# Integrating Reliability and Sustainability: A Multi-Objective Framework for Opportunistic Maintenance in Closed-Loop Supply Chain

Abdelhamid Boujarif[1][a], David W. Coit[2][b], Oualid Jouini[1][c],
Zhiguo Zeng[1][d] and Robert Heidsieck[3]

[1]*Industrial Engineering Laboratory (LGI) CentraleSupélec, Paris-Saclay University, Gif-sur-Yvette, France*

[2]*Department of Industrial and Systems Engineering, Rutgers University, U.S.A.*

[3]*General Electric Healthcare, 283 Rue de la Minière, 78530 Buc, France*

Keywords: Multi-Component Systems, Opportunistic Maintenance, Reliability, Economic Dependence, Structure Dependence, Stochastic Dependence.

Abstract: Closed-loop supply chains are at the forefront of sustainable industrial practices since they promote the reuse of products through remanufacturing, recycling, and repair operations. Within this framework, repair centers are increasingly considered an alternative source of spare parts. This creates a need to enhance repair operations to balance the reliability of repaired parts with sustainability. This paper, developed in collaboration with GE Healthcare, presents a multi-objective framework incorporating spare part reliability post-repair estimation into opportunistic maintenance decisions. This research uses real-world data and advanced modeling techniques to refine maintenance strategies and provide a comprehensive solution that acknowledges component interdependencies. By employing NSGA-III, the paper seeks to develop a decision-support mechanism that recommends the proactive replacement of components, thereby enhancing the quality of repaired spare parts.

## 1 INTRODUCTION

Nowadays, closed-loop supply chains (CLSCs) are leading a paradigm shift toward embracing sustainable industrial practices. This transformation focuses on giving products a second life through remanufacturing, recycling, and repair operations. Within this framework, repair centers are increasingly viewed as a second supplier of spare parts.

Maintenance protocols have conventionally used new spare parts in critical domains, such as the medical sector, to guarantee system fidelity. On the other hand, in closed-loop supply chains, repaired parts are treated equally to new ones. This assumption can occasionally fall short of stringent reliability standards. This can lead to increased equipment failures, which impedes the circular efficacy of the supply chain.

Therefore, enhancing repair operations is necessary to balance reliability and sustainability goals. To this end, opportunistic maintenance emerges as a strategic intervention. This methodology replaces failed components and those approaching their end-of-life to reduce the likelihood of future failures proactively.

Nevertheless, existing opportunistic maintenance models have often assumed components independence. This presumption may not always align with reality, where components deterioration is frequently interdependent. Thus, recognizing and integrating these dependencies is imperative for developing a robust maintenance framework that aligns with the dual imperatives of reliability and sustainability within closed-loop supply chains.

This paper, developed in collaboration with GE Healthcare, proposes a framework to address this research gap. We developed a multi-objective framework that leverages estimating the reliability of a spare part after repair and its use for maintenance decisions. Our partnership with GE Healthcare enables us to test and refine the proposed strategies using real-world data and sophisticated modeling techniques. Through a nuanced analysis that captures the interdependencies within the spare parts supply chain,

[a] https://orcid.org/0000-0003-0641-9470
[b] https://orcid.org/0000-0002-5825-2548
[c] https://orcid.org/0000-0002-9498-165X
[d] https://orcid.org/0000-0003-4937-4380



Boujarif, A., Coit, D., Jouini, O., Zeng, Z. and Heidsieck, R.
Integrating Reliability and Sustainability: A Multi-Objective Framework for Opportunistic Maintenance in Closed-Loop Supply Chain.
DOI: 10.5220/0012487400003639

In *Proceedings of the 13th International Conference on Operations Research and Enterprise Systems (ICORES 2024)*, pages 179-189
ISBN: 978-989-758-681-1; ISSN: 2184-4372

we aim to provide a comprehensive solution to this problem.

This research aims to develop a decision-support mechanism that can enhance the quality of repaired spare parts by recommending proactive replacement of components. The study employs NSGA-III to achieve this, which helps balance the various objectives of ensuring component longevity, maintaining spare parts reliability, and achieving sustainability goals. The ultimate goal of this research is to contribute a unique perspective to the literature and establish a framework for maintenance strategies that can be implemented across various industries to improve both sustainability and reliability.

# 2 LITERATURE REVIEW

This work contributes to the body of knowledge in three principal areas: the efficacy of Closed-Loop Supply Chains (CLSCs), the strategic implementation of opportunistic maintenance (OM), and the nuanced reliability modeling of multi-component systems considering inter-component dependencies. The following subsections explore these research streams, highlighting the intersectionality of these domains as they pertain to this study's objectives.

## 2.1 Closed-Loop Supply Chain Efficiency

The concept of CLSCs originated in the 1990s, marks a significant paradigm shift towards sustainable operations (van Nunen, 1995; Fleischmann et al., 1997; Guide and Wassenhove, 2003). It represents the theoretical foundation for much of the recent discussion on the circular economy (Agrawal et al., 2019). The recovery processes integral to CLSCs, including repair, remanufacturing, and recycling, have been established as key drivers in reducing the demand for virgin materials, curtailing energy use, and limiting waste, thereby contributing to both environmental and economic goals (Chen et al., 2021).

