Opportunistic Maintenance of Multi-Component Systems Under Structure and Economic Dependencies: A Healthcare System Case Study

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Abstract: This paper presents an opportunistic maintenance model for a multi-component system. We develop a model that considers the ages and residual values of the non-failed components and component failure time distributions. We also consider the structural and economical dependency between the items by favoring grouped over individual replacement to reduce operation costs. We use a genetic algorithm to derive the optimal opportunistic maintenance plan by minimizing the long-run operational cost considering both maintenance cost and potential penalty costs due to failure in the future. The model recommends additional preventive operations in cases where the reliability does not satisfy the quality condition and to reduce the long-run operational cost. A sensitivity analysis shows that the optimal decision is mainly affected by the logistic cost, the interest rate, and the planning horizon. The model's performance has been evaluated using several real case problems, demonstrating that the proposed method is very efficient.

1 INTRODUCTION

After-sale services are essential in today's business world (Zhang et al., 2019). However, only companies with efficient operations can profit from their client services (El Garrab et al., 2020). The key to a successful service is to design maintenance activities carefully, as it can reduce the system's downtime and enables the desired performance.

Different Maintenance strategies are developed to optimize the reparation process. The corrective strategy (CM) performs maintenance activity only after a system component fails, while under the preventive strategy (PM), a maintenance plan of a system component is made according to the operating rules and could lead to the replacement of non-failed items in a preventive way. However, the availability of spare parts is the primary key to ensure a high maintenance service level. Thus, their procurement may often cause critical issues, especially if they are expensive and when systems require high-reliability (Pascual et al., 2017). To ensure spare parts availability, many companies adopt a closed-loop supply chain strategy where the failed parts, called Line Replaceable Units (LRU), are recovered from the field at system failure and returned to their repair centers. The repaired LRUs are used later to replace defective ones in other systems. Therefore, the reparation event can be viewed as an opportunity for preventive operations since the failed parts must be returned to the repair center. Replacing only the defective components in LRU may shorten the spare part's lifetime after maintenance because of the aging of the non-failed components. As a result, using this unit may increase the probability of the system's failure and lead to additional logistic costs and loss of clients. Thus, opportunistic maintenance is the best strategy to provide high-quality spare parts with minimum costs in this closed-loop supply chain.

This paper presents an opportunistic replacement model, which seeks near-optimal decision at a decision point by explicitly considering the ages and the remaining life of the non-failed components, compo-

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nent failure time distributions, and the scale of the economy. We use a genetic algorithm to derive the optimal maintenance plan by minimizing the long-run operational cost considering both maintenance and potential penalty costs due to failure in the future. The model recommends additional preventive operations in cases with high failure risk. A sensitivity analysis shows that the optimal decision is mainly affected by the interest rate and the planning horizon. We evaluated the model's performance using several real case problems based on real data from **General electric Healthcare** MR machines.

An opportunistic replacement policy (OM) is a particular type of preventive replacement in which working components of complex equipment are replaced simultaneously with a failed one when a downtime opportunity has been created (Haque et al., 2003). Different criteria are developed for components' selection. The age replacement policy is based on replacing parts when it has achieved their estimated lifetime (Jiang and Ji, 2002). In (Wang et al., 2021), the authors propose an imperfect opportunistic maintenance model for two unit series system considering random repair time. When a unit fails, the other is maintained when it meets the required age. The objective is to minimize the average maintenance cost by optimizing the thresholds of opportunistic maintenance. (Li et al., 2021) studies a maintenance strategy for wind farms by considering degradation failures and random incidents. An operating part will only be replaced if it reaches its critical age. However, these strategies become complicated if implemented in a multi-component system, even if it maximizes the usage of a component. As the number of components increases, more maintenance activities are conducted, which may disturb production. Another issue is that components may fail before their lifetime because of environmental and external conditions.

