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► **To cite this version:**

Elodie Robert, Christophe Bérenguer, Kéomany Bouvard, Hocéane Tedie, Romain Lesobre. Joint dynamic scheduling of missions and maintenance for a commercial heavy vehicle: value of on-line information. SAFE-PROCESS 2018 - 10th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes, IFAC, Aug 2018, Varsovie, Poland. pp.837-842, <10.1016/j.ifacol.2018.09.672>. <hal-01902212>

HAL Id: hal-01902212

<https://hal.science/hal-01902212v1>

Submitted on 23 Oct 2018

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Joint dynamic scheduling of missions and maintenance for a commercial heavy vehicle: value of on-line information

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Abstract: Jointly optimizing maintenance and missions schedule for a vehicle has become a priority to improve the profitability for commercial heavy vehicles. Many research works are interested in optimizing either the preventive maintenance planning or the production planning but few researches are focused on scheduling both activities for a system which deteriorates over time. A static approach has previously been developed to jointly schedule missions and maintenance operations while considering the vehicle deterioration to minimize the maintenance costs. However, once the schedule is determined, no update is considered during its completion. This contribution presents a dynamic method to answer the joint scheduling problem based on the failure opportunities and the collected deterioration information. A comparison between the static and the dynamic approaches is drawn to evaluate the possible maintenance cost gain brought by the on-line information availability.

Keywords: stochastic deterioration process, reliability, genetic algorithm, dynamic scheduling, joint missions planning and maintenance scheduling

1. INTRODUCTION

1.1 Context and motivations for the work

The transport solutions offered by the Volvo group do not only consider the industrial vehicle in itself but also all the services offer to improve the solution quality. Among all the proposed services, the aftermarket services are, in a general way, a priority for the Volvo group customers.

The customers can subscribe to a maintenance contract for the vehicle. It handles the maintenance planning to improve the vehicle availability and keep its performances at a specified level. This planning is based on the vehicle configuration and the usage conditions specified by the purchaser. When it only relies on the information provided by the customer at the purchase date, the maintenance planning is static. The maintenance intervals and the maintenance actions to do at each planned stop are defined. If data can be collected to detect a usage change, the maintenance intervals are updated. The planning is then adaptive but not dynamic in the sense that the vehicle health state is never considered. The maintenance time, the immobilization time and the unplanned stops number have also been reduced thanks to preventive maintenance models. Research works have also been led to improve the

maintenance scheduling by considering the components deterioration (Bouvard et al., 2011) or by insuring the vehicle availability on a fixed time period (Lesobre, 2015). But, they schedule the maintenance operations independently from the missions the vehicle has to do.

The interest in considering a joint schedule for missions and maintenance operations is that the customer's operational constraints are considered and its profitability can be maximized by minimizing the maintenance costs. The maintenance operations are scheduled without impacting the operational availability and the missions proceedings. By considering the available monitoring data regarding the vehicle health state, the schedule can be updated and adapted to the real vehicle usage.

1.2 Background and state of the art

Some research works investigate the issue of jointly scheduling maintenance operations and production. They are mainly related to industrial machines and production workshops and consider simple maintenance policies that do not use available dynamic information.

Several criteria are considered to optimize the maintenance performance. An integrated optimization strategy to schedule maintenance and production to minimize the manufacturing system cost for a single-unit system has been proposed (Li et al., 2010). An improvement factor

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estimates the imperfect preventive maintenance operations effectiveness. However, the model only considers the steady-state availability without taking into account more complex constraints like the failure risk. An approach to optimize the flowshop and preventive maintenance planning has been developed (Feng et al., 2016). It minimizes the cost generated by the jobs tardiness and maintenance operations. In this model, unavailability constraint and imperfect maintenance are considered so that maintenance can occur only if the machine is idle. A multi-objective optimization method is also applied on uniform parallel machines to minimize the maintenance cost rate and makespan (Da et al., 2016). Each machine has different deteriorating properties modelled by Weibull parameters, different operational costs and the job processing time depends on the machine age.

The dual problem of production and maintenance planning can be handled with linear programming model to minimize the total production cost (Yalaoui et al., 2014). The production system deterioration reduces the line capacities. A preventive maintenance operation is performed at each cycle beginning to restore it. For each cycle, the maintenance cost is evaluated based on the preventive maintenance cost and the failure rate to estimate the corrective maintenance associated cost. An exact method is adopted for small size problems but heuristic methods are necessary for larger size problems.

Some joint scheduling strategies are sequential. A strategy in two stages is developed in flowshop workshops (Benbouzid et al., 2003). The first stage consists in scheduling the production tasks using heuristic methods. Then, the periodic maintenance operations are integrated by considering the production tasks execution order as a constraint. The maintenance period is chosen to reach a compromise between the maintenance cost and the machine availability loss risk. Preventive maintenance and production scheduling decisions can be jointly considered for a machine to minimize the total expected weighted completion time to do all the jobs (Cassady and Kutanoglu, 2005). An age based preventive maintenance strategy is chosen to periodically restore the system to an "as good as new" condition. If a failure occurs, a minimal repair is performed. In the case of small size problems, the model enumerates all the feasible job sequences. Then, for each sequence, all the feasible preventive maintenance decisions sets are tested to find the one minimizing the objective function. For greater size problems, a heuristic method is applied. In a first step, the job sequence minimizing the weighted short processing time (WSPT) is identified. Then, the preventive maintenance decisions minimizing the total expected weighted completion time for the WSPT job sequence are identified.

