to save previously 645 visited solutions and their fitness so that the GA avoids recomputing their fitness scores. Figure 6 shows the comparison in terms of computational times. We observe that the computational time

is reduced by 3 times because we avoid computing the same fitness functions multiple times for the previously visited solutions. We can explain the variation in the computational time by the number of possible solutions. Unlike the old spare parts, the young ones have large solution space, which increases the computation time.

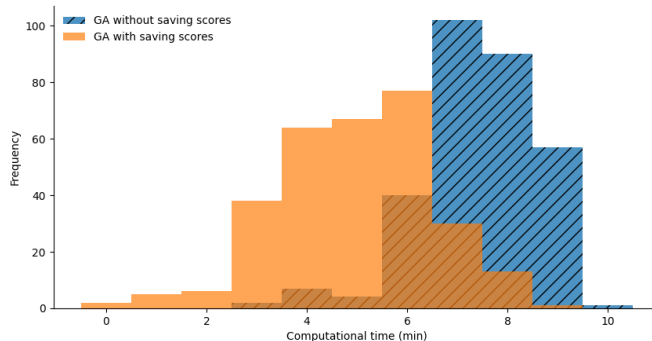


Figure 6: Computational time distribution

6.3. Impact on the reliability of the repaired spare parts

We next evaluate the change in the probability of surviving the warranty period without failure, say $T_{warranty}$, after repair if we apply opportunistic maintenance. In general, the developed strategy improves spare parts reliability. Figure 7 compares the estimated conditional reliability before and after conducting opportunistic replacements. It represents the gain in survival probability of $T_{warranty}$ after the repair operations. Each data point corresponds to a unique spare part with defined ages for its components. The improvement in survival probability is more significant if it is evaluated at the end of the planning horizon. In fact, the model suggests opportunistic replacements for all parts with low reliability. As a consequence, most of the reliability after the period of the simulated parts becomes higher than 0.5. The model also recommends minimum replacements for old units to satisfy the quality constraint. In some cases, parts reliability can be improved by 0.25 points by changing a few sets of components.

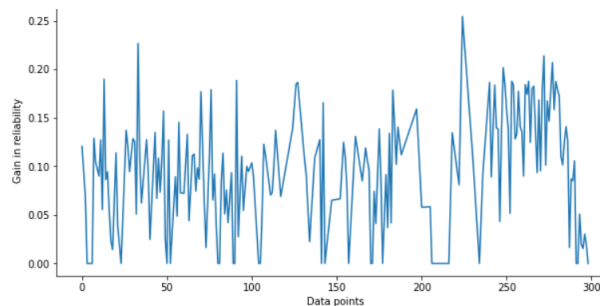


Figure 7: Gain in survival probability.

Consequently, the additional replacements help improve the remaining lifetime of the repaired parts. Figure 8 represents the gain in residual life after opportunistic maintenance. It is the difference between the estimated remaining useful life before and after adopting the OM strategy. For some parts, changing some components opportunistically can extend their lifetime by more than one year.

In addition, applying opportunistic maintenance reduces the long-run cost due to the reduction of failure risk. Figure 9 shows the improvement percentage in the long-run cost after opportunistic

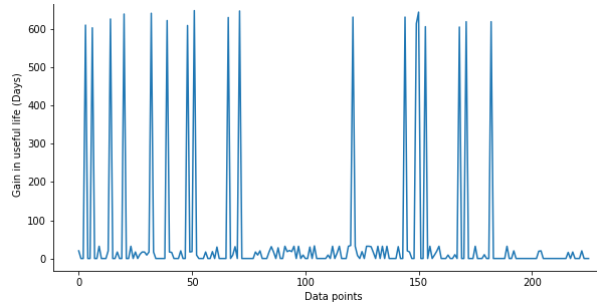


Figure 8: Estimated gain in parts lifetime

670 maintenance. It is the difference between the corrective maintenance cost and the opportunistic cost. For some parts, changing some additional components reduces the total cost by more than 5%.

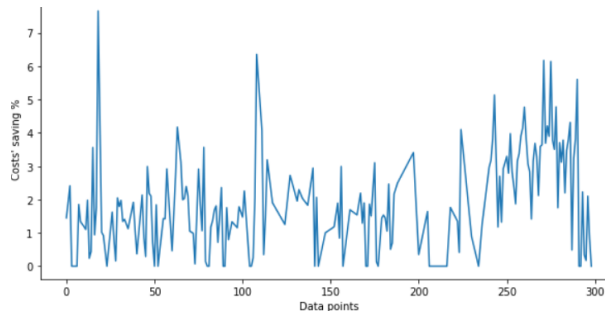


Figure 9: Gain in long-run cost

7. Discussion & Insights for a more efficient CLSC

We next study the impacts of the system parameters on optimal decisions. We also discuss their implications on CLSC performance and the effect of considering stochastic dependency in maintenance decisions.