Different approaches are developed to consider the dependency between components for maintenance planning. The block replacement strategy (*BRP*) suggests that maintenance activities are conducted on a block or a group of components. In (Nakagawa and Zhao, 2013), the authors compared between different modified BRP models using renewal process where replacements are executed at constant and random variable times to minimize the expected cost rates. They analyze when the random replacements would be better than the standard BRP. In (Rebaiaia and Ait-Kadi, 2022), the authors build a model to group parts based on their mean remaining useful life. In (Laggoune et al., 2009), the authors focus on maintenance cost and suggest that deterioration-based decisions can be included to solve the cost issue. The model considers economic dependency between components by replacing multiple units to minimize system downtime. The solution is found by analyzing the cost or benefit balance of the component that can be preventively replaced during CM activities. In (Satow et al., 2000), a model is developed to maximize the global reliability of n subsystem of k parallel components that follow Weibull distributions while considering age conditions and time spent for reparation. Each k parallel items are replaced simultaneously. Nevertheless, the *BRP* policy increases the wasted components due to the early replacement.

Other researchers evaluate the decision based on the operation costs. Saranga estimates how cost-effective opportunistic maintenance is compared to a later grounding (Saranga, 2004). Using a genetic algorithm, the model computes the remaining useful life cost, the down cost, and the cost of risk for each component individually. In (Nilsson et al., 2009), the authors study maintenance plan for power plants. Their results prove the impact of discount interest on maintenance plan. However, to simplify the model, they use a discrete-time space to calculate the cost of failure. In (Haque et al., 2003), the authors develop an optimization model to maximize the net benefit gained from an opportunistic replacement. The model calculates the system's residual life with and without opportunistic operations. The benefit is calculated from savings made in replacement, residual life, labor time, and the profit of increasing lifetime. A genetic algorithm was used to solve the model.

It may be realized from the above review that most of the mathematical models developed so far are either limited in scope or burdened with excessive computation, especially if the part to repair consists of many deteriorating components. In addition, few models consider the time needed to disassemble a component. In addition, because of inflation, the real value of failure cost may be discounted in the future, especially for systems with a relatively long mean useful lifetime.

The formulation of the model is described in Section 2. In Section 3, we present a case problem based on real data. The description of the genetic operators and the optimization technique is also described in Section 3. We discuss the results in Section 4. Finally, Section 5 concludes the paper and highlights some future research.

2 MODELING AND PROBLEM FORMULATION

We consider a closed-loop supply chain of spare parts where the failed units are recovered from the client's system and shipped back to the repair center for reparation. The unit can be repaired only by replacing the failed items. There are two possible choices for each functional component: replace it preventively when another component fails or use it without preventive replacement. Under the second decision, the item will either fail before the other components and lead to a system failure or survive until another fails. We can see that the optimization problem is dynamic because each failure occasion creates a decision point. However, as soon as a replacement is made, one life cycle for a component is ended, and a new one starts with an identical time to failure distribution. The process continues until we finally dispose of the LRU. Thus, unlike many models in the literature where the opportunity for preventive replacement is undefined, we consider a one-time window to decide whether to replace the non-failed components. This decision should be based on the unit's reliability after reparation, the waste of the replaced components' residual lifetime, and the structural dependence between components.

Structural dependence means that components structurally form a connected set so that maintenance of a part requires disassembling the others. A disassembly sequence exists between elements in the system, so dismantling all the preceding components in a disassembly sequence is necessary to reach a particular element for maintenance (Dinh et al., 2020). Disassembly operation may affect maintenance duration and the degradation level of the disassembled components.

Therefore, the objective is to select a set of components that are easy to replace preventively, to provide repaired parts with a minimum failure risk during the planning horizon of T years and a minimum waste of residual lifetime. A minimum required reliability can also be considered as a constraint quality.

Let us define the following notations:

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

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 a series units, the reliability of the part can be expressed as $R_{sys}(t) = \prod_{c\in\zeta} R_c(t;a_c)$.

We then formulate the optimization problem as follows.

Decision Variables: we define the binary decision variable x_c for each component c, with
$x_c = \begin{cases} 1, & \text{if component } c \text{ is replaced preventively} \\ 0, & \text{otherwise} \end{cases}$

Constraints: A failed component must be replaced to restore the system to its operating state. Thus, we can not select a part with a state variable $s_c = 1$ for opportunistic maintenance. As a result, we define the relation between the decision variable x_c and the state variable s_c as follows.

