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A Comparison of Maintenance Policies for Multi-Component Systems Through Discrete Event Simulation of Faults

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ABSTRACT Finding optimal maintenance policies for complex multi-component systems is a real-world challenge in the industry. This paper compares three maintenance policies for complex systems with non-identical components and economic dependencies in case of fault. Discrete event and Monte Carlo simulation are used to replicate fault occurrences, while a genetic algorithm is used to minimize the cost of maintenance by finding optimal groups of maintenance activities. Low total average maintenance cost and high average availability of the system are considered as desirable objectives and the capacity of the studied policies to achieve these goals is analyzed. None of the policies dominates the others (in a Pareto efficiency sense), thus making the policy choice context dependent and subject to decision makers' preferences.

INDEX TERMS Maintenance policies, simulations, genetic algorithm, opportunistic maintenance.

I. INTRODUCTION

This paper studies a set of maintenance policy alternatives available for managing the maintenance of complex systems—policies with and without grouping of maintenance activities are considered. More specifically, three possible real-world maintenance policies are studied and (dynamically) optimized for simulated maintenance schedules that include simulated occurrences of fault events; subsequently, the resulting cost of maintenance and the observed reliability of the system are recorded for each simulation and for each policy, and used to compare the policies.

Besides presenting results, our goal is to show that this approach is sufficiently holistic and general to be used in aiding industry decision making on maintenance policy selection and to illustrate the real-world applicability of the methods. The possibility to test a maintenance policy for suitability in advance is a substantial improvement to the decision making process connected to choosing a maintenance policy, a task typically carried out by a maintenance department in an industrial company.

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The need to choose a suitable maintenance policy is especially pressing in the context of industries with high setup and downtime costs due to maintenance operations. A few examples of high downtime cost industries are the oil and gas industry, where reaching offshore extraction facilities is costly; the steel making industry, where the shutdown of blast furnaces requires long times and causes large losses of material; and the production of pulp and paper, where the cost of missed production is high enough to justify a 24/7 operation. Other examples are electrical networks [18] and manufacturing systems [19].

The result of choosing a maintenance policy is also practical: each policy produces a set of actions, or a *maintenance schedule*, that can be implemented in practice.

A. MOTIVATION

Finding a good maintenance policy is a challenge of primary importance for many production-based industries running physical production assets. Some authors [5], [27] claimed that maintenance costs in the industry could range between 15 and 70 % of total production costs. It is then clearly in the best interest of these organizations to try to minimize maintenance related costs and to maximize the reliability and availability of their machines. Previous research in the field of maintenance policy research has produced a rather wide range of policies for the management of maintenance of complex multi-component systems [8], [9], [30], [45]. These theoretical policy-models typically optimize the maintenance schedule with regards to several objectives and are able to integrate short-term information on system status. A sudden fault is a typical short-term occurrence (information) which negatively influences the performance of a machine and of a maintenance-system. It may be impossible to fully insulate a system against sudden faults, but having a maintenance policy in place that is able to minimize the costs from a sudden fault can work to decrease the associated costs. The question is then about how to choose a good maintenance policy. By knowing the lifetime distributions of system components, the failure process can be quite accurately replicated, and the performance of different maintenance models can be estimated in advance. Using a simulation-based approach allows the effective comparison of different maintenance policies and is a suitable tool for analyzing them [4]. Simulation models are also able to consider the dependencies between components. Modeling of economic dependencies, such as (high) setup costs of activities, is of fundamental importance for systems with series of components.

The ability to intelligently group maintenance activities, when failures take place, increases the ability of an organization to minimize maintenance related costs. In addition to the optimization results any further exploitation of statistics from simulation-based analyses may help managers to obtain additional insight in the reliability of a system and on the robustness of a maintenance policy.

B. STATE OF THE ART

Manufacturing systems are increasingly complex and their effective maintenance is a challenge for maintenance managers and researchers. The complexity of the resulting models is often on such a level that analytical solutions for optimal maintenance schemes are seldom available [30] and simulation-based approaches are often used.

The literature on the topic proposes a great number of different models to study and create policies for the maintenance of single- and multi- component systems. Reviews and a classification of existing models were done by Cho and Parlar [8], and by Dekker *et al.* [9]. Both reviews agree on categorizing maintenance models into five groups; out of these five, four are of interest for this research: *group/ block/ cannibalization/ opportunistic models* aim at identifying the components that may be changed during preventive, or corrective, maintenance.

Component dependencies can be exploited in multi-unit systems to reduce maintenance costs. There are three types of dependence: structural, which identifies the possibility to maintain components independently [14]; stochastic, where failure of one component may influence the lifetime of other components [10], [22], [35], [40]; and economic dependence. Economic dependence is typically investigated to establish whether it is possible to save on maintenance costs by contemporarily executing multiple activities, or if, instead, the execution of activities separately is economically more feasible. Although there is potential in considering the three dependencies together, in the literature they are usually considered separately [9]; only Van Horenbeek and Pintelon [42] presented an all-encompassing approach to model all types of dependencies. Maintenance models for multi-component systems with economic dependencies were exhaustively reviewed by Nikolai and Dekker [30].

Maintenance-models can be further classified as *static* or *dynamic*, depending on their ability to include (pieces of) short-term information about the status of the system. Static models are usually based on an infinite length planning horizon and they are devoted to optimizing the maintenance frequency of a component. A clear limit of static models is their inability to consider new information about unforeseen events. Other authors [9], and [45] presented reviews on static maintenance models.