How to select the best planning horizon? The proposed model selects components to be replaced preventively based on the evaluated risk using Equation (8). To determine the best planning horizon, we consider the number of replacements and the benefit of the operation for different values of planning horizon, as shown in Table 5, where MUL_{sys} represents the mean lifetime of the new-buy part. The results in Table 5 lead to a two-fold conclusion. First, the total cost increases over time because of the increased failure risk. Therefore, it is advantageous to replace more components preventively if the planning horizon is long. **Moreover, extending the planning horizon raises the risk of failure (8), thereby enhancing the advantages of OM decisions.** However, setting a very long horizon would reduce the solution's efficiency. If the remaining useful life of many components is lower than the horizon plan, it would be better to change the planning duration to minimize the number of replacements and waste costs. In conclusion, we suggest selecting the planning horizon as the average useful life of the new-buy spare parts. It can be reduced if more conservative decisions are preferred and in case we need to evaluate the failure risk in a shorter period.

How to minimize components consumption due to preventive maintenance? **To examine the factors most influencing component consumption for preventive replacement, we multiply the penalty term**

Table 5: Impact of planning horizon T

T (U.T)	$T_{warranty}$	$\frac{MUL_{sys}}{2}$	MUL_{sys}	$2 \cdot MUL_{sys}$
Average TC (U.C)	4451	5936	8788	11735
Average Total replacement	3	4	2	4
Average NB (U.C)	665	2709	4248	3125
Average Benefit (%)	12.98	31.34	32.58	21.02

C_w in Eq. (3) by an adjustment factor α and analyze how preventive replacement frequency varies with changes in α . In the original model, C_w only considered the price of the component itself. By adding the adjustment factor α , the underlying assumption is that there are indirect storage costs or additional costs due to procurement problems. The new total cost in the opportunistic maintenance optimization model is expressed now as $TC = C_r + \alpha \cdot C_w + C_f + C_L$.

From Figure 10, we notice that the number of preventively replaced components decreases as α increases. This indicates that the less expensive the preventive maintenance cost, the higher the number of replacements. This is intuitive, as preventively replacing low-cost items is more profitable: it significantly enhances the reliability of repaired spare parts and reduces total operational costs by minimizing potential field failures.

Another insight from Figure 10 is that when the total costs of the components are comparable to the logistic costs $Cost_0$, the net benefit of the optimal decisions may turn negative. This implies that for the components that are very expensive or hard to procure, it is better to avoid replacing them preventively unless absolutely necessary, *e.g.*, without preventively replacing them, the constraint on the reliability after repair cannot be satisfied. This fact can be considered in the model by increasing the value of RV of these components to prevent replacing them preventively.

