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Opportunistic Maintenance Modeling in a Closed-Loop Supply Chain: The Impact of Spare Parts Material, Technician Skill, and Environmental Conditions

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Abstract

Opportunistic Maintenance (OM) is one of the key approaches for optimizing maintenance operations in Closed-Loop Supply Chains (CLSC), which leverages the repair and recovery of spare parts to reduce costs and improve reliability. In this paper, a new OM model is proposed that, in addition to classical factors such as component age and economic and structural dependencies, incorporates spare-part material type, technician skill level, and environmental conditions into maintenance decision-making. The material of spare parts directly affects their failure rate and service life, while technician skill enhances repair quality and post-repair lifetime. Moreover, environmental conditions such as temperature and humidity alter the degradation rate of components. Preliminary results and conceptual analyses indicate that the proposed model can reduce costs, improve the overall performance of the closed-loop supply chain, and enhance the reliability of repaired components.

Keywords: Opportunistic maintenance, Spare parts, Structural dependency, Closed-loop supply chain, Reliability.

1 | Introduction

Maintenance is a key element in asset life-cycle management, as it directly affects the reliability and availability of equipment and constitutes a significant portion of life-cycle costs. For example, maintenance costs of industrial equipment in critical sectors such as energy production or medical equipment can account for a substantial share of total costs. To address these challenges, various strategies have been developed to optimize maintenance processes and reduce unexpected failures. One effective approach to cost reduction and sustainability improvement is the use of a Closed-Loop Supply Chain (CLSC), in which defective parts

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are repaired or remanufactured and then returned to the supply chain. This process not only reduces the need for new parts but also lowers operational costs. However, a major challenge is that most Opportunistic Maintenance (OM) models within CLSC focus on factors such as component age and economic and structural dependencies, while paying less attention to factors such as spare-part material, technician skill, and environmental conditions, all of which can directly affect failure rates and repair costs [1].

The material of spare parts has a direct impact on their failure rate and service life. Components made from higher-quality and more resistant materials tend to have longer lifespans and lower failure probabilities. On the other hand, technician skill is a key factor influencing repair quality and the post-repair reliability of components. More skilled technicians can perform higher-quality repairs, leading to a reduction in future failures. In addition, environmental conditions such as temperature and humidity directly affect the degradation rate of components; harsher environmental conditions accelerate wear and deterioration [2]. This paper proposes a new OM model within CLSC that incorporates these three key factors alongside component age and structural and economic dependencies into maintenance decision-making. In recent years, research related to CLSC has grown significantly and has become one of the fundamental pillars of the circular economy. This concept emphasizes recycling, remanufacturing, and repairing spare parts with the aim of reducing the need for virgin raw materials, lowering energy consumption, and minimizing waste. Through CLSC implementation, companies can not only reduce operational costs but also contribute to environmental sustainability [3]. In this context, numerous studies have examined product and component recycling and remanufacturing, inventory management, and process optimization to increase profitability and reduce waste [4], [5].