Dynamic models are more flexible than static models: they exploit short- and long-term information together in order to combine corrective maintenance (CM) with preventive maintenance (PM) interventions. Dynamic models that combine interventions on different components of the same system are also known as opportunistic dynamic grouping models. They exploit component dependencies to defer activities from their initially scheduled dates and thus try to make savings on setup cost of activities. A cornerstone in dynamic grouping of maintenance activities is the work by Wildeman *et al.* [48], which was subsequently extended by several authors. Meaningful improvements of the model regarded the inclusion of health status and failure occurrence of components [6], criticality of components [43], [44], and multi-level condition based maintenance (CBM) [29]. One further improvement of the model consists of the addition of activities duration, which had previously been considered to be zero: Do Van *et al.* [12] added multiple maintenance activities with different durations, Pargar *et al.* [32] proposed grouping and balancing of activities, Sheikhalishahi *et al.* [39] accounted for human influence on quality of maintenance and illustrated it with a case study on an offshore oil plant in Iran.

Given the complexity of the dynamic grouping models under analysis, a simulation-based approach seems to be the most suitable approach to solve these types of problems [1]. Simulation-based models have been shown to be effective in bringing results in many industries, including semiconductor manufacturing, plastic industry, transportation infrastructure, and train maintenance facilities [3]. Alrabghi and Tiwari [2], [3] reviewed the literature on maintenance-system simulations and provided several examples, where Discrete Event Simulation (DES) was proficient in modeling fault occurrences.

The principle behind DES is easy to understand: each time the state of the system changes, the simulator applies the required changes to the system in accordance with the adopted maintenance policy (e.g., CM, PM, or CBM) and the result with statistics is registered. DESs can be used to reach many kinds of results, e.g., to find the optimal capacity of inter-operational buffers which minimize the cost of a plant downtime [28], to optimize spare parts availability [20], [47], to estimate reliability of systems made of rotable parts [13], to optimize thresholds in CBM policies [7], [16], to optimize maintenance intervals [31], and to develop knowledge for maintenance management [33].

The aforementioned DES models analyze a single policy at a time. Finding a suitable (optimal) maintenance-policy for a complex multi-component systems requires the comparison of policy alternatives—in the past, only limited efforts have been made to compare different maintenance policies under operative conditions [3]. There are few exceptions: Hani *et al.* [17] compared policies for train maintenance, Van der Duyn Schouten and Vanneste [41] for management of buffers in production systems subjected to maintenance, and Van Horenbeek and Pintelon [42] for multi-component systems dependencies on the components. Only [38] tested maintenance policies for flexible manufacturing systems, i.e., systems where wear out risk is higher than in standard systems, operating under different failure rates. One can say that the literature on comparing maintenance-policies is not complete.

An improvement in DES for maintenance, was provided by the framework of Alrabghi and Tiwari [4]. They designed a general procedure for DES with different policies (including CM, PM, and CBM), and this work will partly follow their footsteps. In order to deduce meaningful insights about the policies under analysis, our study combines DES in Monte Carlo experiment. Rao and Bhadury [36] showed how the comparison of opportunistic maintenance policies is possible by using the Monte Carlo technique. In addition, the complexity of the combinatorial problem pushed us to use a genetic algorithm (GA) to obtain satisfactory solutions in a reasonable time. While our research uses GA, we acknowledge that also other optimization methods can be used. Although the Monte Carlo method and a GA can provide useful insights on suitable (optimal) maintenance-policy identification, they have been the subject of only few publications in the past [23].

C. CONTRIBUTION

The body of literature is populated by several complex maintenance models, as shown in Section I-B. A multitude of optimization problems were tackled regarding cost minimization, or availability and reliability maximization. Only few simulation studies [17], [36], [41], [42] and a simulation methodology [4] are available to compare maintenance policies. This study differs from those already presented in the literature, thanks to the combination of tools that is used and by the methodology that is followed. In this research, a hypothetical industrial system is modeled taking into account the presence of multiple non-identical components connected in a series. Activities duration is also considered when the maintenance schedule is drafted, by using a genetic algorithm to optimize the grouping structure. Cost minimization is the only objective, while the reliability of the system is considered for policy evaluation. an opportunistic maintenance policy similar to that of Wildeman *et al.* [48] against other heuristic policies is an element of novelty of this study, which, to best of our knowledge, has never been done before. The policies analyzed here can be considered realistic approximations of real-world maintenance needs. The numerical results are used to compare different maintenance policies, when the setup cost of the activities varies. The setup cost is the key factor which pushes the algorithm to group maintenance activities whenever possible. Descriptive statistics like the expected cost of each policy, the distribution of the variance of a policy's costs, and the average reliability of the system are calculated to compare the effectiveness and robustness of the studied policies.

The rest of this paper is organized as follows. Section II describes the model and the optimization technique used in the analysis and the determination of the lowest cost solution for each policy. Section III describes the simulation procedure for comparison of policies and summarizes the obtained results. Discussion, conclusions, and suggestions for further research are presented in Section IV.

II. THE MODEL

The model presented below is developed according to the five phases, rolling horizon approach, proposed by Wildeman *et al.* [48], with the addition of activities duration, which can be summarized in the following steps:

1) *Decomposition*: determine the optimal frequency for maintenance of each component separately; the planning horizon is considered to be of infinite length during this step.
2) *Penalty functions*: a penalty function is determined for each activity, and it is used to quantify the cost for deferring the activity from its ideal execution date. Activities can be shifted backward or forward in time.
3) *Tentative planning*: the duration of the plan is now considered finite and multiple maintenance activities are possible for each component.
4) *Grouping maintenance activities*: the maintenance activities are allowed to be moved within the planning horizon. The aim of this step is to maximize the save on set-up cost due to grouping of activities, and to minimize the cost due to shifting of activities.
5) *Rolling-horizon step*: once new short-term information is available, it can be supplied to the model and the model can be executed again to obtain an optimized maintenance schedule.