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

Objective Function: An optimal solution minimizes the total cost of maintenance, denoted by TC. The model would suggest not replacing any component preventively when opportunistic maintenance is inefficient.

The total maintenance cost consists of four components. The first cost, denoted by C_r, is the sum of the newly-bought components' price to replace the selected units. It includes the corrective replacements as well as the preventive ones and can be calculated as given in Eq.2.

$$C_r = \sum_{c\in\zeta}(x_c + s_c) \times Cost_c, \quad (2)$$

The second cost, denoted by C_w, penalizes for the unused remaining life of the items to be replaced preventively. It is given by

$$C_w = \sum_{c\in\zeta} x_c \times \frac{RV_c}{R_{sys}(0; a_1(1-s_1),..,a_n(1-s_n))} \times \int_0^{+\infty} t f_c(t;a_c)\,dt. \quad (3)$$

The waste weight of a component, denoted by RV_c, monetizes the useful life of an item based on its purchase price. Eq.3 represents the loss value of the selected items since a portion of their life is lost for opportunistic activity.

The third component, denoted by C_f, represents the expected cost of failure during 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 $t \leq T$, the conditional probability of failure after reparation can be expressed as follows:

$$P(T_{sys} < t) = \frac{F_{sys}(t; a_1(1-(x_1+s_1)),..,a_n(1-(x_n+s_n))}{R_{sys}(0; a_1(1-(x_1+s_1)),..,a_n(1-(x_n+s_n))}. \quad (4)$$

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

$$C_f = \frac{Cost_0}{R_{sys}(0; a_1(1-(x_1+s_1)),..,a_n(1-(x_n+s_n))} \times \int_0^T \frac{f_{sys}(t; a_1(1-(x_1+s_1)),..,a_n(1-(x_n+s_n))}{(1+r)^t}\,dt. \quad (5)$$

The last cost component, denoted by C_L, reflects the needed time to repair the part. We use an approach developed by (Dinh et al., 2020) to calculate the disassembling time for a component group. Based on the structure connection between components, the disassembly matrix D is constructed. The elements of the matrix are binary coefficients. The parameter $D_{i,j} = 1$ if component j must be disassembled to reach component i for maintenance. The cumulative disassembling time of a component c, denoted by τ_c^D, can be defined as the sum of disassembling times for all the components on the path of disassembly (Eq.6).

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

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.7 gives the total disassembly time, denoted by τ_{group}, of the replaced components. We have

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

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 will be equal to zero. Therefore, the total labor cost is the total reparation time times the labor cost per time unit, i.e,

$$C_L = 2 \times LC \times \tau_{group}. \quad (8)$$

Finally, the objective function can be written as

$$\mathbf{min} TC = C_r + C_w + C_f + C_L. \quad (9)$$

3 INDUSTRIAL CASE STUDY

We propose in this section an application of the developed model based on a real industrial case that we describe below. First, we present the historical data and the approach to extract the reliability functions. Then, we explain the solution technique used to solve the optimization problem.

GE Healthcare is the medical branch of conglomerate General Electric, one of the global leaders in sales and services of medical systems, notably those of medical imaging. 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. Global service and operations (GSRO) department within the company is responsible for service parts. This department covers parts supply chain management, warehouse management, choice of transport, inventory management policies throughout the network, and repair strategies for defective parts.

3.1 Experiments Design

We study the impact of the developed strategy on a critical LRU for MR machines. We consider spare parts composed of 11 components in series. Figure 1 and Table 1 represent the physical structure between components and the disassembling time for each one, respectively. For example, components 4, 5, and 7 must be disassembled before component 10 is reached for replacement.

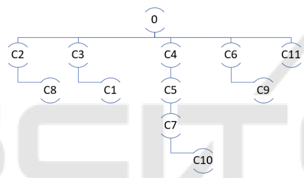

Figure 1: System's structure.

Table 1: Components' dismantling time.