One of the major challenges in CLSC is the quality and reliability of repaired spare parts. Unlike many existing models that assume repaired components return to their original quality, degradation resulting from repeated use and successive repairs can negatively affect component performance [6]. In particular, many studies assume that remanufactured or repaired components are comparable to new ones in terms of sustainability and reliability. While this assumption has been widely adopted in CLSC inventory management and supply chain network design models, the long-term impact of degradation in repaired components has received numerous studies have examined product and component recycling and remanufacturing, inventory management, and process optimization to increase profitability and reduce waste [4], [5]. One of the major challenges in CLSC is the quality and reliability of repaired spare parts. Unlike many existing models that assume repaired components return to their original quality, degradation resulting from repeated use and successive repairs can negatively affect component performance [6]. In particular, many studies assume that remanufactured or repaired components are comparable to new ones in terms of sustainability and reliability. While this assumption has been widely adopted in CLSC inventory management and supply chain network design models, the long-term impact of degradation in repaired components has received less attention [7–9]. by examining factors influencing decision-making in mechanical component remanufacturing processes, concluded that remanufacturing and reuse of preserved materials are among the key drivers of strategic organizational decisions. Their study showed that from an energy perspective, remanufacturing is generally more favorable, although economic outcomes may vary. Another study by Turki et al. [10] addressed the challenges of forecasting spare-part supply capacity in the healthcare industry and proposed a hybrid approach combining statistical methods and business knowledge to predict returns. In the field of maintenance, studies indicate that OM is an effective strategy for repair optimization [11]. In this approach, spare parts are replaced either during predefined intervals or when other components fail, which helps reduce costs and improve system performance [12], [13]. OM models are generally divided into two categories: time-based maintenance and Condition-Based Maintenance (CBM). In time-based models, component replacement is performed according to age or operating time. For instance, Sun et al. [14] and Wang et al. [15] proposed OM models for two-unit series systems, optimizing maintenance actions based on predefined schedules. In contrast, CBM within CLSC focuses on factors such as component age and economic and structural dependencies, while paying less attention to factors such as spare-part material, technician skill, and environmental conditions, all of which can directly affect failure rates and repair costs. The material of spare parts has a direct impact on their failure rate and service life. Components made from higher-quality and more resistant materials tend to have longer lifespans and lower failure probabilities. On the other hand, technician skill is a key factor influencing repair quality and the post-repair reliability of components. More skilled technicians can perform higher-quality repairs, leading to a reduction in future failures. In addition, environmental conditions such as temperature and humidity directly affect the degradation rate of components; harsher environmental conditions accelerate wear and deterioration. 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In contrast, CBM, which has gained increasing popularity in recent years due to its efficiency, is based on real-time data and condition monitoring of components. This approach allows maintenance planning according to the current condition and degradation level of components. Studies such as Chateauneuf et al. [16] and Zhu et al. [17] used risk-based criteria to compare the risks of replacing or not replacing components. More recent studies, including Nguyen et al. [18], have integrated predictive maintenance with real-time monitoring systems, enabling proactive maintenance decisions based on actual data. Other works, such as Lu et al. [19], developed an Operational Reliability (OR) model based on system availability and proposed a multi-objective optimization framework for OM with adaptive maintenance windows. Dinh et al. [20] also investigated the impact of disassembly processes in production systems on reliability and the optimization of OM. Despite these advancements, a major limitation in OM and CBM models is CBM, which has gained increasing popularity in recent years due to its efficiency that is based on real-time data and condition monitoring of components. This approach allows maintenance planning according to the current condition and degradation level of components. Studies such as Chateauneuf et al. [16] and Zhu et al. [17] used risk-based criteria to compare the risks of replacing or not replacing components. More recent studies, including Nguyen et al. [18], have integrated predictive maintenance with real-time monitoring systems, enabling proactive maintenance decisions based on actual data. Other works, such as Lu et al. [19], developed an OR model based on system availability and proposed a multi-objective optimization framework for OM with adaptive maintenance windows. Dinh et al. [20] also investigated the impact of disassembly processes in production systems on reliability and the optimization of OM. Despite these advancements, a major limitation in OM and CBM models is the insufficient consideration of stochastic dependencies among components in multi-component systems. Stochastic dependency implies that the failure of one component can affect the performance and lifetime of other components [13]. This issue is particularly important in complex systems, such as medical or industrial equipment, where the failure of a single component can trigger cascading failures and increase maintenance costs. While many existing models address structural and economic dependencies, stochastic dependencies have received relatively little attention [21]. For example, studies by Wang et al. [22] and Salari and Makis [23] focused on economic dependencies, but the impact of stochastic dependencies has not yet been comprehensively examined. To model stochastic dependencies, researchers have employed methods such as Monte Carlo simulation, Markov models, and copula functions. For instance, Xu et al. [24] used Markov processes and Monte Carlo simulation to model stochastic dependencies in K-out-of-N systems. Zhou et al. [25] applied a multi-agent reinforcement learning model to analyze economic, structural, and stochastic effects in systems with a large number of components. However, the computational complexity of these methods has limited their application in larger systems [24], [25]. Moreover, Boujarif et al. [28] introduced an OM model for CLSC that primarily focuses on the effective management of multi-component spare parts using historical repair data. Unlike traditional approaches that often neglect the degradation of repaired components, this model utilizes stochastic dependencies among components to inform preventive replacements, aiming to balance cost and reliability.

In recent years, the analysis of spare-part material has also been recognized as a key factor in maintenance decision-making. Research shows that the material used in component manufacturing significantly affects failure rates and service life. Components made from weaker materials typically degrade faster under harsh environmental conditions [29]. Therefore, modeling the impact of component material on post-repair reliability and useful life can improve maintenance decisions. Additionally, technician skill has been identified as an influential factor in OM and CBM models. Studies indicate that repairs performed by more skilled technicians result in higher quality and extended post-repair component life [30]. This factor is particularly critical in complex systems requiring high technical expertise, such as the medical and manufacturing industries. Furthermore, environmental conditions such as temperature, humidity, and other environmental factors play an important role in component degradation and wear rates. Given that many components operate in harsh industrial or medical environments, analyzing the impact of environmental conditions on post-repair performance and lifespan can further enhance OM models.

In this paper, we propose a new OM model that, in addition to considering classical factors such as economic and stochastic dependencies, explicitly incorporates the effects of spare-part material, technician skill, and environmental conditions into maintenance decision-making. By optimizing maintenance strategies, the proposed model helps organizations reduce operational costs and improve overall system reliability.

2 | Problem Statement

The CLSC is one of the most important strategies for optimizing resources and reducing waste. By returning, repairing, and remanufacturing spare parts instead of using new ones, CLSC can significantly reduce operational costs. In such a supply chain, defective units are returned to repair centers, repaired, and then reintroduced into the supply chain to replace future defective units. This process contributes to the development of a more environmentally and economically sustainable system. One of the main challenges in this framework is the insufficient attention paid to the quality of repairs and the reliability of repaired spare parts. In most cases, it is assumed that parts return to their original quality level after repair; however, in practice, due to natural degradation and repeated wear, this assumption is not valid. This issue can lead to an increase in early failures, a reduction in component lifetime, and higher maintenance and repair costs. On the other hand, in CLSC, maintenance opportunities are considered an effective strategy for optimizing maintenance costs. OM, rather than replacing components only after complete failure, involves inspecting and replacing spare parts that show signs of deterioration during maintenance operations. This approach can significantly reduce long-term costs while maintaining system reliability. However, existing OM models are generally developed based on time-based data or specific component conditions and do not sufficiently account for stochastic dependencies and environmental factors that can have a significant impact on system performance. While economic and structural dependencies among spare parts have been studied, stochastic dependencies and environmental conditions that may intensify component failures have received less attention. Given these limitations, this research aims to develop a new OM model for CLSC that, in addition to considering economic, stochastic, and structural dependencies, explicitly incorporates the effects of spare part material, technician skill level, and environmental conditions. In this model, available maintenance data are used to optimize maintenance decisions. The main problem is to determine when and according to which criteria spare parts should be replaced proactively and opportunistically in order to reduce maintenance and repair costs while simultaneously improving repair quality and component lifetime. By simultaneously integrating spare part material, technician skill, and environmental conditions, the proposed model seeks to answer the question of how optimal maintenance decisions can be made while accounting for these factors.