We consider a multi-component system with N components connected in series, which means that all the components are considered critical; Namely, a fault of one component compromises the whole system. The choice to analyze a series system reflects the approach of previous studies on the opportunistic maintenance policy [24], [49], [50], where the criticality of each component makes the opportunistic approach particularly effective.

A. THE COST STRUCTURE

We assume that only two types of maintenance activities are possible: (i) preventive maintenance activities and (ii) corrective maintenance activities; the first are considered to be planned activities, whereas the second are unplanned. Both these activities, in terms of costs, are treated as the sum of three factors: a set-up cost, a cost for replacement of the component, and a cost for missed production, this is similar to what was used by [44]. The cost of a *preventive* maintenance activity i is:

$$C_i^p = S + c_i^p + C_{sys}^p\, d_i, \tag{1}$$

where S is the set-up cost, c_i^p is the cost for replacement of the component, and $C_{sys}^p\, d_i$ is the cost of missed production, which is calculated as the product of a coefficient C_{sys}^p [\$/time] and the duration of the i-th activity d_i. On the other hand, the cost of an *unplanned* maintenance activity i is:

$$C_i^c = S + c_i^r + C_{sys}^u\, d_i, \tag{2}$$

where S is the set-up cost, c_i^r is the cost for replacement of the component, and $C_{sys}^u\, d_i$ is the coefficient for unplanned missed production.

B. DECOMPOSITION

The model we use is the dynamic grouping maintenance model with the opportunistic approach proposed by Wildeman *et al.* [48], with some changes. The time to failure of each component is considered as a random variable X_i, and its probability of occurrence before time t is characterized by a two parameter Weibull distribution with the cumulative density function (CDF):

$$\Pr\{X_i \leq t\} = F_i(t) = 1 - \exp\left(-\frac{t}{\lambda_i}\right)^{\beta_i}, \tag{3}$$

with scale parameter $\lambda_i > 0$, shape parameter $\beta_i > 1$, and probability density function (PDF):

$$f_i(t) = \left(\frac{\beta_i}{\lambda_i}\right)\left(\frac{t}{\lambda_i}\right)^{\beta_i - 1} \exp\left(-\frac{t}{\lambda_i}\right)^{\beta_i}, \tag{4}$$

As recalled in the literature [26], Weibull distributions are sufficiently general to fit a wide range of empirical distributions, and the lower bound imposed on the shape parameter ($\beta > 1$) implying increasing failure rate is not restrictive for our analysis. In fact, with $\beta_i \leq 1$ implies a non-increasing failure rate which, in turn, makes preventive maintenance activities on single components unreasonable. Moreover, with today's high quality standards, infant mortality of components is often a negligible phenomenon and, as claimed by Love and Guo [26], "most often a rising force of mortality is assumed".

At this point, the mathematical treatment to obtain the optimal interval length for preventive maintenance x_i^* is contained in [48] and the full presentation is thus omitted here. However, it has been shown that, if the duration of a PM activity is $d_i \ll x_i^*$, then x_i^* can be approximated as:

$$x_i^* = \lambda_i \sqrt[\beta_i]{\frac{(C_i^p + S)}{C_i^c\,(\beta_i - 1)}}. \tag{5}$$

Eq. (5) allows us to compute the value of the minimal long-run average cost of maintenance per unit time:

$$\phi_i^* = \phi_i(x_i^*) = \frac{(C_i^p S)\,\beta_i}{x_i^*\,(\beta_i - 1)}. \tag{6}$$

The minimal long-run average cost of maintenance per unit of time for the whole system can be calculated as the sum of all these costs for all the components:

$$\phi_{sys}^* = \sum_{i=1}^{N} \phi_i^*. \tag{7}$$

C. TENTATIVE MAINTENANCE

A finite length planning horizon is now considered in order to realize the grouping of activities. The initial time of the plan is t_{begin}, whereas the date of the last maintenance action on component i is t_i^e ($\leq t_{begin}$). The cumulative duration $D_i^{\sum}$ of all the replacement activities between t_i^e and the first activity on i is used jointly with the length of the preventive maintenance cycle x_i^* in order to determine the date t_{ij} of the first repair action $j = 1$ on component i. The date t_{i1} can be calculated by using the following equation:

$$t_{i1} = t_{begin} - t_i^e + d_i + D_i^{\sum} + x_i^* \tag{8}$$

where d_i is the duration of the maintenance activity on component i. Instead, the end date of the planning horizon t_{end} is equal to a multiple of:

$$t_{end} = \max_{i=1,\ldots,N}(t_{i1}) + d_i. \tag{9}$$

It is important to note that the maintenance activity of each component i might be executed more than once within the interval $[t_{begin}, t_{end}]$, therefore the maintenance dates of activities with $j \geq 2$ are calculated as follows:

$$t_{ij} = t_{ij-1}^* + d_i + D_{ij}^{\sum} + x_i^* \quad \forall t_{ij} \leq t_{end}, \tag{10}$$

where t_{ij-1}^* is the optimal execution date of the previous maintenance activity on component i, $D_{ij}^{\sum}$ is the cumulative duration of the preventive maintenance (PM) activities within the interval $[t_{ij-1}^*, t_{ij}]$. The process is represented in a simplified manner in Fig.1.

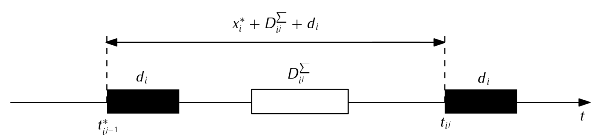

FIGURE 1. Representation of how the dates of the activities are calculated.