Strategic and tactical considerations, such as network design and inventory management, dominate the literature, highlighting the centrality of these factors in optimizing CLSC performance (Souza, 2013). Within this strategic framework, (Gobbi, 2011) examined the influence of product residual value (PRV) on recovery options, advocating for nuanced decisions based on the residual value of returned products. Scenario-based models for spare parts supply, such as those developed by (Esmaeili et al., 2021), offer a methodological approach to redesigning sales and after-sales services within the CLSC, offering various supply options. The challenges of uncertainty in sustainable network design were tackled by (Guo et al., 2022), who considered the return rates of first and second-hand products. The valuation of remanufactured products, assuming parity in quality with new products, was explored by (Zhang et al., 2021b). Furthermore, (Tahirov et al., 2016) presented a mathematical model to compare production, remanufacturing, and their combination within the CLSC framework.

Despite the extensive research on CLSCs, there remains a paucity of literature addressing the quantification of repaired part quality and its consequential impact on the efficiency of the CLSC. This study endeavors to fill this void, proposing a quantitative model that factors in the reliability of repaired parts to enhance the efficacy of the CLSC.

## 2.2 Opportunistic Maintenance

Opportunistic maintenance (OM) is recognized for its preventive approach, which extends maintenance activities beyond failed components to include those at risk during opportunistic downtime (Haque et al., 2003). A comprehensive review of OM strategies by (Ab-Samat and Kamaruddin, 2014) covers literature up to 2014, while (Diallo et al., 2017) focused on maintenance strategies for second-hand products. The literature identifies age-based and block replacement as two prevalent OM policies. Age-based policies, as outlined by (Jiang and Ji, 2002), advocate for replacement based on the estimated lifetime of components. However, few studies address age-replacement in multi-component systems. The work of (Wang et al., 2021) introduced an age-based OM model accounting for random repair times, while (Li et al., 2021) proposed a maintenance strategy for wind farms that considers both degradation failures and stochastic incidents.

Block replacement policies are predicated on the replacement of components in groups, based on various criteria such as remaining useful life and maintenance requirements (Rebaiaia and Ait-Kadi, 2022). Research in this area has produced models that factor in perfect and imperfect maintenance, as well as economic and structural dependencies (Geng et al., 2015; Gunn and Diallo, 2015). The literature on OM often assumes component independence, with limited consideration given to inter-component dependencies that are critical in complex systems (Diallo et al., 2017). The goal of this paper is to address this gap by incorporating economic, structural, and stochastic dependencies into a comprehensive OM model.

### 2.3 Multi-Component System Reliability Considering Dependencies

Assessing the reliability of complex, interdependent systems presents a formidable challenge. Stochastic models, fault tree analysis (FTA), and Markov chains are the primary methods employed in reliability estimation (Wang et al., 2013; Zhang et al., 2021a; Fazlollahtabar and Niaki, 2018; Bhangu et al., 2015). (Kabir, 2017) highlighted the complexities involved in FTA, necessitating the exploration of automated methods for dependability synthesis. Markov models are another cornerstone technique used to evaluate system states and transitions, exemplified by (Ahmad et al., 2022) and (Issa and Hassan, 2023). However, the limitations of Markov modeling in repairable redundant systems were pointed out by (Simpson and Kelly, 2002).

An alternative approach involves copula functions and Nataf transformations to model the joint distribution of survival functions for components (Navarro and Durante, 2017; Lin et al., 2021). The work of (Xiao, 2014) and (Lin et al., 2020) has advanced this methodology, enhancing the evaluation of system reliability in complex scenarios. In this paper, we adopt these advanced techniques, applying Nataf transformation to map the stochastic dependencies of component failures, informed by historical repair data, thus advancing the reliability estimation for multi-component systems within the CLSC context.

## 3 MODELING AND PROBLEM FORMULATION

In this section, we define the problem setting and describe the opportunistic maintenance optimization model developed for managing spare parts within a Closed-Loop Supply Chain (CLSC). Our approach aims to balance operational costs and system reliability, under the constraints of economic, stochastic, and structural dependencies.

### 3.1 Problem Description

We consider a CLSC framework where failed medical equipment units, consisting of various components, are replaced in the field with spare parts from an inventory local to the client site. These failed units are then sent to a repair center for thorough testing and analysis. The objective is to identify and replace defective components, and subsequently reintroduce the refurbished spare parts into the supply chain for future maintenance needs.

Within this system, maintenance decisions are made opportunistically. Each time a unit fails and is returned, the repair center is presented with a decision: to replace only the failed components or to also proactively replace non-failed but aged components. This decision aims to reduce the likelihood of future failures and, in doing so, minimizes the long-term operational costs while maintaining the reliability of the spare parts within the CLSC.

This optimization problem is inherently dynamic; each failure and subsequent repair decision resets the life cycle of the affected components, creating a new decision point. Unlike many existing models that optimize the timing for preventive replacements, this model introduces a single opportunity window to make these decisions, aligning with real-world maintenance scenarios. The model accounts for three types of dependencies that influence maintenance decision-making:

- **Economic Dependence:** Where the collective maintenance of a group of components incurs different costs compared to individual maintenance actions, typically leading to cost savings when multiple components are serviced simultaneously.
- **Stochastic Dependence:** Where the failure of one component can have immediate, detrimental effects on the remaining components, potentially accelerating their degradation or causing immediate failure.
- **Structural Dependence:** Where components are part of an interconnected assembly, necessitating the disassembly of some parts to access others for maintenance, as detailed in (Dinh et al., 2020). This can impact both the duration of maintenance activities and the condition of the components involved.