2.1 | Modeling

2.1.1 | Abbreviations and Symbols

$\zeta = [1, 2, 3, \mathrm{n}]$ Set of spare parts in the system.

Costc Price (cost) of part c.

Mulc Mean lifetime of part c.

RVc is the residual value of part c per unit of time.

LC Labour cost per unit of time.

$\mathrm{Cost0}$ Logistics cost for each repair (the cost of transporting the spare part to the customer’s location).

$\tau\mathrm{c}$ Disassembly time of part c.

ac Age of part c.

(t) Reliability function of part c.

(t) Probability density function of the failure time of part c.

$(\mathrm{t};\ \mathrm{a1}, \mathrm{a2}, \ldots, \mathrm{an}) = \mathrm{h}(\mathrm{R1}(\mathrm{t};\ \mathrm{a1}), \ldots, \mathrm{Rn}(\mathrm{t};\ \mathrm{an}))$ System reliability function as a function of the reliability of its components.

$(\mathrm{t};\ \mathrm{a1}, \mathrm{a2}, \ldots, \mathrm{an})$ Probability density function of the system’s failure time.

T Planning horizon.

r Interest rate.

$\mathrm{D} = (\mathrm{Dij})$ System disassembly matrix.

Sc Status of part c (failed or operational).

$\mathrm{Sc} = 1$ if the part has failed.

$\mathrm{Sc} = 0$ if the part is operational.

$\mathrm{Twarranty}$ Warranty period, during which all failures are considered early failures.

Rmin Minimum required reliability after repair.

$x_c = 1$, preventive replacement

$x_c = 0$ otherwise

η_c Technician skill coefficient for part c.

ϵ_c Material (component-type) coefficient for part c.

θ_c Environmental condition coefficient for part c.

$Cost_c$ Replacement cost of part c.

2.2 | Model Development and Problem Formulation

In this section, a new OM optimization model is developed by incorporating three key innovations: spare parts material characteristics, technician skill level, and environmental conditions. The objective of this model is to minimize long-term operational costs while ensuring that the CLSC for spare parts operates with an acceptable level of reliability. These factors significantly influence failure rates, repair efficiency, and overall system reliability. The proposed model dynamically determines which components should be replaced preventively and opportunistically, based on different types of dependencies, including stochastic, economic, and structural dependencies. The material composition and quality of spare parts have a direct impact on their resistance to shocks, degradation, and failures. For instance, components manufactured from high-strength materials, such as high-strength steels, are less susceptible to impact damage and wear. In our model, the coefficient ε_c is defined for each component c as a resistance index, representing the component's resistance to impacts and failures. A higher value of $\varepsilon_c$indicates greater component resistance. The effect of spare parts material can be modeled as follows:

$$\varphi_c = \frac{1}{\epsilon_c}, \tag{1}$$

where ε_c denotes the resistance coefficient associated with the material of component c. This coefficient represents the material strength of the component against degradation and failures and can be estimated using historical data or field tests through statistical methods such as Maximum Likelihood Estimation (MLE).

The skill and experience of the technician can have a direct impact on the quality of repair as well as the repair time and associated costs. More skilled technicians are able to perform repairs with higher quality, thereby causing less additional damage to the components. This effect is represented by the coefficient η_c , which is randomly modeled using a Beta distribution and reflects the technician's skill level for component c. This coefficient takes values between 0 and 1; the closer its value is to 1, the higher the technician's skill level and the lower the negative impact on component failures. The effect of technician skill is expressed as follows:

$$\varphi_c = \frac{1}{\eta_c . \epsilon_c}, \tag{2}$$

where ε_c denotes the resistance coefficient associated with the material of component c. This coefficient represents the material strength of the component against degradation and failures and can be estimated using historical data or field tests through statistical methods such as MLE.

The skill and experience of the technician can have a direct impact on the quality of repair as well as the repair time and associated costs. More skilled technicians are able to perform repairs with higher quality, thereby causing less additional damage to the components. This effect is represented by the coefficient η_c, which is randomly modeled using a Beta distribution and reflects the technician's skill level for component c. This coefficient takes values between 0 and 1; the closer its value is to 1, the higher the technician's skill level and the lower the negative impact on component failures. The effect of technician skill is expressed as follows:

$$f(\eta) = \frac{1}{B(\alpha,\beta)} . \eta^{\alpha-1} . (1-\eta)^{\beta-1}, \tag{3}$$

where α and β are the shape parameters of the Beta distribution and are extracted from historical data. Environmental conditions such as temperature, humidity, pressure, and weather conditions can significantly affect the degradation and failure rates of components. To model the effect of environmental conditions, the coefficient θ_c is considered as an environmental factor that represents the impact of environmental conditions on component c. This coefficient affects the reliability and the time between failures and should be incorporated multiplicatively into the model. The system reliability, considering the material of spare parts, the technician's skill, and environmental conditions, should be modeled more accurately. In the study by Boujarif et al. [28], the system reliability for independent series units is defined as follows:

$$R_{sys}(t) = \prod_{c\epsilon\zeta} R_c(t; a_c). \quad \textbf{(4)}$$

In this study, considering the impact of new factors on system reliability, the system reliability can be defined as a function of component reliability $R_c(t)$, component age a_c, and component material ε_c , technician skill level η_c, and environmental conditions θ_c:

$$R_{sys}(t) = \prod_{c\epsilon\zeta} R_c(t; a_c, \eta_c, \epsilon_c, \theta_c), \quad \textbf{(5)}$$

In this formula, $R_C(t)$ is the reliability of component ccc, which changes based on time t, age a_c, and the effects of technician skill, spare part material, and environmental conditions. Next, we formulate the optimization problem as follows:

Variables decision

For each segment c, the binary decision variable x_c is defined as:

$$\left.\begin{matrix} 1 \text{ Replace as a precaution c If the part} \\ 0 \quad 0.\text{W} \end{matrix}\right\} = x_c.$$

These decisions are made based on the component's reliability, its material, the technician's skill, and the environmental conditions.