D. GROUPING MAINTENANCE ACTIVITIES

The economic dependence among the components of the system is a key variable of the optimization model and it is used to produce savings on maintenance costs. Savings on setup costs are generated when maintenance activities are executed in the same moment; Namely, one activity is subsequent or simultaneous to the other, and it is equal to:

$$U_{G^k} = \left[|G^k| - 1\right] S, \tag{11}$$

where $|G^k|$ is the cardinality of the group, namely the number of activities simultaneously executed. The higher the number of activities in G^k the greater the savings. The shifting of maintenance activities from their ideal date leads to costs. Suppose that the activity i^j is shifted from its ideal date t_{ij}, to the date t_{G^k} of the group it belongs to: the new date of execution is equal to $t_{G^k} = t_{ij} + \Delta t_{ij}$, where the temporary shift Δt_{ij} can be "positive" or "negative", i.e., the activity can be anticipated or postponed. In order to avoid infeasible shifts of activities, the following constraint is imposed: $\Delta t_{ij} > -x_i^*$. In order to quantify the cost of activities shifting penalty functions are introduced. The change of date of an activity i^j has effect on the following activities on component i, which are moved using a long term shift; namely, the interval between the first two maintenance activities becomes $x_i^* + \Delta t_{ij}$, whereas the remaining intervals remain x_i^*. The process is graphically represented in Fig. 2. Once this choice has been made, the penalty function for each activity is composed of two parts:

1) an increase of the expected cost with regards to the j-th renewal cycle, which is given by $E_i(x_i^* + \Delta t_{ij}) - E_i(x_i^*)$,
2) and a changing cost due to the deferments of the future activities executed after t_{ij}, which is calculated as $\Delta t_{ij}\, \phi_i^*$.

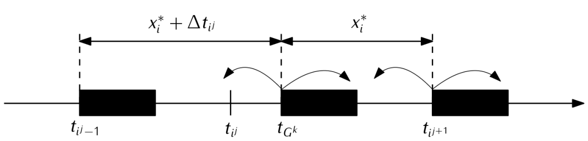

FIGURE 2. The rectangles represent activities on the time axis; with a long term shift all the activities after t_{ij} are moved accordingly to t_{ij}.

Therefore, a penalty function $h_i(\Delta t_{ij})$ for the shifting of activity i^j on component i can be expressed as:

$$\begin{aligned} h_i(\Delta t_{ij}) &= E_i(x_i^* + \Delta t_{ij}) - E_i(x_i^*) - \Delta t_{ij}\phi_i^* \\ &= \underbrace{\left[C_i^p + C_i^c \left(\frac{x_i^* + \Delta t_{ij}}{\lambda_i} \right)^{\beta_i} \right]}_{E_i(x_i^* + \Delta t_{ij})} \\ &\quad - \underbrace{\left[C_i^p + C_i^c \left(\frac{x_i^*}{\lambda_i} \right)^{\beta_i} \right]}_{E_i(x_i^*)} - \Delta t_{ij}\phi_i^*. \end{aligned} \tag{12}$$

Details of this formula were presented by Wildeman *et al.* [48]. The cost $\Delta H_{G^k}(t_{G^k})$ of shifting all the activities i^j within a group G^k to a new execution date t_{G^k} can be expressed as:

$$\Delta H_{G^k}(t_{G^k}) = \sum_{i^j \in G^k} h_i(t_{G^k} - t_{ij}) = \sum_{i^j \in G^k} h_i(\Delta t_{ij}), \tag{13}$$

which in turn is strictly convex ($\Delta H''_{G^k}(\cdot) > 0$). The optimization of the ideal execution date of the group $t^*_{G^k}$ is represented graphically in Fig. 3. The economic profit $EP(G^k)$ generated by a group is then calculated as:

$$EP(G^k) = U_{G^k} - \Delta H^*_{G^k}; \tag{14}$$

a negative value of EP means that the grouping of the activities within a group G^k is not convenient, and that it is possible to split the group in two or more subgroups which lead to higher savings. The set of all groups is called *grouping structure*, is identified with SGM, and represents a partition of the set of preventive maintenance activities.

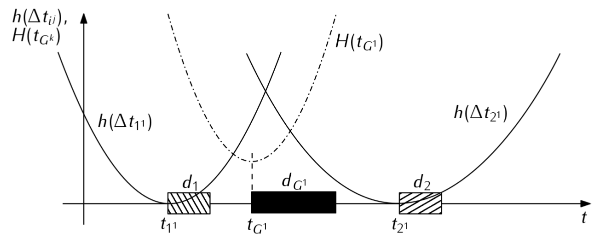

FIGURE 3. The solid curves in the plot represent the value of the penalty function of each activity as function of the deferment Δt_{ij}. The dot-dashed curve is the penalty function of group G^1, within which we suppose to group activities 1^1 and 1^2. The minimum of the curve corresponds to the ideal execution date $t^*_{G^k}$ of the group.

The economic profit of a grouping structure $EPS(SGM)$ is defined as:

$$\begin{aligned} EPS(SGM) &= \sum_{G^k \in SGM} EP(G^k) \\ &= \sum_{G^k \in SGM} (U_{G^k} - \Delta H^*_{G^k}). \end{aligned} \tag{15}$$

The goal of the problem is to maximize the profit given by the grouping structure. More formally, we search the optimal grouping structure SGM_{opt}:

$$SGM_{opt} = \arg\max_{SGM} EPS(SGM). \tag{16}$$

E. OPPORTUNISTIC APPROACH

The model for dynamic grouping maintenance presented above can be modified to include special needs of maintenance managers. With special needs we mean the occurrence of a sudden fault, or any planned activity that must be performed at a certain time. An opportunity to perform maintenance at a time t_{opp} on a component i is modeled with the following penalty function:

$$h_i(t) = \begin{cases} 0, & \text{if } t = t_{opp} \\ +\infty, & \text{if } t \neq t_{opp}. \end{cases} \tag{17}$$

Eq. (17) reads that if the maintenance activity on the faulty component i is executed at time t, with $t \neq t_{opp}$, the cost for shifting the activity is extremely high. Therefore, the activity on the faulty component will most likely be executed at t_{opp} and other activities will possibly be anticipated and grouped with it.