The objective of this opportunistic maintenance optimization model is, then, to select a set of components that need to be replaced preventively during each maintenance opportunity. The model seeks to minimize the maintenance cost, environmental impact, and risk associated with spare parts repair, while also minimizing the deviation from a predefined reliability threshold.

### 3.2 Mathematical Formulation

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

**Parameters:**

- $\zeta = [1,2,3,..n]$: set of components in the spare part,
- $Cost_c$: price of component $c$,
- $M_c$: the average lifetime of component $c$,
- $RV_c = \frac{cost_c}{M_c}$: residual value of component $c$,
- $LC$: labor cost,
- $Cost_0$: logistic cost for each repair (shipping cost to replace the LRU with a new one at the client site),
- $\tau_c$: 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 $c$,
- $R_{sys}(t;a_1,a_2,..,a_n) = h(R_1(t;a_1),...,R_n(t;a_n))$: reliability function of the spare part as a function of reliability of its components,
- $f_{sys}(t;a_1,a_2,..,a_n)$: probability density function of system's lifetime,
- $T$: planning horizon,
- $r$: interest rate,
- $D = (D_{ij})_{CXC}$: disassembly matrix for the system,
- $s_c$: state of component $c$, $s_c = \begin{cases} 1, & \text{if component } c \text{ is in a failing state,} \\ 0, & \text{otherwise.} \end{cases}$,
- $S_{price}$: selling price of the spare part,
- $R_{min}$: minimum required reliability.

One of the characteristics of spare parts reparation is that the components may have different ages with a large variance; the fragile ones usually would have young ages, while the robust items would be ancient. Therefore, estimating the unit reliability is not straightforward. We propose to express the unit's reliability $R_{sys}$ as a function of components' reliability and ages. For example, for multi-independent units in series, the reliability of the part can be expressed as $R_{sys}(t) = \prod_{c\in\zeta} R_c(t;a_c)$.

**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:** The model incorporates constraints that ensure failed components are replaced correctively 1 and the positive operational benefit 2.

$$x_c + s_c \leq 1, \quad \forall c \in \zeta. \tag{1}$$

$$S_{price} - C_{maintenance} > 0. \tag{2}$$

**Objective Functions:** The multi-objective optimization problem aims to minimize the following costs:

$$\min \quad \{C_{maintenance}, \quad C_{environement}, \quad C_{risk}, \quad R_{deviation}\} \tag{3}$$

$$\begin{aligned} \text{s.t.} \quad & S_{price} - C_{\text{maintenance}} > 0, \\ & x_c + s_c \leq 1, \quad \forall c \in \zeta, \\ & x_c \in \{0,1\}, \quad \forall c \in \zeta. \end{aligned}$$

**Maintenance Cost ($C_{\text{maintenance}}$):** This cost includes expenses due to corrective and preventive replacements (5 as well as labor costs involved in the maintenance process:

$$C_{\text{maintenance}} = C_r + C_L, \tag{4}$$

where $C_r$ is the replacement cost calculated by summing the costs of components that are replaced either correctively or preventively:

$$C_r = \sum_{c\in\zeta} (x_c + s_c) \times Cost_c. \tag{5}$$

$C_L$ represents the labor costs, which are proportional to the disassembly time required to replace the components. 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 $\tau_c^D$, can be defined as the sum of disassembling times for all the components on the path of disassembly (Eq. (6)).

$$\tau_c^D = \sum_{k\in\zeta} \tau_k \times D_{c,k}. \tag{6}$$

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. (3.2) gives the total disassembly time, denoted by $\tau_{group}$, of the replaced components:

$$\begin{aligned} \tau_{group} = & \sum_{c\in\zeta} (s_c + x_c) \times \tau_c^D \\ & - \sum_{c\in\zeta} \tau_c^D \times max(\sum_{k\in\zeta} (s_k + x_k) \times D_{k,c} - 1, 0), \end{aligned} \tag{7}$$

where the first term represents the total disassembly duration of all replaced components when they are replaced separately; the second term is the time saving due to intersections among the disassembly paths.

Note that $\sum_{k\in\zeta}(s_k + x_k) \times D_{k,c}$ represents the total number of components in the replaced group that have component $c$ on their disassembly path. In case there is no intersection, the second part in Eq. 3.2 equals to zero. Therefore, the total labor cost is the total reparation time times the labor cost per time unit, *i.e.*,

$$C_L = 2 \times LC \times \tau_{group}. \tag{8}$$

**Environmental Impact ($C_{\textbf{environment}}$):** The environmental cost is associated with the waste of unused remaining life of components that are replaced preventively:

$$C_{\text{environment}} = \sum_{c\in\zeta} x_c \times \frac{RV_c}{R_{sys}(0; a_1(1-s_1), .., a_n(1-s_n))} \times \int_0^{+\infty} t\, f_c(t; a_c)\, dt. \tag{9}$$

**Risk Cost ($C_{\textbf{risk}}$):** The risk cost accounts for potential failures within the planning horizon. When a failure occurs, the logistic cost $Cost_0$ must be counted. However, to compare the future payment to the present time, its *present value* must be calculated. It means the amount of money that should be deposited into the bank now at a specific interest rate $r$ to pay for an outlay $C$ after duration $T$. At time $t \le T$, the conditional probability of failure after reparation can be expressed as follows:

$$P(T_{sys} < t) = \frac{F_{sys}(t; a_1(1-(x_1+s_1)), .., a_n(1-(x_n+s_n)))}{R_{sys}(0; a_1(1-(x_1+s_1)), .., a_n(1-(x_n+s_n)))}. \tag{10}$$