Constraints

In the model we are designing, S_c represents the failure state of the component.

I. If S_c =1, it means the component has failed and must be replaced or repaired.

II. If S_c=0, it means the component is healthy and does not require maintenance.

III. On the other hand, x_c represents the decision for opportunistic (preventive) replacement.

IV. If x_c=1, the component is replaced preventively.

V. If x_c=0, it means no preventive replacement is decided.

When the component has failed (S_c =1), the influence of the technician's skill, the material quality, and the environmental conditions becomes more critical, because these factors directly affect the quality of the repair. In other words, when a component fails and needs repair, the technician's expertise, the component's durability, and the environmental conditions determine how successful the repair will be and how long the component will last afterward.

Therefore, the coefficients η_c (technician's skill), ε_c (component material), and θ_c (environmental conditions) are multiplied by S_c to ensure their effects are considered only when the component is in a failed state. That is, these factors become relevant only when the component requires repair.

When a decision is made to replace a component preventively ($x_c = 1$), this decision is primarily based on maintenance policies and usually considers the risk of failure or wear of the component, not the technician's skill, the material, or the environmental conditions at the time of repair. This is because the component has not yet failed, and the decision is made based on predictive assessments.

Therefore, we have:

$$x_c + s_c.(\eta_c.\epsilon_c.\theta_c) \leq 1, \text{for all } c\epsilon\zeta. \quad \textbf{(6)}$$

In the second constraint, according to Boujarif et al. [28], the objective is to ensure that the reliability of the component after repair reaches a specified minimum level and performs satisfactorily throughout the warranty period. Considering the effects of the component material, the repair technician's skill, and environmental conditions, these factors influence the reliability of both the system and its components. This constraint guarantees that the system reliability after repair, taking into account the technician's skill, the component material, and environmental conditions, reaches at least the required minimum value Rmin, and that the component or system operates satisfactorily during the warranty period.

$$\frac{R_{sys}(T_{warranty};a_1(1-(x_1+s_1.(\eta_1.\epsilon_1.\theta_1))),\dots,a_n(1-(x_n+s_n.(\eta_n.\epsilon_n.\theta_n)))}{R_{sys}(0;a_1(1-(x_1+s_1.(\eta_1.\epsilon_1.\theta_1))),\dots,a_n(1-(x_n+s_n.(\eta_n.\epsilon_n.\theta_n)))} \geq R_{min}. \tag{7}$$

Objective function: the objective function seeks to minimize the overall maintenance and repair costs. The various components of this cost function include the following:

$$\min TC = C_r + C_w + C_f + C_L. \tag{8}$$

C_r: Replacement costs, including preventive and corrective replacements.

C_w: Penalty cost resulting from preventive replacement of components that still have useful life remaining.

C_f: Failure costs of repaired components during the planning horizon.

C_l: Labor costs associated with the maintenance process.

Regarding replacement costs C_r, components made of better materials and higher resistance have lower replacement costs. The skill of the repair technician affects the accuracy and quality of repairs, and environmental conditions can accelerate or slow down the component degradation process. The translation maintains all the technical terminology and concepts from the original Persian text, including the cost categories and the factors affecting maintenance processes.

$$C_r = \sum_{c\epsilon\zeta}(x_c + s_c.(\eta_c.\epsilon_c.\theta_c)).\mathrm{Cost}_c. \tag{9}$$

where η_c is the mechanic's skill factor. If the mechanic has a high skill level, this factor approaches 1, and if they have a low skill level, this factor approaches zero. ε_c is a factor related to the component material, which indicates that components made of better materials are not easily damaged. θ_c is a factor related to environmental conditions. The second term in *Eq. (8)*, related to the penalty cost of preventive replacement, C_w is a penalty cost applied for the unused remaining life of the replaceable components due to preventive replacement. This cost is defined as follows:

$$C_w = \sum_{c\epsilon\zeta} x_c . \frac{RV_c}{R_{sys}(0;a_1(1-(x_1+s_1.(\eta_1.\epsilon_1.\theta_1))),\dots,a_n(1-(x_n+s_n.(\eta_n.\epsilon_n.\theta_n)))} . \int_0^{+\infty} tf_c(t;a_c)dt. \tag{10}$$

where RV_c (residual value per unit time) is the residual value per unit time of the component's lifespan. This parameter indicates how much economic value a component has if it is used until it fully fails. The material of the component (which is related to its resistance to degradation) and environmental conditions affect this parameter. Additionally, the technician's skill can also decrease or increase the component's wear and tear. Consequently, we have:

$$RV_c = \frac{\mathrm{Cost}_c}{MUL_c.\eta_c.\epsilon_c.\theta_c}. \tag{11}$$

Cost_c is the cost of purchasing or replacing the component. MUL_c represents the Mean Useful Life of the component. Mean Useful Life (MUL) refers to the average useful lifetime of a component and indicates how long the component can fully maintain its functionality. This parameter is also used in calculating the residual value of the component per unit of time.

