Dynamic Rescheduling in the Context of Distributed Maintenance

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***Abstract*— Economic growth and global competition are pushing manufacturing companies to have several production sites, often relatively close to each other. We are interested in the maintenance management of geographically distributed production sites. This paper deals with the problem of unexpected failures that usually disrupt maintenance operations. The objective is to manage a fleet of homogeneous vehicles in charge of performing preventive and corrective maintenance operations at several production sites. The major difficulty lies in the number of sites to be considered, which makes the optimisation time exponential if the classical methods of the literature are used. Nevertheless, some studies allow to obtain an expected scheduling of maintenance operations considering the uncertain aspect of failures. The novelty of this paper is the development of an approach and an algorithm allowing to quickly and simply update the order of maintenance operations in case of unexpected events on line. Through an industrial case study in oil & gas field, we determine the optimal framework based on heuristics in which to modify the expected vehicle scheduling. The results show that with the appropriate parameters, simple rules can handle unexpected failures in a cost-effective way.**

Keywords—automation; manufacturing systems; maintenance scheduling; mobile maintenance workshop; vehicle rescheduling problem;

I. INTRODUCTION

Every production system is subject to uncertain failures that must be considered in the activities of manufacturing companies [1]. Maintenance is one of the best-known solutions, consisting of organizing operations in the best case before failures and in the worst case after. The objective is to ensure the dependability of production equipment while optimising the costs of the resources involved (spare parts, operators and tools) [2]. Logically, the more production equipment a company has, the higher the maintenance costs are likely to be. This scale factor is usually compounded by the distance between the equipment being managed. Fortunately, pooling resources can help overcome these problems [3].

In this article, we examine the concept of distributed maintenance [4] with the aim of pooling maintenance resources in a central workshop (CMW). Unlike other strategies where each production site has its own maintenance resources, a mobile maintenance workshop (MMW) is designed in distributed maintenance to circulate common resources between sites. These are vehicles that act as physical links between production sites. A vehicle is supplied by the CMW and moves from one production site to another to perform maintenance operations in an optimal order.

Several studies in the literature model and optimise the routing of MMW between production sites. If a site is considered as a customer with a certain demand and the MMW as a set of vehicles with a limited transport capacity, then a MILP (Mixed-Integer Linear Programming) is appropriate to optimise the vehicle routing [5]. This first approach is similar to the resolution of a classical CVRP (Capacitated Vehicle Routing Problem) in Operations Research [6]. A homogeneous fleet of vehicles has to serve customers with a known demand [7]. However, demand from production sites is not determined due to the uncertain nature of equipment failures.

To consider the constraints linked to the uncertainty of failures, [8] proposes a combination of two iterative models under the name of CMR (Combined Maintenance and Routing). The first model determines the optimal periodicity of maintenance operations for each production site. This model uses the probability distribution of the number of failures over time to estimate the optimal number of preventive maintenance operations to perform for each site. The second model takes the previously optimised periodic requests as input to calculate the shortest path between the sites to be visited.

Although it considers the uncertainties associated with failures, the CMR model has certain shortcomings. Indeed, the journey of a vehicle is assumed to be cyclical between production sites. This assumption could work in a classical CVRP problem, but this is not the case when considering failures, as production sites may have a different maintenance periodicity. Thus, [9] proposes a model under the name of OMCR (Optimised Maintenance and Capacitated Routing) which, instead of optimising a cyclic path between production sites, considers a path linking all maintenance operations during a time horizon.

Once the optimal vehicle path is determined offline, a new problem arises: what to do in case of an unexpected disruption online? This problem is known as the "Vehicle Rescheduling Problem" [10]. This paper focuses on this rescheduling problem which has not yet been solved in the distributed maintenance literature. In general, there are several rescheduling methods [11]. As shown in Figure 1, the first question to ask is whether it is possible to model vehicle path disruption scenarios. If the

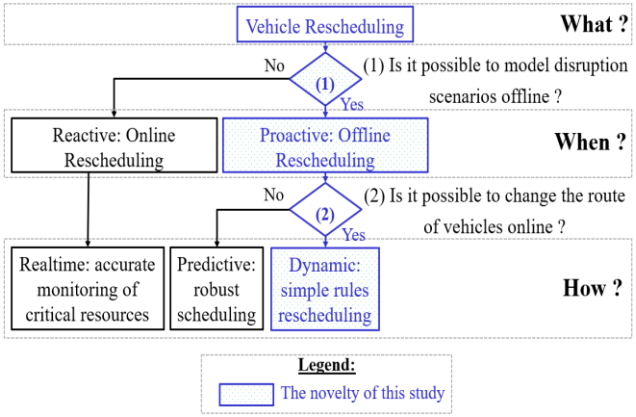


Fig. 1. State of the art on Vehicle Rescheduling

answer is yes, the rescheduling is done offline considering the disruptions, otherwise it is done online using real-time trip tracking. We focus on the case where disruptions can be anticipated offline to define simple vehicle rescheduling rules for unexpected events.