III. SIMULATIONS

A. METHODOLOGY

The goal of the simulation approach is to analyze the cost of different maintenance policies in a multi-component system environment with randomly generated faults and variable set-up costs. We have designed a set of discrete event simulation (DES) procedures that mimic different maintenance policies.

Three preventive maintenance policies are tested for 8670 hours, namely one year of simulated time, in a Monte Carlo experiment using different setup costs $S \in \{0, 50, 100, 150, \ldots, 600\}$. Each combination of policy and setup cost is tested 1,000 times in order to obtain information about the average cost of maintenance, the average availability of the system, and maintenance frequency. Independently of the policy, the system is shut down every time that a corrective or preventive maintenance policy is performed, and, when maintenance is executed, there is no ageing of components. After a component has been repaired, its degradation state is considered as-good-as-new. The experiment mimics the dynamic environment that we have in the real world by simulating the occurrence of faults according to the time to failure distribution of each component.

Maintenance activities are scheduled and managed according to the following three maintenance policies:

- **Minimal repair policy (MRP)**: A preventive maintenance activity is scheduled for all the components at time intervals of x_i^* (> 0) working hours based on the age. According to the rolling horizon approach, the event with the earliest date is processed and it can be either a corrective or a preventive maintenance intervention; after a component has been processed, a new PM is scheduled.
- **Adaptive grouping policy (GPa)**: According to this policy, maintenance activities are initially planned at time intervals x_i^* for all the components. The grouping structure is optimized using the GA and the first group of activities, i.e. group G_1 in Fig. 4, is added to the maintenance plan. According to the rolling horizon approach, the system starts to process the first event, which could be either a group of PM activities, or a CM activity. If the upcoming event is a group of activities it is regularly executed, then new PM activities are planned and a new grouping structure is found using the GA. The process loops until a failure event occurs, in which case the system executes maintenance only on the faulty component; indeed, in case a fault occurs, no grouping is performed, but the faulty component is immediately repaired. A new grouping structure needs to be found taking into account that a new PM activity has been added to the plan at $t_{opp} + x_i^*$, where i is the faulty component.
- **Opportunistic grouping policy (OGP)**: According to the rolling horizon approach, a preventive maintenance intervention is planned for all the components, thus making available a temporary schedule. Based on the information contained in the schedule, the grouping structure is optimized using a genetic algorithm (GA) and the system produces a new maintenance schedule made of groups of activities, which resembles that of Fig. 4.
If the upcoming event in the simulation is a preventive maintenance intervention, i.e. group G_1 in Fig. 4, this is regularly executed and new PM activities are planned for each component. The grouping structure is then optimized again using the GA and the new maintenance dates of the components just maintained; subsequently, the group of PM activities with the earliest date is executed, unless a fault event occurs. When a fault occurs, the GA is called down to optimize the grouping structure implementing (17), which has the aim to lock down the CM activity at the time of fault t_{opp}. The effect produced on the schedule is represented in Fig. 5, where it is possible to see that the activity on the faulty component

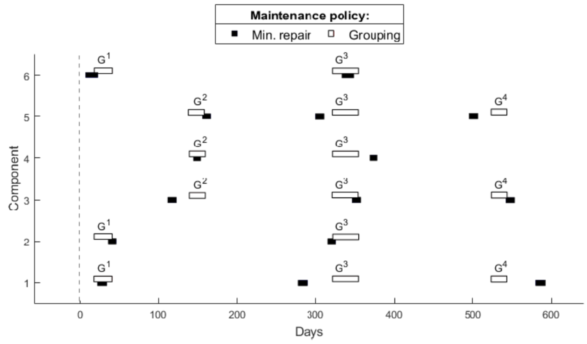

FIGURE 4. The black rectangles represent the activities planned at their optimal date, whereas the white rectangles represent the groups of activities; each group is identified with a label G^k. The example is realized with data from Table 1, and $S = 100$.

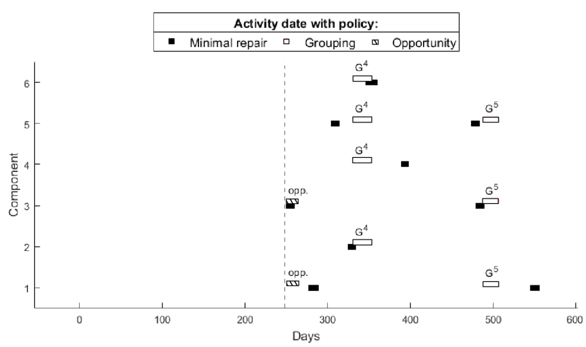

FIGURE 5. OGP: When component 3 fails the maintenance on component 1 is anticipated at t_{opp}.