For the replaced components correctively or opportunistically ($x_c + s_c = 1$), their age would be restored to zero, while it won't change for the other components. So for a small variation of time, this probability can be expressed using the calculated probability density function (*pdf*) of the system $f_{sys}$ and the present value of the logistic cost is $Cost_0 \times (1+r)^{-t}$. Thus, the total present value of the expected cost of failure during the planning horizon, $C_f$, can be expressed as

$$C_{failure} = \frac{Cost_0}{R_{sys}(0; a_1(1-(x_1+s_1)), .., a_n(1-(x_n+s_n)))} \times \int_0^T \frac{f_{sys}(t; a_1(1-(x_1+s_1)), .., a_n(1-(x_n+s_n)))}{(1+r)^t}\, dt. \tag{11}$$

**Reliability Deviation ($R_{\textbf{deviation}}$):** This metric quantifies the deviation of the part's reliability from the required minimum. The reliability of the part is defined as the probability to survive the warranty period $T_{warranty}$ given the components age after repair.

$$R_{deviation} = 100 \times \frac{\max\left(R_{min} - \frac{R_{sys}(T_{warranty}; a_1(1-(x_1+s_1)), ..)}{R_{sys}(0; a_1(1-(x_1+s_1)), ..)}, 0\right)}{R_{min}}. \tag{12}$$

# 4 SYSTEM RELIABILITY MODELING CONSIDERING STOCHASTIC DEPENDENCY

Computing the joint distribution of components' lifetimes is crucial for incorporating stochastic dependency into optimization models. As reviewed in Section 2, extant system reliability models that account for stochastic dependencies, such as Monte Carlo simulations (Son et al., 2016; Issa and Hassan, 2023; Ahmad et al., 2022), and copulas (Lin et al., 2021; Navarro and Durante, 2017), are often computationally intensive, rendering them impractical for high-dimensional problems. To surmount this challenge, we introduce a dimensionality reduction technique that computes the joint distribution of dependent components' lifetimes, subsequently utilizing Nataf's transformation to accommodate the dependencies among clusters of components.

## 4.1 Components Clustering

The construction of dependent clusters begins by calculating covariance coefficients between each pair of components from historical repair data. A distance matrix $H = (h_{i,j})$ is derived from the correlation coefficients $R = (\rho_{i,j})$; $(h_{i,j} = 1 - |\rho_{i,j}|\ \forall i, j)$. This inverse relationship ensures that stronger dependencies correspond to shorter distances. Components are then clustered using the Agglomerative Hierarchical Clustering algorithm, a common hierarchical clustering method that groups objects based on similarity (Sasirekha and Baby, 2013).

The reliability distribution for each cluster is then constructed, considering each cluster as an independent 'super component'. The failure of any individual component within a cluster implies the failure of the entire cluster. The system reliability function under the independence assumption is given by:

$$R^*_{sys}(t) = \prod_{g\in\zeta} R_g(t; a_g) \tag{13}$$

We assess the configurations based on the likelihood and the number of components per group, aiming to select a threshold $\delta$ that minimizes group size and maximizes the likelihood of the system's time-to-failure distribution. Analogous to the Akaike Information Criterion (AIC), we formulate an index to evaluate the optimal solution. For a statistical model with $k$ parameters and a maximized likelihood function $L$, the AIC is $AIC = 2k - 2ln(L)$. 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

Upon establishing the optimal grouping configuration as detailed in Section 4.1, the Nataf transformation is employed to compute the joint distribution of each component group. Pioneered by (Liu and Der Kiureghian, 1986) and further innovated by (Lebrun and Dutfoy, 2009), the transformation is a statistical method for dealing with correlated random variables by mapping them from their original distribution space to a standard normal space.

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

$$\begin{aligned} where: \\ & T_1 : X \to W = [F_{x_1}(x_1), ..., F_{x_n}(x_n)]^T \\ & T_2 : W \to Z = [\Phi^{-1}(w_1), ..., \Phi^{-1}(w_n)]^T \\ & T_3 : Z \to U = L^{-1}Z \end{aligned}$$

$\Phi^{-1}(.)$ 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 $R_Z = (\rho^Z_{i,j})$ the correlation matrix of the standard normal vector $Z$. The joint probability of random vector $X$ is then formulated as follows:

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

The correlation matrix of the random vector $X$, denoted by $R_X$, is transformed into a standard normal space using a linear search technique as described by (Li et al., 2008; Xiao, 2014). The search is iteratively refined until the difference between $b$ and $a$ falls below a predetermined error threshold $\Delta$.

The joint probability density function for a group of components in a serial system, represented by the survival function $R_g(t)$ can be expressed as follows:

$$\begin{aligned} R_g(t) &= P(min_{c \in g}(X_c) \geq t) \\ &= P(\bigcap_{c \in g} X_c \geq t) \\ &= 1 - P(\bigcup_{c \in g} X_c \leq t) \\ &= 1 - \sum_{c \in g} F_c(t) + \sum_{1 \leq c_1 \leq c_2 \leq n_g} P(X_{c_1}, X_{c_2} \leq t) + ... \\ &+ (-1)^k \sum_{1 \leq c_1 \leq c_2 ... \leq c_k \leq n_g} P(X_{c_1}, X_{c_2}, ..., X_{c_k} \leq t) \\ &= 1 + \sum_{1 \leq k \leq n_g} (-1)^k \sum_{1 \leq c_1 \leq c_2 ... \leq c_k \leq n_g} P(X_{c_1}, X_{c_2}, ..., X_{c_k} \leq t) \end{aligned} \tag{16}$$

This approach simplifies the computational process and enables system reliability evaluation for high-dimensional problems involving multiple dependent components.