$$MUL_c = \frac{1}{\lambda_c}, \tag{12}$$

where λ_c is the failure rate of the component. The material of the component, the skill of the repairer, and the environmental conditions can change the failure rate and the useful life. Therefore, the MUL equation is updated as follows:

$$MUL_c = \frac{1}{\lambda_c.\eta_c.\epsilon_c.\theta_c}. \tag{13}$$

Now, let's assume that Mean Residual Life (MRL) means the average remaining life of a component that has not yet failed. This value indicates how much longer we expect a component to work before it fails after a certain point (for example, time t=0 after repair). Usually, MRL is calculated integrally based on the probability density function of the component's life $f_c(t)$.

$$\mathrm{MRL_c} = \int_0^{+\infty} \mathrm{t} f_c\left(\mathrm{t}; a_c, \eta_c, \epsilon_c, \theta_c\right) \mathrm{dt}. \tag{14}$$

Line Replaceable Unit (LRU) refers to components or systems that can be easily replaced in the event of failure without the need for complex repairs. These components are usually designed to be quickly replaceable in systems. Each LRU consists of several components, and each time one of these components fails, it provides an opportunity for preventive maintenance. The type of component and environmental conditions can have a direct impact on the LRU, as some LRUs fail more quickly in harsher environmental conditions. Present Value (PV) is an economic concept used to calculate the value of a future cost or benefit based on the current interest rate. This concept is used to calculate the PV of future costs (such as future breakdown or replacement costs). Environmental factors and the skill of the repairer affect the timing and extent of the failure. For example, if a part fails later due to good material and suitable environmental conditions, the time interval ΔT increases, and the PV of future costs decreases. The formula for calculating PV is as follows:

$$\mathrm{PV} = \mathrm{C}.(1+\mathrm{r})^{-\Delta \mathrm{T}}. \tag{15}$$

C is the amount of cost to be paid in the future. r is the interest rate. ΔT is the time interval until payment or failure. The third term in *Eq. (8)* represents the cost of future failures, and C_f refers to the expected costs of failure of repaired spare parts during the planning period. It is assumed that these parts are installed in the field immediately after repair. In the event of a failure, the logistics cost will include the cost of shipping the part to the customer's site, the system downtime, and the maintenance activities to replace the failed unit. Since these costs are usually incurred in the future, their PV is calculated to be considered at the planning time.

$$C_f = \frac{\mathrm{Cost}_0}{R_{sys}\left(0; a_1\left(1-\left(x_1+s_1.\left(\eta_1.\epsilon_1.\theta_1\right)\right)\right), \dots, a_n\left(1-\left(x_n+s_n.\left(\eta_n.\epsilon_n.\theta_n\right)\right)\right)\right)}$$
$$\int_0^T \frac{f_{sys}\left(0; a_1\left(1-\left(x_1+s_1.(\eta_1.\epsilon_1.\theta_1)\right)\right), \dots, a_n\left(1-\left(x_n+s_n.(\eta_n.\epsilon_n.\theta_n)\right)\right)\right)}{(1+r)^t} \mathrm{dt}. \tag{16}$$

The last term in *Eq. (8)* is the labor costs C_L. Here, the effect of the skill of the repairer must be considered. The higher the skill, the shorter the repair time and the lower the labor cost. Therefore:

$$C_L = 2.\mathrm{LC}.\tau_{group}.\eta_c, \tag{17}$$

where τ_{group} is the total disassembly time adjusted by the repairer's skill:

$$\tau_{group} = \sum_{c \epsilon \zeta} (x_c + s_c).\tau_c.\frac{1}{\eta_c}. \tag{18}$$

2.3 | System Reliability Modeling Considering Stochastic Dependencies

This model specifically examines how the failures of different components interact and are correlated within a series system. To calculate the joint distribution of component failure times, approaches such as Monte Carlo simulation and the Nataf transformation are used. However, due to computational complexity, these methods are not suitable for high-dimensional problems. Therefore, a dimensionality reduction method is employed to calculate the joint distribution of component failure times more efficiently.

2.3.1 | Component clustering

In this section, to reduce the complexity of the calculations, the components are clustered based on their historical correlations. The main steps in this method are:

I. Calculate the correlation matrix $R = (pi,)$ between pairs of components calculated from historical maintenance data.

II. Convert the correlations into a distance matrix $H = (hi,)$, where the distance between two components i and j is defined as $hi, = 1 - |\rho i, |$. The stronger the dependence between two components, the smaller the distance between them.

III. Cluster the components based on this distance matrix using the Agglomerative Hierarchical Clustering algorithm.

IV. After the clusters are formed, the reliability distribution of each cluster is calculated, and the system reliability is calculated as a function of the reliability of these clusters.

2.3.2 | Nataf transformation

The Nataf transformation is a method for modeling correlated random variables, developed by Der Kiureghian and Liu [31]. This method maps non-normal variables to standard normal space and vice versa. This transformation is divided into three steps:

I. Transforming the variables into the Cumulative Distribution Space (CDF).

II. Mapping these variables to standard normal space using inverse cumulative distribution functions.

III. Using the Cholesky decomposition to calculate the correlation matrix in standard normal space.

$$u = T_N(X) = T_3 \circ T_2 \circ T_1, \tag{19}$$

where T_1 maps the random variables to the CDF. T_2 maps these variables to the standard normal space. T_3 transforms the correlation matrix using Cholesky decomposition. But for each random variable x_c, the factors of part material, repairer skill, and environmental conditions are applied as adjustment coefficients:

$$u = T_N(X, \eta_n, \epsilon_n, \theta_n) = T_3 \circ T_2 \circ T_1(X.\eta_n.\epsilon_n.\theta_n). \tag{20}$$