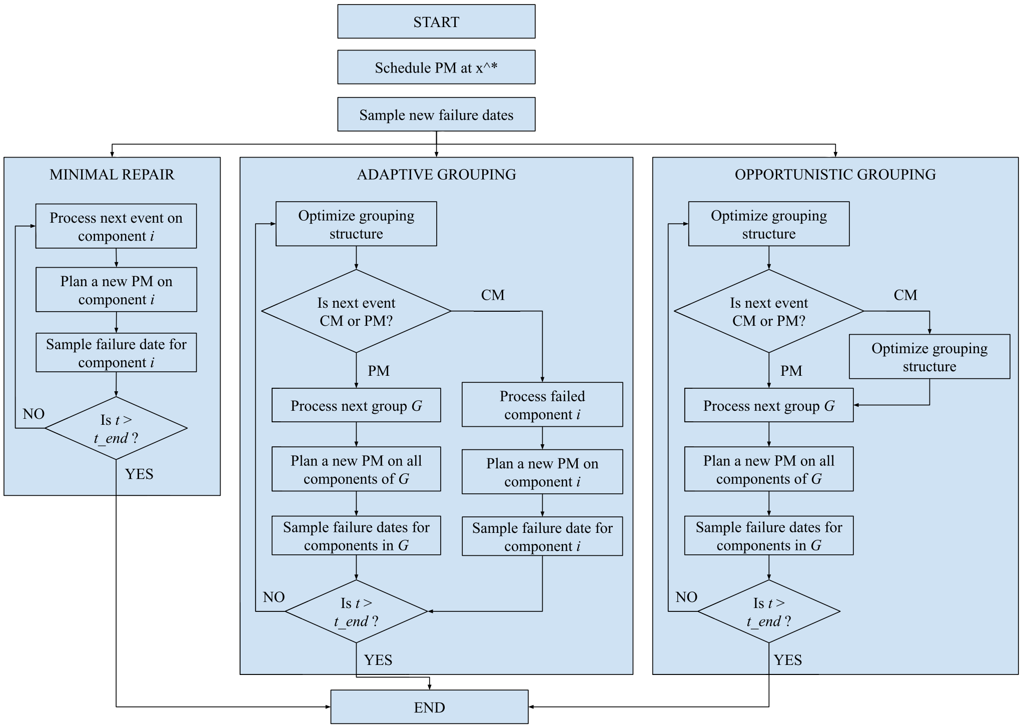

FIGURE 6. Simulation procedures for the different policies analyzed.

(component number 3) is grouped together with component 1 at time t_{opp}, thus saving one setup cost S. The simulation restarts by planning new PM activities for the components that were maintained in the last group and subsequently a new grouping structure is optimized based on this schedule.

In all the policies, the algorithm continues to process events according to the previous rules until the end of the simulation horizon t_{end} is reached.

After a group of activities has been executed, its cost C is calculated according to the following equation for all the policies:

$$C = \sum_{i \in G \setminus f} C_i^P + C_f^C + S \tag{18}$$

The equation is valid for groups with one or more components, among which at most one can be failed. The set of components involved in the group maintenance is indicated by G, C_i^P is the cost of preventive maintenance of a component, and C_f^C is the cost of corrective maintenance on the failed component f (if there is a faulty component). The last term represents the setup cost S which, as stipulated in (11), is paid only once instead of $|G|$ times.

The policies studied in this paper are summarized in the flowchart presentation in Fig. 6, which can also be considered a small, but original, contribution to the field of maintenance-systems simulation.

TABLE 1. Characteristics of the components of the system.

Comp.	λ_i	β_i	C_i^P	C_i^C	d_i
1	450	2.1	300	500	5.61
2	550	1.4	500	700	5.28
3	340	2.2	300	500	6.12
4	440	1.3	300	490	5.85
5	450	2.0	500	1010	4.50
6	340	1.9	300	450	4.38

1) DATA

The data used to simulate the system are similar to those of previous studies [11], [12], [43], [48]. Table 1 lists the data about the six components used to simulate the system.

Durations of maintenance activities, d_i's in Table 1, are assumed to be deterministic in the experiment. Testing of the model assuming a stochastic duration d_i of maintenance activities was carried out and no meaningful effects on results were observed; therefore, we report the results for the deterministic case in order to avoid overparametrization of the experiment.

2) GROUPING STRUCTURE OPTIMIZATION WITH A GENETIC ALGORITHM

Grouping structure optimization is a complex combinatorial problem. It has been demonstrated that similar optimization problems [43], [44] are $\mathcal{NP}$-complete. The reason why we decided to use a genetic algorithm (GA) in the optimization of the grouping structure is the known ability of GAs to find (near-optimal) solutions for combinatorial problems, as confirmed by many authors [11], [17], [31], [43], [44]. In the context of this research, the GA was written for this specific purpose and includes a feasibility check of the individual solutions for the initial population in the hope of speeding up the optimization. Further details on the GA implementation can be found in the appendix.

The simulation procedure was implemented using the object oriented programming approach in Python 3.7. The realization of the discrete event simulation is based on the Python library SimPy distributed freely under MIT license.

The total set of simulations required roughly 30 hours to run on a desktop computer with the following characteristics: 64-bit Windows Server 2016, Intel® Xeon® Platinum 8160 CPU 2.10 GHz, and 768 GB of RAM. The time to run a single optimization of the grouping structure required few seconds using the *stall generations* stopping criteria; that is, the algorithm stopped after the best value had not changed in the last 15 iterations.

B. SIMULATION RESULTS

The results of the simulations offer insight on the costs associated with different maintenance policies. As shown in Fig. 7, the minimal repair policy (MRP) is the least efficient policy with the highest cost in all cases, while the opportunistic grouping policy (OGP) is the lowest cost policy. This result is not completely unexpected since the OGP is the most sophisticated policy. However, given the complexity of the problem, it was not obvious, at least for us, to observe a linear relation between setup costs and total maintenance costs.