This paper is organised in five sections. After this introduction, the second section is devoted to assumptions and modelling. The third section implements experiments in the oil and gas field. The fourth section deals with the results obtained and the discussion. The last section concludes the paper by presenting the perspectives for future research.

II. Assumptions and Modelling

A. Unexpected disruption online

Let's consider N geographically distributed production sites (PS). m vehicles are tasked to visit the PS over a time horizon τ. Each vehicle starts at the central maintenance workshop (CMW)

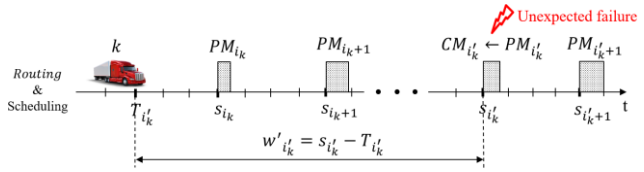


Fig. 2. A case of online equipment failure

with a limited capacity of spare parts Q. Preventive maintenance (PM) operations are optimally scheduled offline and assigned to each vehicle. Then, when scheduling is executed, the next PM operation to be performed by a vehicle $k \in \{1,2,\dots,m\}$ is denoted by i_k. Thus, i_k is incremented each time a PM operation is completed. Once a vehicle is empty, it returns to the CMW to be supplied.

As shown in Figure 2, the main assumption is that, during vehicle routing, the only disruptions to be considered are unexpected failures at the PS levels. In the online occurrence of an unexpected failure denoted by i'_k, the objective is to update the routing of the associated vehicle while minimising the downtime of the faulty equipment $w'_{i'_k}$ and the impact of rescheduling on routing costs. In this case, the scheduled PM will be transformed into corrective maintenance (CM) consisting in replacing the faulty equipment with a spare part as soon as possible. The other assumptions can be summarised as follows:

- Each PS has one piece of equipment subject to uncertain failures.
- A piece of equipment starts in "as good as new" condition, and, after a PM or a CM replacement, it returns to "as good as new" condition.
- A PM or CM operation is a deterministic time T_M spent by a vehicle in a PS.
- Travel times between PSs are deterministic and the vehicles are reliable enough to be considered as never failing over the scheduling horizon.
- If a failure occurs in a PS then the next PM operation of the faulty equipment becomes a CM with an associated penalty cost per unit of downtime (c_w).

In the following we will describe the methodology that will be used to reschedule vehicles in case of unexpected failures.

B. Rescheduling approach

This study aims to use a scheduling method from the literature and to include a rescheduling algorithm in case of unexpected failures. The scheduling of PM operations can be