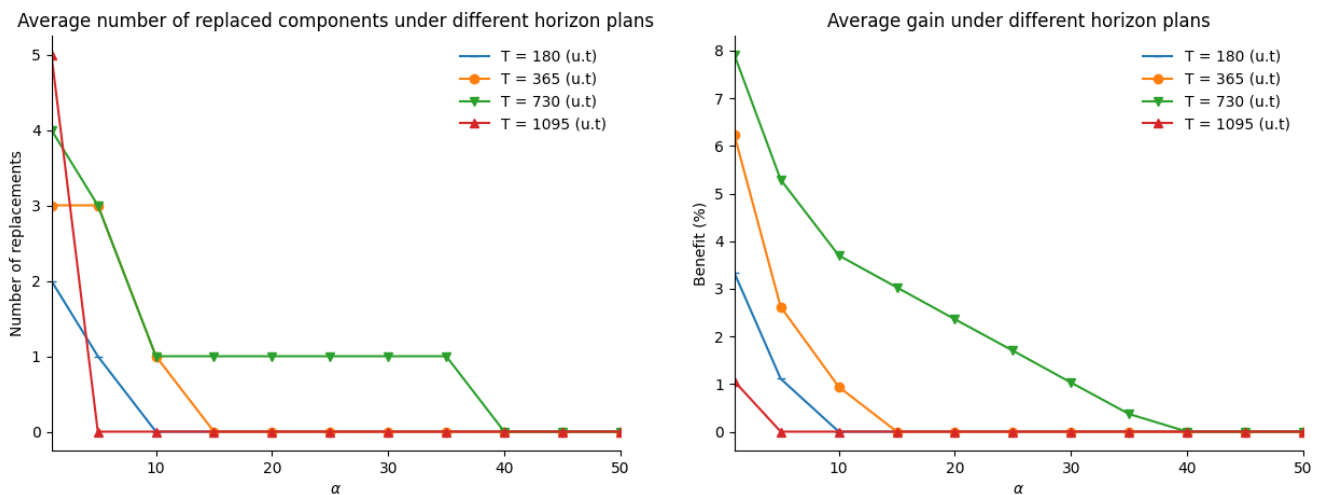


Figure 10: Impact of waste cost on maintenance decision

Impact of the time value of money. The interest rate r is introduced to account for the effect of time value of money. We investigate here how the interest rate can impact preventive decisions and how it can be used to minimize unnecessary replacements.

As illustrated in Figure 11, the higher the rate r , the lower the number of replacements that occur for a fixed planning horizon and coefficient α . It can be explained by the fact that a high rate means we can focus more on the present time and do not care as much about future payments. As a result, the optimal solution of the model is more conservative than the one under a lower interest

rate. Generally, when a spare part is approaching its end-of-life cycle, we can select a higher interest rate, like 0.5 or 0.6, since we need to focus only on the performance over a short-term planning horizon.

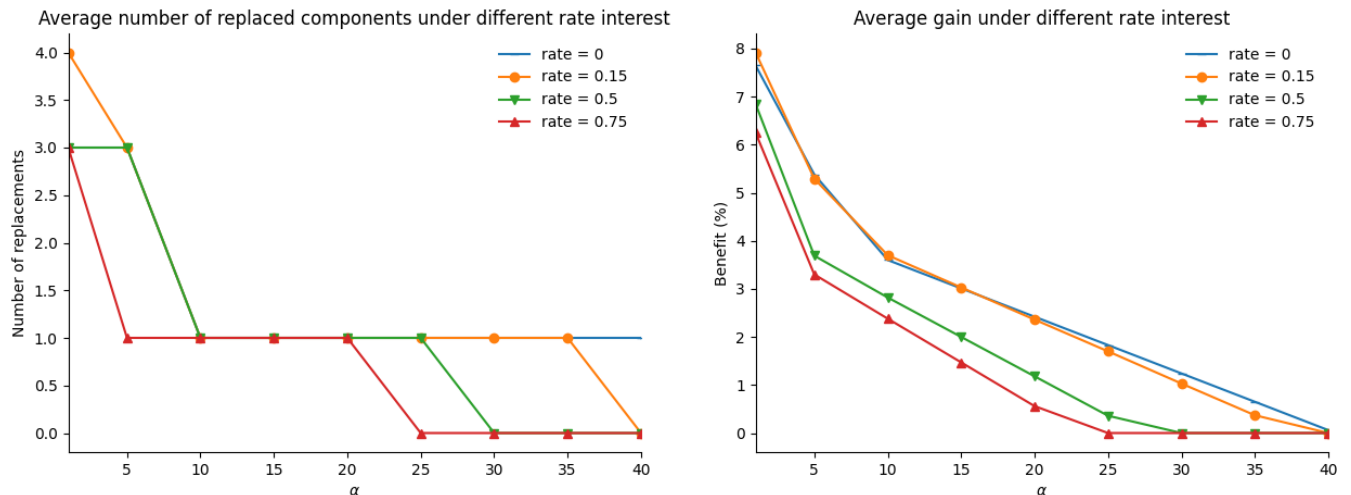


Figure 11: Impact of interest rate on maintenance decision

Impact on CLSC efficiency. Compared to a traditional CLSC, after applying the developed opportunistic maintenance model, two major contradictory effects could occur during the operation of the CLSC. The opportunistic maintenance is based on replacing components before failure, which may increase components consumption. On the other hand, it also reduces system failures, indirectly impacting components demand. We next investigate the impact of opportunistic maintenance on the CLSC, considering the consumption of the additional components, the client machine downtime, and logistic costs. We also consider the impact on the sustainability of the CLSC by calculating the overall CO_2 production during the operation of the CLSC.