# 5 INDUSTRIAL CASE STUDY

We present in this section an application of the developed model based on a real industrial case from our industrial partner GE Healthcare. GE Healthcare (GEHC) is one of the global leaders in sales and services of medical systems, notably those of medical imaging with 4 million of millions 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 occurrence) while reducing unavailability simultaneously. As the spare parts are expensive and also because of diposal the failed parts directly will create circularity problems, a CLSC is implemented in GEHC.

In this study, we implement the developed OM optimization model on the power supply of MRI machines, and investigate the strategy impact on the efficiency of the CLSC. The considered spare part composes of 11 components connected in series. Figure 1 and Table 1 represent the physical structure between components and the disassembling order and the necessary operation times for each component, respectively. For example, components 4, 5, and 7 must be disassembled before component 10 can be replaced. Table 2 represents the purchase price for new components and their average useful life *Mul* in *(U.T)*.

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 |

GEHC spare parts supply chain is so particular

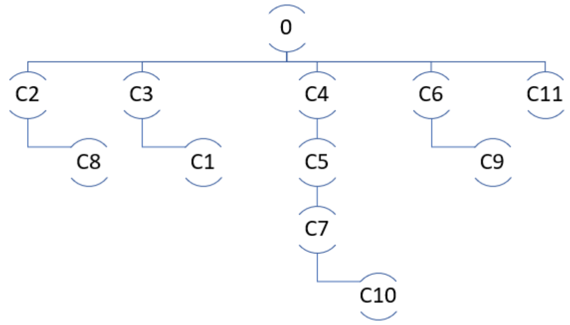


Figure 1: System's structure.

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 |

because its efficiency mainly depends on the quality of their repaired parts. The repair center provides around one thousand of repaired power supply per year to maintain Thousands of MRI systems. Besides, depending on forecasted demand and stock levels, one part can be reallocated multiple time to different warehouses around the world before being installed on a system which makes gathering parts' lifetime 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 replaceable unit (LRU).

We have collected 13200 operating time and maintenance records for 7514 spare parts. 3490 LRUs were repaired multiple times. We consider the operating time of the functioning parts as censored. We randomly selected 120 LRUs that was 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.

In implementing the opportunistic maintenance model delineated by equations (3), we estimate the lifetime distributions from the data detailed in table 3 and take into account the stochastic dependencies as detailed in section 4. Due to the complex nature of the problem, an analytical solution remains elusive for two primary reasons. Firstly, the failure cost evaluation in equation (11) requires calculating the conditional reliability post-maintenance, which complicates any attempt to linearize the objective function. Moreover, the problem is classified as NP-hard because each component presents two potential scenarios, leading to $2^n$ possible configurations for a system with $n$ components. To navigate this computational complexity and derive a near-optimal solution for the opportunistic maintenance strategy, we employ the Non-dominated Sorting Genetic Algorithm (NSGA). This algorithm is particularly adept at handling multi-objective optimization problems since it provides a set of Pareto-optimal solutions representing the trade-offs among the objectives. The decision-making process will involve selecting the most appropriate solutions based on the operational goals and constraints of the CLSC.

## 6 RESULTS AND ANALYSIS

This section reports the results of our opportunistic strategy on the test subset. First, we present the performance of the clustering method described in section 4 to model dependency in 6.1. Then, we present the trade-off between different objectives and their impact on decisions in section 6.2. Finally, we present the opportunistic maintenance effect on parts' reliability in section 6.3.

### 6.1 Reliability Functions Under Dependency

To build a system reliability model under dependency, we select replacement records for the failed parts and compute the correlation matrix between components replacement using the Pearson method (Li et al., 2012). Figure 2 shows the obtained correlation matrix. Visually examining the results reveals 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 threshold and groups represent 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

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 | 399 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 1 | 0 | 508 | 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 |

grouping components is 0.6 because it maximizes the loglikelihood and minimizes the number of components per group. It can be verified that by grouping like this, the resulting marginal distributions can satisfy the positive definite constraint needed for applying Nataf transformation.

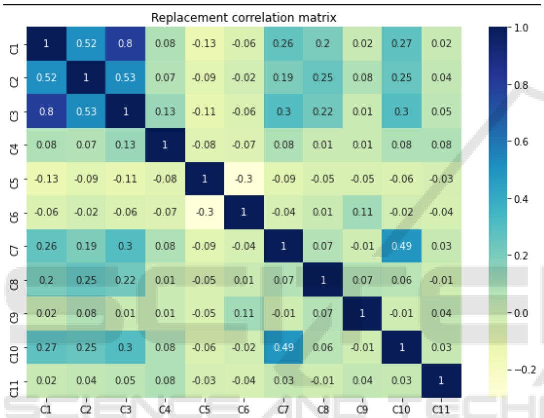


Figure 2: Correlation matrix.

The system reliability is then calculated based on Eq. (16) considering the stochastic dependencies and the forming clusters. Figure 3 shows the result and compare it to the empirical estimations directly from data. As we can see, the computed system lifetime distribution from the proposed model fits well the empirical data.