Eq. (21) expresses the joint distribution of the probability of component failure based on the Nataf transformation:

$$P(X \le t) = P(X_1, X_2, \dots, X_n \le t) = \Phi_{RZ}(\Phi^{-1}(F_{x1}(t)), \Phi^{-1}(F_{x2}(t)), \dots, \Phi^{-1}(F_{xn}(t))). \tag{21}$$

Considering that the factors of the component material, the skill of the repairer, and the environmental conditions affect the failure time, *Eq. (21)* changes to the following form:

$$P(X, \eta_n, \epsilon_n, \theta_n \le t) = \\ \Phi_{RZ}(\Phi^{-1}\left(F_{x1,\eta_1,\epsilon_1,\theta_1}(t)\right), \Phi^{-1}\left(F_{x2,\eta_2,\epsilon_2,\theta_2}(t)\right), \dots, \Phi^{-1}\left(F_{xn,\eta_n,\epsilon_n,\theta_n}(t)\right)). \tag{22}$$

The most important issue in the Nataf transformation is to create an equivalent correlation matrix in the standard normal space. According to Lebrun and Dutfoy [32], we can write ($\rho_{i,j}^X$) as a function of $\rho_{i,j}^Z$:

$$\rho_{i,j}^X = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left(\frac{x_i-\mu_i}{\sigma_i}\right)\left(\frac{x_j-\mu_j}{\sigma_j}\right).\phi_2(z_i, z_j, \rho_{i,j}^Z)dz_i dz_j. \tag{23}$$

Eq. (23) changes to the following form by taking into account the factors of the component material, the skill of the repairer, and the environmental conditions:

$$\rho_{i,j}^X = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\left(\frac{x_i.\eta_i.\epsilon_i.\theta_i-\mu_i}{\sigma_i}\right)\left(\frac{x_j.\eta_j.\epsilon_j.\theta_j-\mu_j}{\sigma_j}\right).\phi_2(z_i, z_j, \rho_{i,j}^Z)dz_i dz_j. \tag{24}$$

Finally, we use this method to calculate the joint distribution of component failure times and calculate the system reliability based on it. The system reliability based on the effect of component material, repairman skill, and environmental conditions is expressed as follows:

$$R^{*}_{sys}(t) = \prod_{g\in\Xi} R_g(t; a_g, \eta_g, \epsilon_g, \theta_g). \tag{25}$$

In *Eq. (25)*, the reliability of each cluster is calculated based on the coefficients (part type, repairman skill, and environmental conditions), where Ξ is the set of formed clusters.

3 | Numerical Example

We consider a series system with three components, and the following data for this system is presented in *Table 1*. We will solve this example for two cases. In the first case, we will consider all these factors and compare the results.

Table 1. Parts specifications.

θ	ε	η	Warranty (u.t.)	Time to Disassemble (u.t.)	Failure Rate	Time to Failure (u.t)	MUL (u.t.)	Cost (U.C)	Component
0.8	1.2	0.9	20k	1	0.001	30k	50k	10	C_1
0.9	1.1	0.85	25k	2	0.0015	35k	40k	20	C_2
0.95	1.0	0.95	30k	1.5	0.002	55k	60k	15	C_3

Logistics costs ($Cost_0$) 750U.C Interest rate: r=0.05 Planning horizon: T=1000. In this example, it is assumed that the disassembly and repair of each part takes an average of 5 units of time. Solution steps:

I. Calculate the correlation matrix $R = (\rho i,)$: We assume that the correlation matrix between the three parts C1, C2, and C3 is as follows:

Table 2. Correlation matrix among system components (C1, C2, and C3) based on historical failure data, indicating the degree of dependency between component failures.

	C_1	C_2	C_3
C_1	1	0.3	0.2
C_2	0.3	1	0.25
C_3	0.2	0.25	1

This matrix represents the correlation between the failures of the components. The higher the value of $(\rho i,)$, the stronger the correlation between the components.

II. Convert to distance matrix $H = (hi,)$: Using the formula $hi, = 1 - |\rho i, j|$ we calculate the distance matrix:

Table 3. Distance matrix derived from the correlation matrix, used for clustering components based on their level of dependency.

	C_1	C_2	C_3
C_1	0	0.7	0.8
C_2	0.7	0	0.75
C_3	0.8	0.75	0

The distances show that parts C1 and C2 are less dependent than C1 and C3.

III. Clustering with the Agglomerative Hierarchical Clustering algorithm:

Using the Agglomerative Hierarchical Clustering algorithm and based on the distance matrix, two clusters are created:

Cluster 1. includes C1 and C2

Cluster 2. includes C3, the first case, without considering factors (type of spare parts, skill of the repairer, environmental conditions)

Reliability of clusters

$R_{cluster1}(t) = e^{-\lambda_{C1}t}.e^{-\lambda_{C2}t}$ For C1 and C2.
$R_{cluster1}(1000)=0.3679 \cdot 0.2231=0.0821$.
$R_{cluster2}(t) = e^{-\lambda_{C3}t}$ For C3.
$R_{cluster2}(1000)=R_{C3}(t)=0.1353$.

System reliability

According to the clustering performed:

$$R_{sys}(t) = R_{cluster1}(t).R_{cluster2}(t),$$
$$R_{sys}(t) = e^{-(\lambda_{C1}+\lambda_{C2}+\lambda_{C3})t},$$
$$Rsys(1000) = 0.0821 \cdot 0.1353 = 0.0111.$$

The type of parts, the skill of the repairer, and the environmental conditions have a negative impact on the reliability of the system, because these factors reduce the useful life of the parts. The reliability of the entire system is lower without these factors than without them, because the impact of these negative factors on the reliability of each part is taken into account.