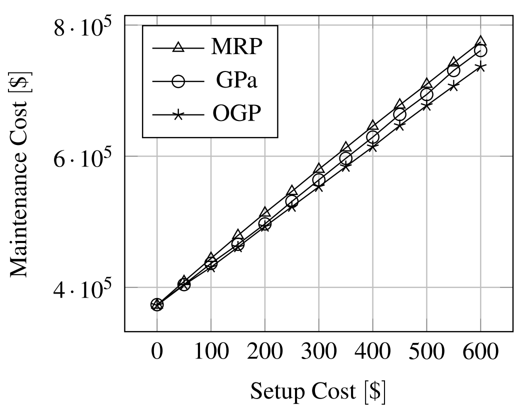

FIGURE 7. The average cost of maintenance with different policies with respect to different set-up costs.

The analysis also returned the number and the type of maintenance activities performed within the simulation horizon. The number of corrective interventions was always higher on average than the number of preventive interventions for all the policies, as it is possible to see in Fig. 8.

colorblue It is possible to notice that the number of corrective interventions increases as a function of the setup costs. In fact, exploiting the grouping strategy can induce the algorithm to increase the risk of component failures. Also, already with a small setup cost, e.g. $S = 50$, there is a substantial reduction of preventive maintenance activities, due to their grouping.

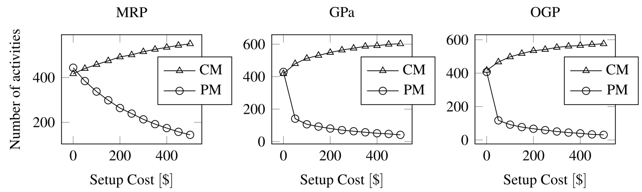

FIGURE 8. The average number of maintenance activities divided by type. The execution of PM on a group of components is counted as a single maintenance activity.

The values in Fig. 8 count the amount of groups, but they provide no information on the duration of interventions and on the number of components maintained within a group. According to the MPR and GPa policies, CM activities are carried out singularly, whereas according to OGP, a CM activity might involve multiple components; this difference significantly affects the availability of the system. The availability of the system is a relevant and practical metric of system effectiveness. Therefore the average availability produced by each policy for each setup cost was measured. In this experiment, the availability of a system at time t (in the past) corresponds to its state and is assumed to be binary, as follow:

$$A(t) = \begin{cases} 1, & \text{if the system was working at time } t \\ 0, & \text{if the system was not working at time } t. \end{cases}$$

In particular, we are interested in measuring the average availability of the system over the simulation horizon. This is defined as follows [37]:

$$\bar{A} = \frac{1}{t_{end} - t_{begin}} \int_{t_{begin}}^{t_{end}} A(t)dt. \tag{19}$$

where t_{begin} and t_{end} are the beginning and the end of the simulation horizon, respectively.

The average cost of maintenance and the average availability of the system were compared using a bi-objective analysis: in Fig. 9, each policy is represented by a point in the cost-reliability space at a given value of S. The coordinates of each point are the average value of maintenance cost and availability produced by the relative policy. Uncertainty about cost and availability are not represented in Fig. 9 since the standard deviations of the underlying distributions are too small to provide clear information.

To achieve the best operating performance, a policy should maximize availability and minimize the expected cost of maintenance.

The results in Fig. 9 show that there is not a dominating policy, and the final choice is a matter of trade-offs. This result highlights the fact that the maintenance policies studied so far aim at minimizing the maintenance cost, but they overlook the availability of the systems.

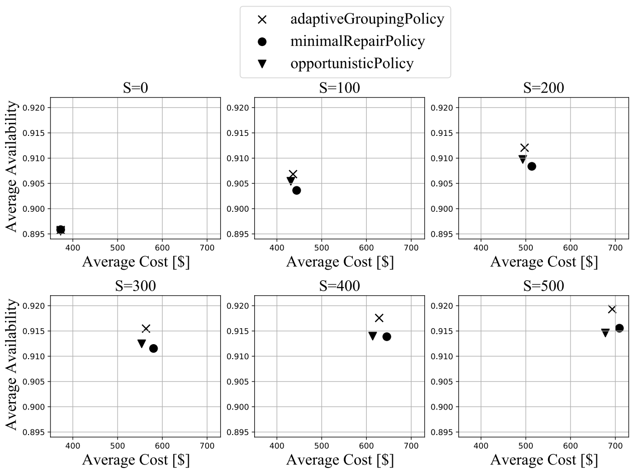

FIGURE 9. Bi-objective (cost vs. availability) comparison of policies for different setup costs ($N = 6$). Costs are expressed in 1,000 units.

More specifically, the greater availability associated to the GPa policy compared to the OGP may be due to the fact that OGP tends to anticipate some maintenance activities on the ground of purely economic reasons, but by doing so it results in a larger number of maintenance activities which ultimately leads to a worse availability of the system. Note that, with large setup costs even the MRP beats the OGP in terms of availability.

We also explored the case with $N = 10$ where four additional components — with characteristics similar to the already existing six — were added in the system. The results are shown in Fig. 10 with three setup costs and strengthen the results obtained with $N = 6$: in this case, the loss of availability associated with the opportunistic policy is even more evident.

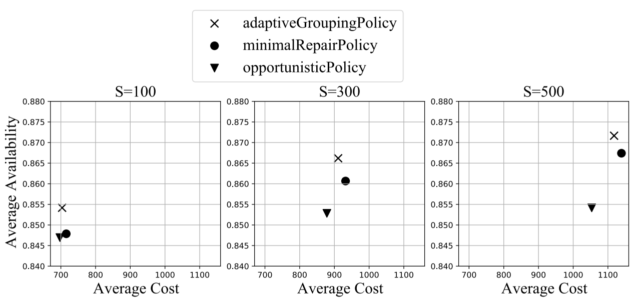

FIGURE 10. Bi-objective (cost vs. reliability) comparisons of policies for different setup costs ($N = 10$). Costs are expressed in 1,000 units.