## 6.2 Pareto Frontier Analysis and Decision-Making Insights

The radar charts in figures 4 and 5 portray the Pareto optimal solutions for two studied parts derived from our multi-objective optimization framework. These charts serve as a graphical elucidation of the trade-offs between competing objectives within the context of opportunistic maintenance scheduling.

**Interpretive Analysis.** Each axis on the radar chart quantifies an objective: maintenance costs ($C_{\text{maintenance}}$), environmental impacts ($C_{\text{environment}}$), risk levels ($C_{\text{risk}}$), net benefits, the number of total replacements, and regulatory compliance penalties ($R_{\text{penalty}}$). The shape and reach of each solution's polygon on the chart indicate its performance across these objectives. The farther a vertex extends from the center, the higher the value in that specific objective, thus facilitating a comparative analysis of the trade-offs involved.

**Equilibrium and Trade-Offs.** The essence of the Pareto frontier in a multi-criteria context is the balance between objectives. For instance, solutions that extend towards the periphery for net benefit illustrate a preference for financial optimization, potentially at the expense of elevated risk. Meanwhile, solutions with a more even distribution of vertices suggest a more balanced approach, likely representing an equilibrium amidst the conflicting objectives.

**Managerial Implications.** The model provides profound insights into the strategic allocation of resources for maintenance. It highlights the necessity of a nuanced approach that transcends singular objective optimization:

- Solutions skewed towards net benefit might resonate with profit-maximizing agendas, albeit with a vigilant eye on the rise in risk cost.
- Eco-centric solutions emphasize sustainability, aligning with environmental compliance and social responsibility mandates.
- Risk-averse profiles cater to scenarios where the cost of failure or downtime is prohibitive, underscoring the need for meticulous risk management.
- The minimization of $R_{\text{penalty}}$ reflects compliance-centric strategies vital for adhering to regulatory frameworks and avoiding fiscal penalties.

**Conclusion.** In conclusion, the Pareto frontiers underscore the multifaceted nature of decision-making in maintenance strategy optimization. Through a visual and quantitative articulation of trade-offs, the model endows decision-makers to discern a balanced

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 |

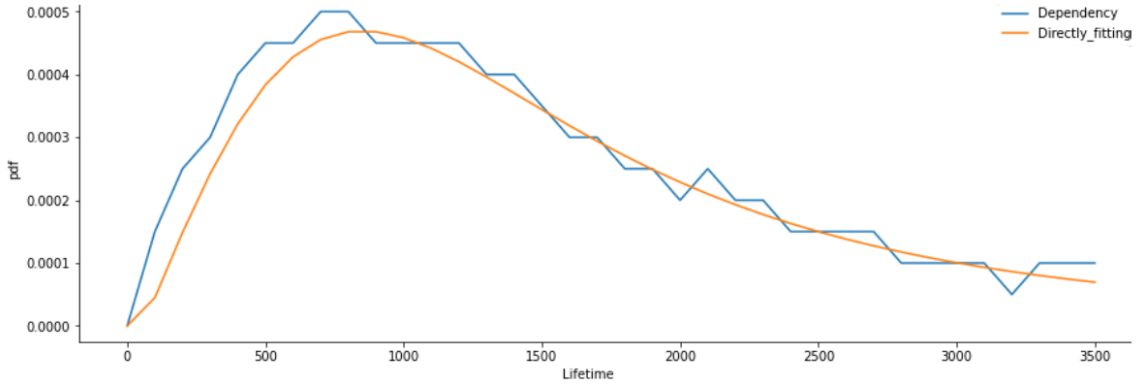


Figure 3: Modeling failure distribution under dependency.

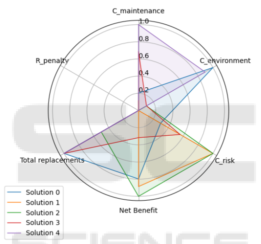


Figure 4: Pareto frontier for the first case.

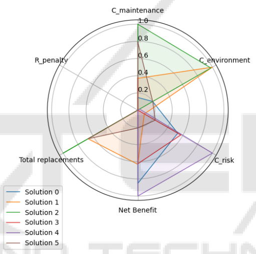


Figure 5: Pareto frontier for the second case.

and holistic strategy that aligns with the broader spectrum of operational objectives.

## 6.3 Impact on the Reliability of the Repaired Spare Parts

Figure 6 compares the reliability at the end of the horizon plan $T$.Adopting a proactive maintenance strategy has significant implications for the reliability of components after their horizon period. The model's performance is intrinsically linked to the management's risk tolerance. Preferences that lean towards maximizing benefits could adhere to the minimum quality constraints, yet this approach carries an inherent risk of failure, potentially leading to lower reliability post-warranty.

Conversely, a strategy focused on minimizing risk would enhance the reliability to its highest attainable level, albeit at the cost of reduced benefits. This conservative approach ensures a robust system that maintains performance beyond the horizon period, mitigating the likelihood of over-quality.

An average solution, representing a balance between the two extremes, offers a compromise that aligns with intermediate managerial risk preferences. This equilibrium point provides a performance between maximizing benefits and minimizing risks. This midpoint strategy can be particularly advantageous for sustaining moderate reliability while achieving reasonable benefits, effectively balancing the trade-offs between risk, cost, and reliability.