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

GE spare parts supply chain is so particular that it makes gathering parts' lifetime challenging. Depending on forecasted demand and the stock level of warehouses, one part can be shipped to different warehouses in different countries before being installed on a system. It can also be used as a test unit on various systems for a few hours before reaching its destination. In addition, the same part can be repaired multiple times in different centers.

Under these conditions, using shipments' transactions, we use a tracing system to reconstruct parts' history. We build a timeline using the collected transactions set linked to the part. Finally, we extract installation and failure dates. Based on the calculated age of the spare parts and the number of repairs, we estimate the age of components using the replacements record. Component age is restored to 0 if replaced during reparation, while we accumulate the operating times if the component did not fail. We construct the lifetime distribution for each component separately by fitting different known distributions and selecting the one with the minimum value of **Akaike information criterion** (AIC) metric. For a statistical model of some data with a number k of estimated parameters and a maximized value L of the likelihood function, the AIC value is the following $AIC = 2k - 2ln(L)$. We model parts' reliability as the product of component reliability distributions.

3.2 Solution Approach

We use genetic algorithm to get a near-optimal solution for the opportunistic strategy. This heuristic has been widely applied in many cases to solve nonlinear problems. It is characterized by balancing exploitation and exploration in the search space. This balance is strongly affected by strategy parameters such as population size, maximum generation, crossover probability, and mutation. The procedure for the solution of the opportunistic replacement model is described below:

- We select the possible solutions based on two conditions :
  - The failed components should not be replaced opportunistically to satisfy constraint 1.
  - Since the main objective of the company is to minimize the early failure of the repaired units, we define the constraint below to set the number of failures before 6 months less than 10%.

$$\frac{R_{sys}(180; a_1(1-(x_1+s_1)), ..)}{R_{sys}(0; a_1(1-(x_1+s_1)), ..)} \geq 0.9. \quad (10)$$

- The classic genetic algorithm chooses a single fixed mutation rate for all solutions, regardless of their fitness values. As a result, mutations can disturb good and bad chromosomes equally. We use the adaptive technique with two fixed probabilities $p_{max} = 1$ for the low-quality solutions and $p_{min} = 0.4$ for the good ones. The bad solutions have a fitness value less than the population's average, while the high-quality chromosomes are those with a higher value.
- We terminate the algorithm evolution if the fitness does not change for 25 consecutive generations.
- To minimize the fitness function computational time, we save the evaluated individuals' score so it can easily be extracted if the solution has already been evaluated in previous iterations.

4 RESULTS AND ANALYSIS

Table 2 represents the purchase price for new components and their average useful life *Mul* in *Unit of time (U.T)*. We consider logistic cost equal to 750 *Unit of Cost (U.C)* and an interest rate of 15%. To evaluate the model, we define two metrics: the net benefit and benefit ratio, to compare the CM strategy to the opportunistic one. The net benefit, denoted by NB, is the difference between the cost TC_0 of the corrective solution ($x_c = 0, \forall c \in \zeta$) and the best solution, denoted by TC_{best}. We calculate the benefit ratio as the saved ratio of the total corrective cost, $\frac{NB}{TC_0}$.

Table 2: Costs parameters.

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

4.1 Computational Time

We have collected reparation data for 260 LRUs with different ages and multiple sets of failed components. Each part is composed of 11 components in series. We calculate the ages of the components for all the items. We apply the optimization model on the selected parts for a planning horizon of 2 years. Depending on the set of possible solutions, the computational time can vary from 1 min to 30 min. Figure 2 represents the computational time distribution. Unlike weak LRU, parts with higher strength (good global reliability) have many possible solutions. As a result, computing the best solutions usually takes 15 to 20 min.

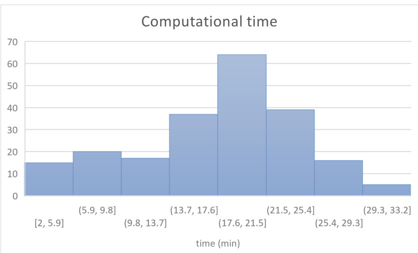

Figure 2: Computational time distribution.