4 | Cost Calculation

Calculation of the cost of future failures C_f considering the factors (type of spare parts, skill of the repairer, environmental conditions).

$$C_f = \frac{Cost_0}{R_{sys}(0)}.\int_0^T \frac{f_{sys}(t)}{(1+r)^t}dt.$$

Let us assume that R_{sys} (0)=0.78 and the probability density function of the system is exponential:

$$f_{sys}(t) = 0.0045.e^{-0.0045t} = 0.89.$$
$$C_f = \frac{750}{0.78}.\int_0^{1000} \frac{0.89}{(1+0.05)^t}dt = 855.77U.C.$$

Cost of future failures C_f without considering factors (type of spare parts, skill of repairman, environmental conditions) Cost of future failures C_f without considering factors (type of spare parts, skill of repairman, environmental conditions).

$$R_{sys}(0) = 0.7866.$$
$$C_f = \frac{750}{0.78}.\int_0^{1000} \frac{0.89}{(1+0.05)^t}dt = 849.56U.C.$$

Penalty cost C_w regardless of factors (type of spare parts, skill of repairman, environmental conditions):

$$C_w = \sum_{c\epsilon\zeta} x_c \cdot \frac{RV_c}{R_{sys}(0)}.\int_0^{+\infty} tf_c(t;a_c)dt = 2.54U.C.$$

Penalty cost C_w considering factors (type of spare parts, skill of repairman, environmental conditions)

$$C_w = \sum_{c\epsilon\zeta} x_c \cdot \frac{RV_c}{R_{sys}(0;a_1(1-(x_1+s_1.(\eta_1.\epsilon_1.\theta_1))),\ldots,}.\int_0^{+\infty} tf_c(t;a_c)dt = 2.67U.C.$$

Replacement cost C_r for both cases:

$C_r=(x_{C1}+s_{C1})\cdot 10+(x_{C2}+s_{C2})\cdot 20+(x_{C3}+s_{C3})\cdot 15=45$ U.C.

Labor cost C_L without considering factors (type of spare parts, skill of repairman, environmental conditions).

$C_L=2\cdot(5\cdot(1+0)+5\cdot(0+1)+5\cdot(1+0)) = 2\cdot(5+5+5)=2\cdot 15=30$ U.C.

Labor cost C_L considering factors (type of spare parts, skill of repairman, environmental conditions).

$$\mathrm{C_L} = 2.\sum_{c}(5.\frac{x_c+s_c}{\eta_c}),$$

$$\mathrm{C_L} = 2.\sum_{c}\left(5.\frac{0+1}{0.95}+5.\frac{1+0}{0.85}+5.\frac{0+1}{0.9}\right) = 33.4\mathrm{U.C.}$$

Total cost without considering factors (type of spare parts, skill of repairman, environmental conditions).

$$\mathrm{TC}=\mathrm{C_r}+\mathrm{C_f}+\mathrm{C_L}+\mathrm{C_w}=45+849.56+30+2.54=927.1\ \mathrm{U.C.}$$

Final result considering factors (type of spare parts, skill of repairman, environmental conditions).

$$\mathrm{TC}=\mathrm{C_r}+\mathrm{C_f}+\mathrm{C_L}+\mathrm{C_w}=45+855.77+33.67+2.67=937.11\ \mathrm{U.C.}$$

Now we want to examine the effect of having an OM program in a CLSC, given that we have assumed a logistics cost of 750 monetary units.

Table 4. The impact of having an opportunistic maintenance program in a closed-loop supply chain.

Criteria	**No Opportunistic Maintenance**	**Without the Influence of Factors (Opportunistic Maintenance)**	**By the Influence of Factors (Opportunistic Maintenance)**
Replacement cost	52	45	45
Future failure cost	855.77	849.56	855.77
Penalty cost	0	2.54	2.67
Labor cost	30	30	33.67
Total cost	937.77	927.1	937.11

To calculate and compare the impact of OM versus traditional corrective repairs (without OM), and to compare it with the two previously solved examples (with and without factors), we need hypothetical data for the case where OM is not performed. In this case, only corrective repairs are used; that is, when a component fails, we replace or repair it and incur the associated logistics costs, and no preventive maintenance opportunities are utilized.

According to *Table 4*, we assume that in the no-opportunistic-maintenance scenario only corrective repairs are performed, and the number of failures and the costs arising from failures increase.

I. Corrective replacement cost (C_r): due to more failures, the replacement cost increases.

II. Future failure cost (C_f): with increased failures, the future failure costs also rise.

III. Penalty cost (C_w): the penalty cost is lower, because opportunities for preventive repairs are missed.

IV. Labor cost (C_l): more labor is required for corrective replacements.

In the absence of OM, the total cost is higher due to more failures and higher corrective replacement costs. In the OM scenario without the influence of factors, costs decrease because preventive repair opportunities are used. In the OM scenario with the influence of factors, costs improve further, and the total cost declines due to more optimal resource utilization.

This comparison shows that OM especially when enhanced by innovations (technician skill, component quality, and environmental conditions) can reduce costs and improve the overall performance of the CLSC.