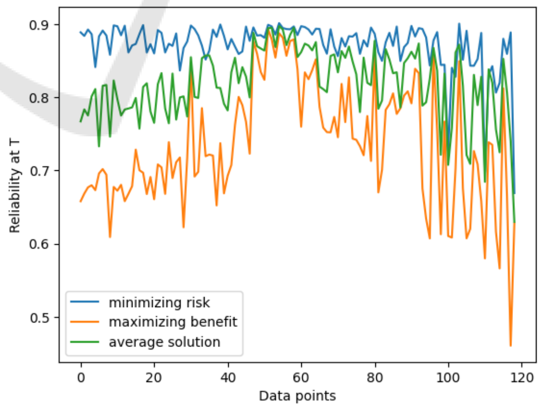


Figure 6: Impact of OM strategy on reliability at $T_{warranty}$.

Decision-makers need to consider the long-term implications of their chosen maintenance strategy on the reliability of parts. As the warranty period concludes, a maintenance plan overly focused on immediate benefits may result in increased costs due to failures and replacements. In contrast, prioritizing reliability can lead to sustained performance and reduced long-term expenses, aligning with the overarching objectives of reliability-centered maintenance practices.

## 7 CONCLUSIONS AND PERSPECTIVES

This research has presented a multi-objective optimization framework for opportunistic maintenance within Closed-Loop Supply Chains, focusing on the medical systems domain. By integrating NSGA-III, an advanced evolutionary algorithm, our model handles the intricate balance of maintenance costs, environmental impacts, risk, net benefits, total replacements, and regulatory penalties. The empirical results, underpinned by real-world data from GE Healthcare, have demonstrated the efficacy of the proposed model in navigating the complex trade-offs inherent in maintenance strategy optimization.

The Pareto frontiers elucidated through radar charts visualize the trade-offs among competing objectives, empowering decision-makers to identify strategies that align with their specific operational goals and risk appetites. Whether the preference is for cost minimization, risk aversion, or environmental sustainability, the model offers the flexibility to tune the maintenance strategy accordingly.

We have also highlighted the chosen maintenance strategy's significant impact on the parts' reliability after the warranty period. The preference towards maximizing benefits may lead to cost efficiencies in the short term but can result in lower reliability post-warranty. Conversely, a risk-averse approach that prioritizes part reliability ensures system robustness but may compromise on immediate financial benefits.

In summary, this study contributes a novel perspective to the literature on maintenance strategy optimization within CLSCs and sets a precedent for future research. Future work will aim to refine the optimization framework further and explore its applicability across different industry sectors, thereby broadening the impact of this research.

## ACKNOWLEDGEMENT

We would like to thank Didier Rault and Stephane Borrel from GE HealthCare for their helpful discussions and results validation. The research of Zhiguo Zeng is financially supported by ANR under grant number ANR-22-CE10-0004 and partially supported by the chaire of Risk and Resilience of Complex Systems (Chaire EDF, Orange and SNCF). The participation of David Coit in this research is partially financed by the international visiting grant from Centralesupélec, and the Bourses Jean d'Alembert from Université Paris-Saclay.

## REFERENCES

Ab-Samat, H. and Kamaruddin, S. (2014). Opportunistic maintenance (om) as a new advancement in maintenance approaches: A review. *Journal of Quality in Maintenance Engineering*, 20(2):98–121.

Agrawal, V. V., Atasu, A., and Van Wassenhove, L. N. (2019). Om forum—new opportunities for operations management research in sustainability. *Manufacturing & Service Operations Management*, 21(1):1–12.

Ahmad, H. H., Almetwally, E. M., and Ramadan, D. A. (2022). A comparative inference on reliability estimation for a multi-component stress-strength model under power lomax distribution with applications. *AIMS Math*, 7:18050–18079.

Bhangu, N. S., Pahuja, G., and Singh, R. (2015). Application of fault tree analysis for evaluating reliability and risk assessment of a thermal power plant. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 37(18):2004–2012.

Chen, H., Dong, Z., Li, G., and He, K. (2021). Remanufacturing process innovation in closed-loop supply chain under cost-sharing mechanism and different power structures. *Computers & Industrial Engineering*, 162:107743.

Diallo, C., Venkatadri, U., Khatab, A., and Bhakthavatchalam, S. (2017). State of the art review of quality, reliability and maintenance issues in closed-loop supply chains with remanufacturing. *International Journal of Production Research*, 55(5):1277–1296.

Dinh, D.-H., Do, P., and Iung, B. (2020). Maintenance optimisation for multi-component system with structural dependence: Application to machine tool sub-system. *CIRP Annals*, 69(1):417–420.

Esmaeili, N., Teimoury, E., and Pourmohammadi, F. (2021). A scenario-based optimization model for planning and redesigning the sale and after-sales services closed-loop supply chain. *RAIRO-Operations Research*, 55:S2859–S2877.

Fazlollahtabar, H. and Niaki, S. T. A. (2018). Fault tree analysis for reliability evaluation of an advanced complex manufacturing system. *Journal of advanced Manufacturing systems*, 17(01):107–118.

Fleischmann, M., Bloemhof-Ruwaard, J. M., Dekker, R., Van der Laan, E., Van Nunen, J. A., and Van Wassenhove, L. N. (1997). Quantitative models for reverse logistics: A review. *European journal of operational research*, 103(1):1–17.

Geng, J., Azarian, M., and Pecht, M. (2015). Opportunistic maintenance for multi-component systems considering structural dependence and economic dependence. *Journal of Systems Engineering and Electronics*, 26(3):493–501.