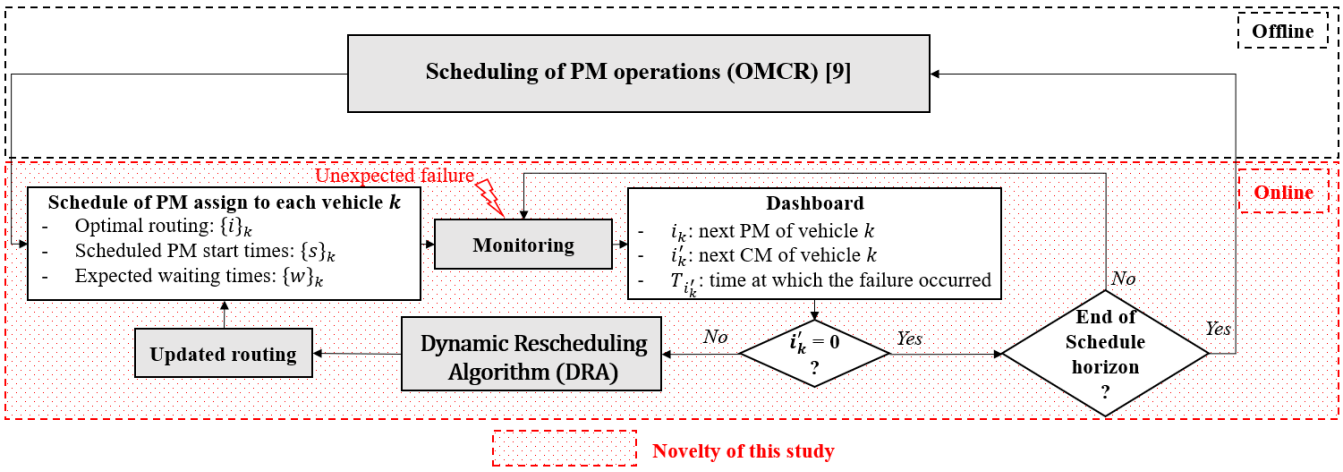


Fig. 3. Distributed Maintenance: offline scheduling and online rescheduling

obtained by several methods. The most recent method in the literature is OMCR (Optimised Maintenance and Capacitated Routing) as explained in section 1. Figure 3 shows the general process of updating the routing of a vehicle online. The OMCR model is required to obtain offline the ordered list of PM operations to be performed, the scheduled PM start times $\{s\}_k$ and the expected waiting times between operations $\{w\}_k$. Each operation corresponds to a single production site.

Online, a tracking dashboard instantly provides the next PM i_k to be performed, for each vehicle k. And, if an unexpected failure occurs, the next CM of the failed equipment is denoted by i'_k ($i'_k \geq i_k$ in the event of failure; 0 otherwise). The time at which the failure occurs is denoted by $T_{i'_k}$ and the effective downtime of the faulty equipment is $w'_{i'_k}$. The novelty of the approach is the Dynamic Rescheduling Algorithm (DRA), which handles failures by making a trade-off between the downtime of the faulty equipment, the routing costs and the disruption of offline scheduling. Once the scheduling time horizon is over, it is necessary to determine a new schedule considering any changes in equipment parameters and the loop starts again. The DRA will be presented in detail in the next subsection.

C. Dynamic Rescheduling Algorithm

This is a set of two algorithms inspired by the back-insert and swap operators, which have already proven their performance in Operations Research [12]. It consists in optimally permuting some elements of a given task list, such as the input and output lists contain the same parts but not in the same order. The "swap" operator leads to the exchange of a pair of elements (i, j) in the list, while the "back-insert" operator consists of removing an element from position j and reinserting it into position i, where $(i < j)$. These are heuristics with simple rules that can be used to modify the list of PM operations in case of an uncertain failure.

The objective is to ensure that i'_k takes over from i_k if a failure occurs. Then, the assigned equipment downtime could be reduced by prioritizing the CM over the other scheduled PM of the vehicle k. But attention should be paid to the potential cost of rescheduling. Therefore, it is necessary to define the frameworks in which an online rescheduling is cost effective. Thus, we define two parameters (α, β) to be determined offline,

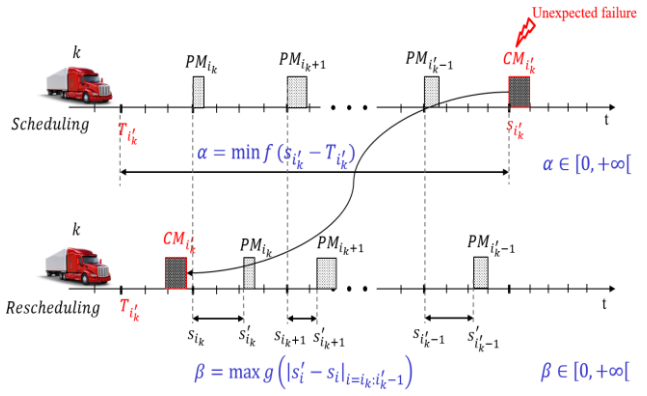


Fig. 4. Definition of parameters (α, β)

in order to explore when it is profitable to change the schedule of a vehicle.

The profit is considered to be the difference between the cost of maintenance before and after the rescheduling. We use the same maintenance cost function as in equation (31) of paper [7].

$$Profit = \bar{C}(s_i) - \bar{C}(s'_i) \quad i = i_k : i'_k \tag{1}$$

Where: $\{s_i\}$ is the set of PM start times before rescheduling and $\{s'_i\}$ is the set after rescheduling.