4.2 Impact on Parts Useful Life

In general, the developed strategy improves spare parts reliability. Figures 3 and 4 compare the estimated conditional reliability before and after conducting opportunistic replacements. They represent, respectively, the gain in survival probability of 6 months and 2 years after maintenance operations. Each data point corresponds to a unique spare part with defined ages for its components. It represents the difference between part's reliability under CM and OM strategies. The improvement in survival probability is larger if it is evaluated at the end of the planning horizon. In fact, the model suggests opportunistic replacements for all parts with low reliability. As a result, most of the reliability after two years of the simulated parts becomes higher than 0.5. The model also recommends minimum replacements for old units to satisfy the quality constraint. In some cases, parts reliability can be improved by 0.5 points just by changing few sets of components.

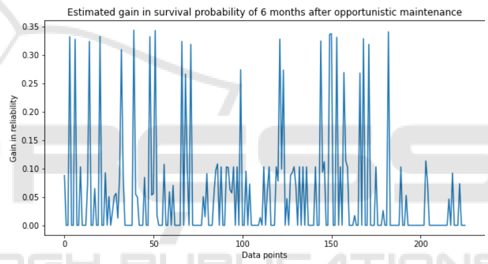

Figure 3: Gain in survival probability of 6 months.

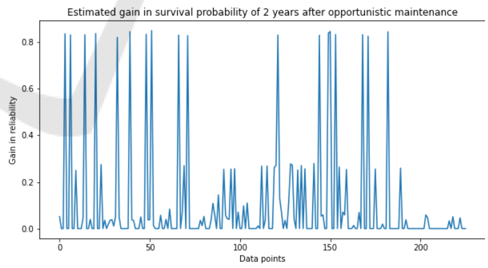

Figure 4: Gain in survival probability of 2 years.

Consequently, the additional replacements help improve the remaining lifetime of the repaired parts. Figure 5 represents the gain in Residual life after opportunistic maintenance. It is the difference between the estimated remaining useful life before and after adopting the OM strategy. For some parts, changing some components opportunistically can add more than one year to their lifetime.

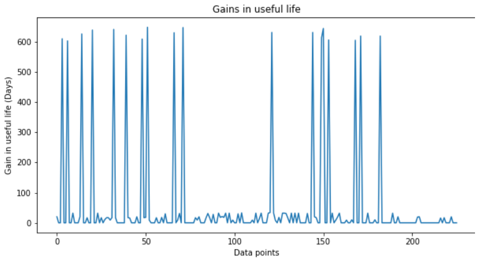

Figure 5: Estimated gain in parts lifetime.

4.3 Cost Analysis

In this section, we analyze the efficiency of the suggested replacements using the defined metrics (net benefit and benefit ratio). We consider 3 cases with different component's average age. Table 3 summarizes the components' ages and the probability of surviving after the first six months. Table 4 represents the decisions taken for each case. A value equal to 1 means the preventive replacement of the component. Columns TC and TC_0 are the total cost of the best and corrective solutions, respectively. *NB* is the benefit defined at the beginning of this section.

Based on Table 4, all the decisions taken outperform the corrective strategy. The net benefit increases with the risk of failure. The more the part is likely to fail, the more consistent OM decisions are. In the first case, the corrective operations satisfy the defined quality constraint. However, the model chooses to preventively change the cheapest and easiest components to reduce the failure cost. In the second case, the model selects linked components to replace, to maximize the part's reliability and minimize the labor cost. In the third case, the model recommends changing the most critical components, *C5* and *C11*, since their *RV* is low compared to the other items.

4.4 Sensitivity Analysis

Sensitivity to the Planning Horizon T. Table 5 results lead to a twofold conclusion . First, the total cost increases over time because of the failure risk. The longer the horizon plan and the lower chance of survival. Thus, the model selects many components to improve part's reliability. In addition, increasing the planning horizon makes the token decision more consistent than the corrective approach. Second, setting a very long horizon reduces the solution's efficiency. If the remaining useful life of many components is less than the horizon plan, it would be better to change the planning duration to minimize the number of replacements and waste costs.