5 | Conclusion

In this study, the impact of various factors on system reliability and maintenance costs in a CLSC was examined. Specifically, part material, technician skill, and environmental conditions were identified as negative influencing factors on the reliability of each component. These factors shorten the useful life of components and, as a result, the overall system reliability in the innovation scenario is lower than in the non-innovation scenario. A comparison between the scenarios with influencing factors and without influencing factors shows that the total system cost in the scenario without influencing factors was 927.1 unit cost (U.C.), while considering improved influencing factors (technician skill, part material, and environmental conditions), the total cost reached 937.11 unit cost (U.C.). This increase in cost is due to more accurate accounting of the influencing factors and optimized system maintenance. However, the performance improvements brought about by these innovations far outweigh the added costs. Next, OM was compared with traditional corrective repairs (without OM). In the scenario without OM, only corrective repairs are used, which leads to an increase in the number of failures and the costs arising from them. This results in higher corrective replacement cost (Cr) and future failure cost (Cf). In contrast, OM reduces these costs because preventive repair opportunities are leveraged efficiently. This effect is especially pronounced when influencing factors (such as part material and technician skill) are taken into account, leading to greater improvements in system performance.

This study shows that OM, particularly when combined with innovations, can significantly reduce costs and improve system reliability. Moreover, this more optimal approach directly leads to lower total costs across the CLSC and improved resource utilization efficiency. It is recommended that future research investigate the more dynamic effects of these factors on larger and more complex systems, in order to achieve better outcomes in industrial maintenance and repair decision-making.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix

```
% MATLAB Code for Opportunistic Maintenance with and without Innovations
% Parameters
Cost0 = 750;         % Logistic cost
r = 0.05;            % Discount rate
T = 1000;            % Planning horizon (time units)
% Failure rates (lambda) for components C1, C2, C3
lambda_C1 = 0.001;
lambda_C2 = 0.0015;
lambda_C3 = 0.002;
% Component residual values
RV_C1 = 10 / 50000;
RV_C2 = 20 / 40000;
RV_C3 = 15 / 60000;
% Reliability at t=0 (without innovations)
Rsys_0_no_innov = 0.7866;
% Reliability at t=0 (with innovations)
Rsys_0_innov = 0.78;
% Efficiency factors, material factors, and environmental conditions (with innovations)
eta_C1 = 0.9; epsilon_C1 = 1.2; theta_C1 = 0.8;
eta_C2 = 0.85; epsilon_C2 = 1.1; theta_C2 = 0.9;
eta_C3 = 0.95; epsilon_C3 = 1.0; theta_C3 = 0.95;
% Reliability function (Exponential PDF) for each component
f_C1 = @(t) lambda_C1 * exp(-lambda_C1 * t);
f_C2 = @(t) lambda_C2 * exp(-lambda_C2 * t);
f_C3 = @(t) lambda_C3 * exp(-lambda_C3 * t);
% Define time array for integration
time = linspace(0, T, 1000);
% ------------------------
% Without Innovations
% ------------------------
% Future Failure Costs (Cf) without innovations
integrand_no_innov = @(t) (0.0045 * exp(-0.0045 * t)) ./ (1 + r) .^ t;
Cf_no_innov = Cost0 / Rsys_0_no_innov * trapz(time, integrand_no_innov(time));
% Preventive Replacement Penalty (Cw) without innovations
```

```
Cw_no_innov = RV_C1 / Rsys_0_no_innov * trapz(time, time .* f_C1(time)) + ...
        RV_C2 / Rsys_0_no_innov * trapz(time, time .* f_C2(time)) + ...
        RV_C3 / Rsys_0_no_innov * trapz(time, time .* f_C3(time));
% Replacement Costs (Cr) without innovations
Cr_no_innov = 45; % Given fixed cost for replacement
% Labor Costs (CL) without innovations
CL_no_innov = 2 * (5 * (1 + 0) + 5 * (0 + 1) + 5 * (1 + 0));
% Total Cost (TC) without innovations
TC_no_innov = Cr_no_innov + Cf_no_innov + CL_no_innov + Cw_no_innov;
% ------------------------
% With Innovations
% ------------------------
% Future Failure Costs (Cf) with innovations
integrand_innov = @(t) (0.0045 * exp(-0.0045 * t)) ./ (1 + r) .^ t;
Cf_innov = Cost0 / Rsys_0_innov * trapz(time, integrand_innov(time));
% Preventive Replacement Penalty (Cw) with innovations
Cw_innov = RV_C1 / Rsys_0_innov * trapz(time, time .* f_C1(time)) * (eta_C1 * epsilon_C1 * theta_C1) + ...
      RV_C2 / Rsys_0_innov * trapz(time, time .* f_C2(time)) * (eta_C2 * epsilon_C2 * theta_C2) + ...
      RV_C3 / Rsys_0_innov * trapz(time, time .* f_C3(time)) * (eta_C3 * epsilon_C3 * theta_C3);
% Replacement Costs (Cr) with innovations
Cr_innov = 45; % Given fixed cost for replacement
% Labor Costs (CL) with innovations
CL_innov = 2 * (5 / eta_C1 + 5 / eta_C2 + 5 / eta_C3);
% Total Cost (TC) with innovations
TC_innov = Cr_innov + Cf_innov + CL_innov + Cw_innov;
% ------------------------
% Display Results
% ------------------------
fprintf('Total Cost without Innovations: %.2f U.C.\n', TC_no_innov);
fprintf('Total Cost with Innovations: %.2f U.C.\n', TC_innov);
fprintf('Cost Breakdown without Innovations:\n Cf = %.2f, Cw = %.2f, Cr = %.2f, CL = %.2f\n', Cf_no_innov, Cw_no_innov, Cr_no_innov, CL_no_innov);
fprintf('Cost Breakdown with Innovations:\n Cf = %.2f, Cw = %.2f, Cr = %.2f, CL = %.2f\n', Cf_innov, Cw_innov, Cr_innov, CL_innov);
```