As shown in Figure 4, the first parameter α is the minimum value of the discrete function f such that the profit is maximised.

$$f\left(w'_{i'_k}\right) = \frac{w'_{i'_k}}{w_{i'_k}} \tag{2}$$

Where: $w'_{i'_k} = s_{i'_k} - T_{i'_k}$ is the effective downtime of the faulty equipment and $w_{i'_k}$ is the expected one.

The second parameter β is the maximum value of the discrete function g such that the profit is maximised.

$$g(|s'_i - s_i|) = max(|s'_i - s_i|) \quad i = i_k : i'_k - 1 \tag{3}$$

The smaller α is, the less attention is paid to failures that occur earlier than expected. The higher the β, the more tolerable the differences between the start times of the rescheduled PM and the scheduled one are. Once the α and β values are set, it is simple and fast for a vehicle to determine whether or not to change its schedule in the event of a failure.

The algorithm below presents the pseudo code of the DRA procedure to be applied online. Once the α and β values have been set offline, the downtime $w'_{i'_k}$ is calculated each time an equipment fails online. If the ratio between the value obtained and the expected waiting time $w_{i'_k}$ is greater than or equal to α, then the rescheduling can be carried out. Then if the difference between the start times of the operations after and before rescheduling is less than or equal to β then rescheduling is performed using either the back-insert or swap operator.

Algorithm: DRA

- **Inputs:** i_k; i'_k; $T_{i'_k}$; $s_{i'_k}$; $w_{i'_k}$; α; β
- **Outputs:** $\{s_i\}\ \forall\ i = i_k : i'_k$

1. $w'_{i'_k} = s_{i'_k} - T_{i'_k}$; // calculating the effective downtime
2. **if** $w'_{i'_k} / w_{i'_k} \geq \alpha$ **then**
3. $\{s'_i\}$ = Operation$(i_k; i'_k)$; // Operation ∈ {Back_Insert; Swap}
4. **for** $i = i_k : i'_k - 1$
5. **if** $|s'_i - s_i| > \beta$ **then**
6. **break;**
7. **end if**
8. **end for**
9. **if** $i = i'_k - 1$ **then**
10. $\{s_i\} = \{s'_i\}$; // Rescheduling
11. **end if**
12. **end if**
13. $i'_k = 0$

The variables used in the proposed DRA algorithm are summarised as follows:

- i_k: next PM of vehicle k
- i'_k: next CM of vehicle k
- $T_{i'_k}$: time at which the failure occurred
- s_i: scheduled start time of PM i
- s'_i: rescheduled start time of PM i
- w_i: expected waiting time before the next PM i
- w'_i: effective downtime before the next CM i
- (α, β): decision parameters for rescheduling

In the following we will conduct experiments in the oil & gas domain to explore the relevance of the proposed algorithm.

III. Experiments

Our case study involves the maintenance of 10 pumping stations spread geographically over a 300 km radius. Every pumping station has a pump that is subject to uncertain failures. Vehicles are used to visit the stations to ensure the dependability of the pumps. This case study is inspired by a real industrial case [8]. The OMCR provides the optimal scheduling of maintenance operations for each vehicle.

The question that remains is: what is the best rescheduling strategy to adopt in the event of unexpected failures? We implement the DRA algorithm. The first objective is to determine the two parameters (α, β) that produce the highest profit after rescheduling. As explained in the previous section, the DRA involves the swap and back-insert operators. Each of these operators allows for a different rescheduling. The second objective is thus to determine the most profitable operator for this case study.

TABLE I. PUMP CHARACTERISTICS

i	C_{PMi}[a] ($)	T_{PMi}[a] (hour)	C_{wi}[a] ($/hour)	$f_i(t)$ [b]
1	183	9	7,344	*N*(45,4)
2	121	5	5,728	*N*(54,4.5)
3	193	6	7,080	*W*(66,3.5)
4	156	8	3,387	*W*(100,3.5)
5	138	8	5,059	*W*(63,3.5)
6	194	10	8,583	*N*(44,4.4)
7	163	9	4,356	*W*(84,3.5)
8	100	9	3,344	*N*(78,7)
9	193	6	2,891	*N*(96,8.728)
10	105	10	5,179	*N*(75,6.819)

a. C_{M_i}: service cost of replacing a pump; T_{M_i}: time necessary to replace a pump; c_{w_i}: downtime cost per time unit

b. $N(\mu, \sigma)$ denotes the Normal probability density function with mean μ and standard deviation σ; and $W(\lambda, k)$ denotes the Weibull probability density function with scale parameter λ and shape parameter k. [hours]