We consider an observation period of 2 years and apply our strategy to the randomly selected failures that happened during this period. We assume that if the opportunistic maintenance model suggests preventive maintenance before the actual failure time, the failure can be prevented. For confidentiality reasons, we do not show the detailed results but only provide the relative performance improvement compared to the traditional CLSC that implements only corrective maintenance, as shown in Table 6. Operator cost represents the needed cost to repair the spare part at the repair center, while the cost to serve includes the downtime cost of the system at the client site and logistic costs to replace the defective part at the hospital. We compute the estimated CO_2 production by considering the total traveling distance and the weight of the parts. The results show that despite the increase in components consumption due to preventive replacement, the developed opportunistic maintenance model can save 42% of total costs. This is related to reducing the global number of failures and the associated logistic costs. In addition, the developed opportunistic maintenance model contributes to the sustainability of the CLSC as it reduces the CO_2 emissions because transportation is one of the most critical components in CLSC CO_2 production.

When to consider dependency ? We analyze the impact of considering stochastic dependency on maintenance decision-making. First, we evaluate the two models (under dependency, referred to

Table 6: Impact of opportunistic maintenance on supply chain performance

	Additional material	Operator cost	Cost to serve	Total cost (U.C)	Total distance km		Estimated Co2 Kt
					km flight	km road	
Corrective maintenance	0	20,908	2,048,000	2,068,908	1,764,869	1,074,681	577,816
Opportunistic maintenance	9,031	10,374	1,228,800	1,241,344	875,698	533,238	286,702
Savings	-9,031	10,534	819,200	820,703	889,171	541,442	291,113

as Model 2, and without dependency, referred to as Model 1) based on their ability to predict failures. We compared the two models recommendations with the next maintenance record of the same selected part. Table 7 indicates how often the model selected the components that caused a failure after a repair. As we can see, both models can predict critical component failures. However, the second model outperforms the first one because it selects the degraded components after the failure of the first one.

Table 7: Accuracy of predicting failures

	Model 1	Model 2
Predicting critical component failures	63%	64%
Predicting other components failures	23%	26%
Predicting all failures	52%	53%

Then, we consider 3 cases with different components average ages to further understand the difference between the two models. Table 8 summarizes the components ages and the probability of surviving after the warranty period. Table 9 shows the decisions taken for each case. In Table 9, 1 means the preventive replacement of the component. Columns TC is the total cost of the best solutions.

Table 8: Components' age

Case	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	$R_{sys}(T_{warranty})$
1	727	727	727	727	0	727	727	727	727	727	727	0.91
2	0	0	0	1364	637	1364	1364	1364	1364	1364	1364	0.86
3	0	0	1649	1649	1649	1649	1649	1649	1649	1649	1649	0.75

Table 9: Replaced components preventively and net benefit

Case	Model	TC (u.c)	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	Benefit (u.c)	Benefit (%)
1	1	6964	1	0	1	0	0	1	0	0	0	0	1	283	4
1	2	6964	0	0	0	0	0	1	0	0	0	0	1	283	4
2	1	9123	0	0	0	0	0	1	0	0	1	0	1	203	2.17
2	2	8767	0	0	0	0	1	1	0	0	0	0	1	559	6
3	1	8919	0	0	0	0	1	0	0	0	0	0	1	3,842	30.11
3	2	8486	0	0	1	0	1	1	0	0	0	0	1	4,274	33.5

Based on the positive benefits indicated in Table 9, all the decisions taken outperform the corrective strategy. The net benefit increases with the risk of failure. The more the part is likely to fail, the more significant the benefits of applying the developed opportunistic models. For Case 1 in Table 8, the corrective operations satisfy the defined quality constraint. However, both models preventively change the cheapest and easiest components to reduce the failure cost. In Case 2, Model 2 outperforms Model 1 because it selects stochastically dependent components, while

760 Model 1 selects structurally dependent components. In Case 3, Model 1 recommends changing a few components compared to Model 2, which increases the risk of failures.

In summary, considering stochastic dependency helps to more accurately anticipate failures and increase the benefit of changing components preventively. However, the first model with no dependency can also produce good results when the studied parts have one critical failure component. Table 7 shows that both models can predict early failures. Moreover, Table 4 shows 765 no notable difference in the estimated likelihood with (threshold = 0.6) and without dependency (threshold $\in [0.7, 0.9]$). Thus, for systems with one critical component, ignoring the dependency between components would be preferable.