Sensitivity to the Waste Cost. To analyze the waste cost impact on the decision, we add a coefficient α to

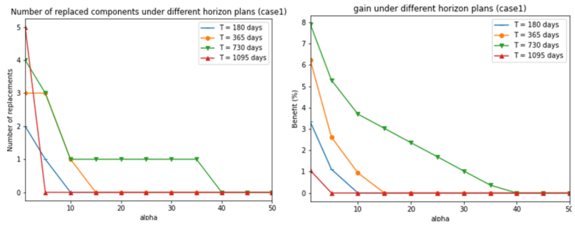

Figure 6: Impact of waste cost on maintenance decision.

Eq.9. The new total cost is expressed now as $TC = C_r + \alpha \times C_w + C_f + C_L$.

From Figure 6, we notice that the number of replaced components decreases with the rise of α. The cheaper the components, the higher the number of replacements. It can easily be understood because cheap items make it profitable to replace them preventively to improve the part's reliability. Nevertheless, when the total costs of the components are comparable with the logistic costs $Cost_0$, the net benefits of the chosen decision may drop to less than zero.

Sensitivity to Interest Rate r. As illustrated in Figure 7, the higher the rate r, the lower the number of replacements for a fixed time horizon and coefficient α. It can be explained because a high rate means we focus on the present time and do not care much about the future. As a result, the solution chosen is more conservative than the one under a lower interest rate.

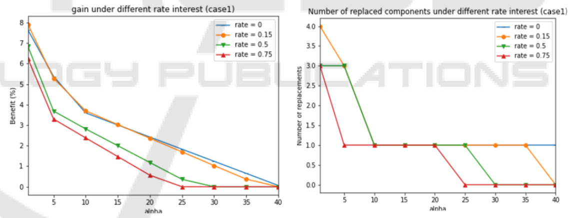

Figure 7: Impact of interest rate on maintenance decision.

5 CONCLUSION

In this paper, we developed a model for opportunistic maintenance selection. The model considers the age of the components, their residual value, and the structural dependence between various items. It also accounts for the present value of future losses due to failures. The model recommends additional preventive operations to minimize the failure cost and when the reliability does not satisfy the quality condition. The decision changes depending on the logistic cost, the interest rate, and the planning horizon. The latter helps control the life cycle of the part. If the system is at the end of its life cycle, replacing many components to repair the LRU may not be efficient. Nevertheless, a high horizon plan makes the model

Table 3: Components' age.

Case	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	$R_{sys}(180)$
1	727	727	727	727	0	727	727	727	727	727	727	0.91
2	0	0	0	1364	637	1364	1364	1364	1364	1364	1364	0.86
3	0	0	1649	1649	1649	1649	1649	1649	1649	1649	1649	0.75

Table 4: Replaced components preventively and net benefit.

Case	TC ($U.C$)	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	TC_0 ($U.C$)	NB ($U.C$)	Benefit (%)
1	7671	1	0	1	0	0	1	0	0	0	0	1	8331	660	7.92
2	9012	0	0	0	0	0	1	0	0	1	0	1	9734	722	7.41
3	8788	0	0	0	0	1	0	0	0	0	0	1	13036	4248	32.58

Table 5: Impact of planning horizon T.

T (*days*)	180	365	730	1095
TC ($U.C$)	4451	5936	8788	11735
Total replacement	3	4	2	4
NB ($U.C$)	665	2709	4248	3125
Benefit (%)	12.98	31.34	32.58	21.02

recommend conservative decisions depending on the corrective $R_{conditional}(180)$. The model suggests not performing other replacements if it satisfies the hard constraint. However, if the corrective conditional reliability is lower than 0.9, the model recommends replacing the cheapest components to satisfy the constraint even though the benefit is negative. Therefore, the net benefit can be used as a metric to evaluate the consistency of the proposed solution. On the other hand, the computational time is still challenging. A neural network can be built and trained to simplify the integral computation time and improve the solutions' quality. In addition, the developed model does not consider stochastic dependency between components. Grouping components based on the correlation coefficient can approximate the dependency. Nevertheless, it will increase the total number of replacements. Therefore, another strategy to overcome this limitation is required.

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