We use Arena software which is well suited for the simulation of discrete event systems. We perform the experiments on Windows 8, 64 bits machine, with an Intel(R) Core (TM) i7-10850H, CPU 2.70 GHz and 32 Go of RAM. The characteristics of each pump are presented in Table 1. The simulation allows several scenarios to be tested by varying the values of α and β. The objective is to introduce random failures while the vehicles are performing the scheduling prescribed by the OMCR and to obtain the profit generated by the DRA algorithm. To do this, we use the different probability distributions $f_i(t)$ provided for each equipment i. The (α, β) values used for each scenario are as follows:

$$\alpha \in \{0; 0.5; 1; 2; 4; 8\} \; and \; \beta \in \{0; 5; 10; 20; 40; 80; 160\}$$

For example, for $\alpha = 0.5$ any failure occurring greater than half the expected time is considered. If $\beta = 5 \; hours$, rescheduling is performed if and only if it does not disrupt the start times of maintenance operations by more than 5 hours. Recall that from the DRA algorithm, it can be deduced that if α is too small and β is too large, there will always be a rescheduling. If α is too large or β is too small, there will never be a rescheduling. The objective in the following is to find the best trade-off.

Each of the 42 scenarios is simulated over a 30-day time horizon and replicated 40 times. A 95% confidence interval of the results is respected. In the next section the results are discussed.

IV. Results

A. Analysis and interpretation

The implementation of the proposed DRA algorithm highlights the importance of (α, β) in the application of the back-insert (Figure 5) and swap (Figure 6) operators for rescheduling. The various experiments carried out thus make it possible to obtain several cases favourable or unfavourable to rescheduling. Indeed, in terms of cost, there are three main categories of profit: negative, positive and optimal.

1) Unprofitable rescheduling

Rescheduling is considered unprofitable when the profit is less than zero. For the back-insert operator, we have 4 out of 42 scenarios where rescheduling is not profitable, representing 9.52%. For the swap operator, we have 2 scenarios out of 42, or 4.76%, i.e. twice as few as the back-insert operator. These cases occur when beta is relatively too large ($\beta \geq 80h$). A too high β value leads to too many reschedules, which significantly disrupt the start time of scheduled preventive maintenance operations. The values of α involved are 0 (all failures are considered indiscriminately) or 4 (failures occur earlier than expected but rescheduling is costly). However, these values remain marginal compared to the rest of the scenarios. And it should be noted that without setting limits on rescheduling by α and β, there would be a negative benefit (this corresponds to the case where alpha is zero and beta tends towards infinity).

2) Profitable rescheduling

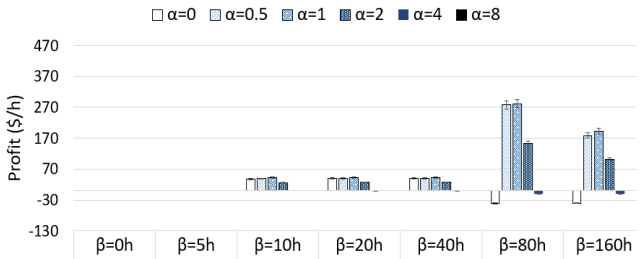
Rescheduling is considered profitable when the profit is greater than or equal to zero. The majority of the scenarios are profitable, i.e. 90.48% for the back-insert operator and 95.24% for the swap operator. The (α, β) pair is therefore useful for rescheduling as a decision parameter. Indeed, 42.86% of the scenarios do not modify the initial schedule despite the occurrence of unexpected failures in order to avoid additional costs. While 47.62% to 52.38% of the scenarios manage to change the original scheduling while reducing costs. The swap operator remains more cost effective than the back-insert operator.