8. Future Research Directions

770 As we move forward, there are several areas where further research could enhance the model's effectiveness and applicability. This section outlines potential directions for future work, focusing on refining cost functions, improving computational efficiency, addressing data quality issues, and expanding the model's applicability.

First, our model currently considers four types of costs to reflect three main objectives: economic efficiency (minimizing material and labor costs), environmental impact (minimizing waste 775 costs), and reliability (minimizing failure costs). However, we formulated the problem as a single-objective function. This approach often leads to the dominant cost function—typically failure costs, due to the significant impact of logistic costs—having the most influence on the solution. Adopting a multi-objective formulation could reveal deeper interactions between these objectives, 780 offering managers a broader range of solutions that effectively balance multiple priorities.

A significant challenge encountered during the implementation of this model in real-world repair lines was the computational time required to arrive at a solution. To address this, future research could explore creating surrogate models for the objective function using neural networks or other machine learning algorithms. These models could be trained either as offline solutions, where the 785 surrogate learns the cost function for specific parameter types (costs and reliability functions) or as integrated components within the optimization process, leading to more general and adaptive solutions. Researchers interested in this area may refer to Blik (2022) for detailed insights on surrogate models.

Data quality is another critical element that can impact the precision of the model. The accuracy of the available data and its completeness might not be sufficient to estimate the true 790 reliability of components and their ages. Making decisions without accounting for these uncertainties can lead to suboptimal outcomes. To mitigate this, risk-based optimization methods could be employed to incorporate the risk profiles of managers and the uncertainty levels in the data, enabling more robust and tailored decision-making. These methods could, for example, suggest 795 postponing a component replacement to gather more data or prioritizing another component to avoid worst-case scenarios.

Deploying this model across multiple types of spare parts repaired by the same organization also requires significant effort in understanding each spare part's configuration and performance structure. This is particularly challenging when repair centers are separate from the original
800 manufacturers, often managed by third-party organizations, leading to potential inaccuracies in documentation and system understanding. Leveraging neural networks could help approximate structural functions and estimate the reliability of spare parts based on their components, while also uncovering interdependencies between components.

Moreover, our model currently approximates stochastic dependencies between components
805 based on the correlation coefficient of their replacements. While this method is useful, it may overlook nonlinear relationships between components. Future research could explore more sophisticated methods to capture these nonlinear dependencies, providing a more accurate reflection of the complex interactions within systems.

Additionally, while monitoring the degradation level of each component in a spare part is
810 challenging and often inefficient, incorporating usage patterns and environmental factors such as room temperature and humidity could provide valuable insights into component degradation. This would allow for more precise maintenance planning and potentially extend the lifespan of components.

Finally, the current model assumes unlimited capacity for component inventory. Although
815 waste costs are considered in the objective function, setting higher thresholds for quality constraints could increase component consumption. Joint optimization of component inventory levels and maintenance actions could help reduce unnecessary replacements, recommend earlier ordering of critical components, and prioritize future corrective replacements for hard-to-procure parts.

9. Conclusion

In this paper, we developed an opportunistic maintenance model tailored to the real-world con-
820 straints of a closed-loop supply chain for spare parts. The model optimizes efficiency by leveraging maintenance events to select components for preventive replacement based on their age, residual lifetime, dependencies, and the present value of future failure costs. When reliability falls short of quality standards, the model recommends additional preventive operations to minimize failure
825 costs. Our case study with GE HealthCare demonstrated the model's effectiveness in predicting component failures and reducing the carbon footprint of supply chain operations.

The model's outcomes are influenced by key parameters such as the interest rate and planning horizon. Our sensitivity analysis suggests that managers should carefully choose a planning horizon equal to the mean lifetime of new parts and select an interest rate below 50%. A longer planning
830 horizon may result in unnecessary replacements, while a higher interest rate can lead to overly conservative decisions.

To address computational challenges, we employed the Nataf transformation to map stochastic dependencies between components, coupled with a simplified clustering technique to reduce the

computational time of joint failure distribution calculations. The GE HealthCare case study indicated that accounting for all dependency types improves the accuracy of preventive maintenance decisions. However, the results also show that neglecting stochastic dependencies can still yield acceptable outcomes when a dominant component primarily drives failures.

Looking ahead, future research could explore integrating component inventory constraints to better understand their impact on proactive decision-making. **Applying risk-based approaches could also help manage uncertainties arising from data quality issues.** Finally, improving computational efficiency and employing artificial intelligence to learn spare part reliability based on component states and external factors present promising avenues for further development.

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