IV. DISCUSSION AND CONCLUSION

As recalled by George-Williams and Patelli [15]: "identifying the optimal maintenance strategy is a challenge". In the hope of helping to solve this challenge, we presented a comparative study of selected maintenance policies and a framework for analyzing them. The policies were tested in an operational environment with randomly generated faults by means of discrete event simulations. The results clearly indicate that there are tangible cost savings that can be reached by using maintenance policies based on taking an opportunistic approach for grouping of maintenance activities. In this sense, this study brings new numerical evidence to support the importance of grouping activities to save on maintenance costs. On the other hand, simulations showed that the majority of maintenance intervention was corrective, as confirmed by Fig. 8. This means that scheduling PM activities according to (10) leads to the execution of a few groups of PM activities along the simulation history; the opportunistic approach is thus particularly useful in practice, when there is uncertainty about which components to maintain in case of a sudden failure. On the other hand, the implementation of a monitoring system and a so-called condition based maintenance (CBM) approach would help optimize the PM schedule by detecting a state of imminent failure of a component. The importance of anticipating a near-to-failure condition is corroborated by the non-negligible amount of CM activities shown in Fig. 8. We conjecture that, in a real-world application, the opportunistic policy would benefit from CBM either by lowering the cost due to unplanned shutdowns, and by relieving their technical consequences. Thus, our results can be also interpreted as additional evidence pushing towards the adoption of condition based maintenance systems.

A further step to approach maintenance to reality is the implementation of imperfect maintenance interventions. The as-good-as-new assumption for repair of components could be relax through the addition of a significant number of new parameters: random variables to describe the degradation level of a component [42], new TTF distributions for imperfectly repaired components [25], and additional repairing costs. Moreover, imperfect maintenance models have already been extensively addressed in the literature [34], [46], and, in the context of this research, a maintenance policy implementing imperfect maintenance interventions would be of little help to clarify our contribution on the comparison of maintenance policies.

Nevertheless, by extending the analysis to consider also the average availability of the system we were unable to find a dominating policy (in a Pareto efficiency sense). This corroborates the importance of a careful *a priori* selection of the preferred policy considering the preferences of a decision maker in terms of cost vs. availability trade-off. Hence, in practice, as argued in the introduction, the discrete event simulation methodology employed in this paper can be seen as a valuable support to choose the most suitable maintenance policy to any given context.

Besides its use to obtain the results analyzed in the previous section, it is possible to imagine that the presented methodology has at least two more uses. Firstly, it can be employed, for budgetary purposes, as a *predictive analytics* tool to forecast the expected maintenance costs for a given period of time. Secondly, it can be used in *prescriptive analytics* to optimize maintenance schedules. In fact, despite the long time required by our simulations (about 30 hours), a single optimization of the maintenance schedule for the near future — i.e. an instance containing the next few PMs on all the components — required few seconds both with $N = 6$ and $N = 10$ components.

Let us remark that, in spite of our simplifying assumption that all groups of activities are feasible and the setup cost is the same for all of them, our framework is flexible and can encompass more specific cases. In fact, different setup costs can be defined for different subset of activity, i.e. instead of a single S we may have S_A $\forall A \subseteq \mathcal{N}$, where $\mathcal{N}$ is defined as the set of all components. This could be useful to model technical dependencies between components. One use could be that of assigning an extremely high setup costs to technically unfeasible groups to make them non-optimal and therefore never appear in the optimal maintenance schedule.

Further work is required to optimize the running time so that more complex model environments become tractable. This may include testing various optimization routines to check which kind of optimization methods perform best in the maintenance policy optimization environment.

Other topics for further research include making modifications to the maximum number of activities grouped together, in order to be compatible with real-world shift duration, and to be in sync with real-world availability of repairmen. A more complex model could be built by including a connection to a spare parts management model or a workforce management model. One important avenue for further research is taking the model to the real world and testing it with real data, further enhancements could then, for example, also include a prognostic learning model for the estimation of the useful life of the components used.

APPENDIX: GENETIC ALGORITHM

The use of an heuristic method becomes necessary due to the computational complexity of the problem, especially for $N = 10$. We chose to represent the grouping structure SGM using a vector of integer numbers. The list of activities (i.e. all the activities on all the components) was sorted by ideal execution date t_{ij} and each element of the SGM vector encoded the group to which one activity belongs. In the case of $n = 6$, each group contains at most 6 activities, therefore a feasible SGM consisted in a partition of the set of activities, where each partition contains at most six activities. Each partition was identified with an integer number, thus the resulting vector looked like the following:

$$SGM = (1, 1, 1, 2, 2, 2, 2, \ldots, 5, 5, 6, 6, 6).$$

The constraint on partitioning can be exploited to generate new feasible SGMs.

The *selection* of parents for the next generation was performed according to the *wheel of fortune method*, i.e. the SGMs showing the highest scores were more likely to be selected as parents for the next generation.

Both mutation and crossover operations were carried out with respect to the structure of the solution. The *mutation* operation required to choose a mutation point, which could be each of the elements of the SGM vector. A single mutation occurred with a probability of 1 for all the selected individuals. The *crossover* operation was performed at a single point of the SGM vector on a selected pool of individuals in order to produce the desired number of modified individuals.

An elitist strategy was adopted, therefore the individuals with the best fitness score were copied to the next generation.

Finally, the adopted stopping criterion was *generation limit*. That is, the algorithm stopped if the average relative change in the best fitness value did not change for more than 15 generations.

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