3) Optimal rescheduling

Among the profitable rescheduling, there are considerable differences in the profits obtained, ranging from $\$0/h$ to $\$282/h$ for the back-insert operator and from $\$0/h$ to $\$436/h$ for the swap operator. The optimal couple for the first and second operator is successively $(\alpha = 1, \beta = 80h)$ and $(\alpha = 0.5, \beta = 80h)$. Therefore, for this case study, if the expected downtime of a pump is 4 days then it is optimal to perform rescheduling for this pump if and only if the following two conditions are met:

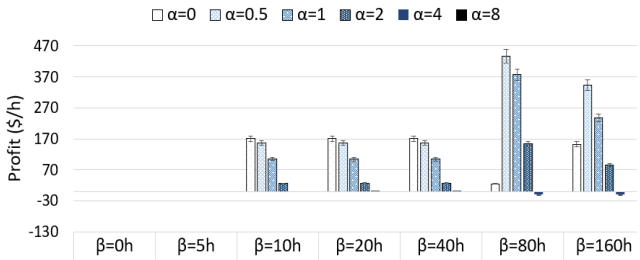
(1) The unexpected failure occurs at least 2 days before the next pump visit.

(2) The rescheduling does not change the other preventive maintenance by more than 80 hours or approximately 3 days.



	β=0h	β=5h	β=10h	β=20h	β=40h	β=80h	β=160h
α=0	0	0	38	40	40	-40	-40
α=0.5	0	0	39	40	40	278	178
α=1	0	0	42	43	43	282	193
α=2	0	0	26	27	27	154	101
α=4	0	0	0	1	1	-10	-10
α=8	0	0	0	0	0	0	0

Fig. 5. Results of back-insert



	β=0h	β=5h	β=10h	β=20h	β=40h	β=80h	β=160h
α=0	0	0	171	170	170	25	153
α=0.5	0	0	157	156	156	436	344
α=1	0	0	105	104	104	377	239
α=2	0	0	26	27	27	154	85
α=4	0	0	0	1	1	-10	-10
α=8	0	0	0	0	0	0	0

Fig. 6. Results of swap

It is important to note that all these calculations prior to the rescheduling decision require only a few milliseconds.

B. Industrial usefulness

This study can be useful only for cases where the most representative unexpected events are equipment failures. However, in some cases there may be other unexpected events related to, for example, vehicle failures, traffic, operators, etc. Thus, in order to implement the DRA algorithm in other industrial applications, it would be necessary to first identify the different origins of unexpected events. It should then be determined whether the equipment failures are the most representative or not. The Pareto chart is one of the best-known tools that can be used in this respect.

This study is inspired by the oil & gas sector but is representative of all industrial sectors (rail, aviation, road, maritime, etc.). Indeed, the probabilities of failure of a piece of equipment can be theoretically represented by a Weibull distribution or a normal distribution (the distributions we used in the experiments of this study) whatever the field studied. It is sufficient to determine the best parameters of one of these families of distribution, for other cases of study.

We considered one piece of equipment per production site in this study. Then the more equipment there is in another industrial case study, the more it may be necessary to modify the DRA algorithm before implementing it. However, in the case where there is a large number of equipment per site, it is possible, for example, to obtain a failure law for each piece of equipment individually and to define the transport distance between equipment at the same site as zero. With this last approximation, the DRA remains industrially useful.

V. Conclusion

The objective of this paper was to propose an approach to rescheduling in distributed maintenance and an algorithm to ensure the cost effectiveness of such operations. We considered a set of vehicles in charge of the preventive maintenance operations of several geographically distributed production sites. As the scheduling of the operations of each vehicle was considered to be known, it was necessary to develop a method to deal with unexpected failures. The issue was therefore the rescheduling of the vehicles. Among the classical approaches in the literature, we have chosen to develop rules that are simple and quick to implement online by the vehicles.

We have thus proposed a novel algorithm with the aim of optimising maintenance costs and ensuring the availability of equipment despite unexpected failures. We were able to experiment with an industrial case study. We have found that rescheduling is not always interesting. In some cases, it may be costly to change the scheduling of a vehicle in the event of an unexpected failure. It is necessary to pay attention to certain parameters that we have defined with the aim of knowing when rescheduling is profitable. This study highlights the impact of the rescheduling algorithm on profits in a distributed maintenance context.

For future research based on this paper it would be interesting to study the influence of the geographical distribution of sites on the rescheduling strategy. In addition, the results

obtained in this study could be compared with other methods that propose the use of standby vehicles in case of unexpected failures. It would also be interesting to study the case where the vehicle fleet is heterogeneous and thus consider the difference in capacity of each vehicle. Finally, it might be interesting to consider other types of unexpected events that might be more severe than equipment failures.

ACKNOWLEDGMENT

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