Gobbi, C. (2011). Designing the reverse supply chain: the impact of the product residual value. *International Journal of Physical Distribution & Logistics Management*, 41:768–796.

Guide, V. D. R. and Wassenhove, L. N. (2003). *Business aspects of closed-loop supply chains*, volume 12. Carnegie Mellon University Press Pittsburgh, PA.

Gunn, E. A. and Diallo, C. (2015). Optimal opportunistic indirect grouping of preventive replacements in multicomponent systems. *Computers & Industrial Engineering*, 90:281–291.

Guo, Y., Shi, Q., and Guo, C. (2022). A fuzzy robust programming model for sustainable closed-loop supply chain network design with efficiency-oriented multi-objective optimization. *Processes*, 10(10):1963.

Haque, S. A., Kabir, A. Z., and Sarker, R. A. (2003). Optimization model for opportunistic replacement policy using genetic algorithm with fuzzy logic controller. In *The 2003 Congress on Evolutionary Computation, 2003. CEC'03.*, volume 4, pages 2837–2843. IEEE.

Issa, L. A. A. A. and Hassan, Z. A. H. (2023). Application of markov models to maintenance-required systems. In *AIP Conference Proceedings*, volume 2591, page 050012. AIP Publishing LLC.

Jiang, R. and Ji, P. (2002). Age replacement policy: a multi-attribute value model. *Reliability Engineering & System Safety*, 76(3):311–318.

Kabir, S. (2017). An overview of fault tree analysis and its application in model based dependability analysis. *Expert Systems with Applications*, 77:114–135.

Lebrun, R. and Dutfoy, A. (2009). An innovating analysis of the nataf transformation from the copula viewpoint. *Probabilistic Engineering Mechanics*, 24(3):312–320.

Li, D.-Q., Wu, S.-B., Zhou, C.-B., and Phoon, K. (2012). Performance of translation approach for modeling correlated non-normal variables. *Structural safety*, 39:52–61.

Li, H., Lü, Z., and Yuan, X. (2008). Nataf transformation based point estimate method. *Chinese Science Bulletin*, 53(17):2586–2592.

Li, M., Jiang, X., and Negenborn, R. R. (2021). Opportunistic maintenance for offshore wind farms with multiple-component age-based preventive dispatch. *Ocean Engineering*, 231:109062.

Lin, S.-W., Matanhire, T. B., and Liu, Y.-T. (2021). Copula-based bayesian reliability analysis of a product of a probability and a frequency model for parallel systems when components are dependent. *Applied Sciences*, 11(4):1697.

Lin, X., Jiang, Y., Peng, S., Chen, H., Tang, J., and Li, W. (2020). An efficient nataf transformation based probabilistic power flow for high-dimensional correlated uncertainty sources in operation. *International Journal of Electrical Power & Energy Systems*, 116:105543.

Liu, P.-L. and Der Kiureghian, A. (1986). Multivariate distribution models with prescribed marginals and covariances. *Probabilistic engineering mechanics*, 1(2):105–112.

Navarro, J. and Durante, F. (2017). Copula-based representations for the reliability of the residual lifetimes of coherent systems with dependent components. *Journal of Multivariate Analysis*, 158:87–102.

Rebaiaia, M.-L. and Ait-Kadi, D. (2022). A remaining useful life model for optimizing maintenance cost and spare-parts replacement of production systems in the context of sustainability. *IFAC-PapersOnLine*, 55(10):1562–1568.

Sasirekha, K. and Baby, P. (2013). Agglomerative hierarchical clustering algorithm-a. *International Journal of Scientific and Research Publications*, 83(3):83.

Simpson, K. and Kelly, M. (2002). Reliability assessments of repairable systems—is markov modelling correct? In *Safety and Reliability*, volume 22, pages 19–39. Taylor & Francis.

Son, K. S., Kim, D. H., Kim, C. H., and Kang, H. G. (2016). Study on the systematic approach of markov modeling for dependability analysis of complex fault-tolerant features with voting logics. *Reliability Engineering & System Safety*, 150:44–57.

Souza, G. C. (2013). Closed-loop supply chains: a critical review, and future research. *Decision Sciences*, 44(1):7–38.

Tahirov, N., Hasanov, P., and Jaber, M. Y. (2016). Optimization of closed-loop supply chain of multi-items with returned subassemblies. *International Journal of Production Economics*, 174:1–10.

van Nunen, T. M. S. M. (1995). J van wassenhove l strategic issues in product recovery management. *California Management Review*, 372:114–135.

Wang, C., Xing, L., and Levitin, G. (2013). Reliability analysis of multi-trigger binary systems subject to competing failures. *Reliability Engineering & System Safety*, 111:9–17.

Wang, J., Miao, Y., Yi, Y., and Huang, D. (2021). An imperfect age-based and condition-based opportunistic maintenance model for a two-unit series system. *Computers & Industrial Engineering*, 160:107583.

Xiao, Q. (2014). Evaluating correlation coefficient for nataf transformation. *Probabilistic Engineering Mechanics*, 37:1–6.

Zhang, J., Kang, J., Sun, L., and Bai, X. (2021a). Risk assessment of floating offshore wind turbines based on fuzzy fault tree analysis. *Ocean Engineering*, 239:109859.

Zhang, X.-m., Li, Q.-w., Liu, Z., and Chang, C.-T. (2021b). Optimal pricing and remanufacturing mode in a closed-loop supply chain of weee under government fund policy. *Computers & Industrial Engineering*, 151:106951.