The deterioration affects directly the system health state. Each job can be defined by a duration and a fixed deterioration value (Ladj et al., 2016). As each job deterioration is strictly known and no accidental failure can occur during the schedule horizon, the deterioration model is deterministic. A failure threshold triggers the maintenance interventions and a meta-heuristic algorithm is applied to schedule maintenance and production to optimize the total maintenance costs. The deterioration can also be modelled by a stochastic process (Robert et al., 2018). In this case, each mission has a different impact on the deterioration

evolution. A method based on a genetic algorithm is developed to schedule missions and maintenance operations to minimize the total maintenance cost that depends on the preventive maintenance costs and the missions failure probabilities to estimate the cost associated with corrective maintenance.

1.3 Chosen approach and contribution

The previous contributions reported in section 1.2 tackle the issue of joint scheduling as a static problem. However, with the communication technologies deployed by the industry (telematic tools,...), monitoring systems can gather real-time data regarding the systems deterioration.

In this work, a dynamic approach is proposed to schedule missions and maintenance while considering the real-time deterioration information. The failure occurrences and the deterioration information enable to adapt to the current failure and deterioration behaviour and to update the initial schedule to minimize the total maintenance costs.

The first step consists in defining the vehicle deterioration evolution model, the different missions effect on this model and in characterizing the maintenance strategy. Then, the static and dynamic approaches to schedule missions and maintenance are explained. A numerical experiment is led to compare the two approaches and a performance evaluation is drawn.

2. PROBLEM STATEMENT

A vehicle deteriorating over time has a mission set to complete. Its deterioration varies with the mission severity and operating conditions.

The objective is to define the vehicle activity schedule by grouping the missions into blocks separated by preventive maintenance operations. These operations aim at restoring the vehicle health state to an "a good as new" state.

The schedule optimization is based on the maintenance costs. The missions, grouped by blocks, and the maintenance operations are arranged so that the maintenance costs are minimum. The vehicle activity is then maximized between two maintenance operations while considering the missions failure risks. The maintenance cost criterion takes into account two elements:

- The preventive maintenance cost C_0 as preventive maintenance operations are planned at each mission blocks end.
- The corrective maintenance cost C_f linked to a failure during a mission block.

A static scheduling method (Robert et al., 2018) is used to define the initial schedule. Then, as the schedule is applied, failures can occur and deterioration information can be collected thanks to the monitoring system. These events represent opportunities to update the schedule and to further minimize the maintenance costs by modifying the initial planning to adapt to the deterioration behaviour (Fig.1.). When a failure occurs, the schedule is immediately modified. However, the on-going mission is still the first scheduled one. When an information on the deterioration is received, rescheduling is not automatic: it depends

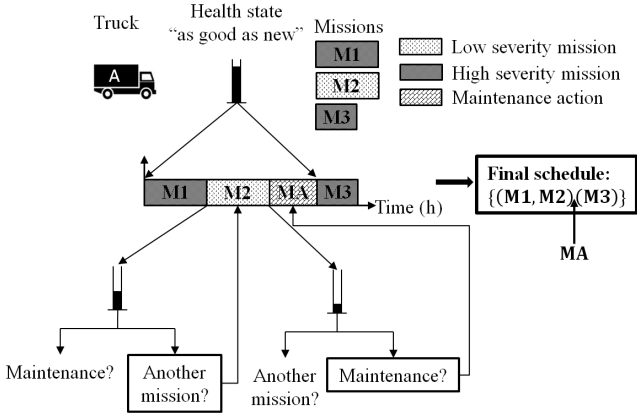


Fig. 1. Framework for the dynamic scheduling principle

on the vehicle health situation, its impact on the actual planning and the maintenance cost gain generated by a new schedule.

To tackle this issue, an integrated approach to jointly schedule the missions and the preventive maintenance operations is developed and presented in the next section.

3. PROPOSED APPROACH FOR JOINT SCHEDULING

This section explains the vehicle deterioration and maintenance model considered to study the joint scheduling problem. Then, the static and dynamic scheduling approaches are presented.

3.1 Vehicle deterioration and maintenance cost

Health deterioration model

The vehicle is considered as a single unit system, i.e. characterized by a single global health indicator. It is assumed that a monitoring system is capable of providing health state information at each mission end. To characterize the deterioration evolution, a deterioration model is then necessary. The challenge lies in the way to integrate the information retrieved by the monitoring system to improve the decision-making process regarding the vehicle schedule. In this paper, the deterioration is considered as a stochastic phenomenon rather than a deterministic one (Ladj et al., 2016).

Two classes of stochastic deterioration models are defined in the literature (Deloux, 2008; Lesobre, 2015): the discrete deterioration models and the continuous deterioration models. The first class refers to a deterioration caused by shocks. Each shock increases the deterioration level and the deterioration evolution appearance is similar to stairs. On the contrary, the second class is more relevant to model phenomena like fatigue, gradual erosion, mechanical components gradual wear and so on. The continuous deterioration models are more suitable to represent observable phenomena on several industrial systems (Lesobre, 2015) as most components are mechanical and subject to gradual wear. It is then relevant to model the global health indicator using a continuous deterioration model. As an example, the Gamma process was chosen to model the deterioration evolution in the following parts. It is

well suited to model the deterioration evolution because as its increments are increasing, the vehicle health state can only improve through an external intervention, i.e. a maintenance operation.

The vehicle deterioration evolution is modelled by a stationary Gamma process $X(t), t > 0$ whose shape and scale parameters are respectively α and β (Van Noortwijk, 2009). By modelling the industrial vehicle this way, the failure occurs due to a deterioration excess. The failure occurs when the cumulated deterioration $X(t)$ has exceeded the failure threshold L . In this case, the failure distribution function is given by Eq.(1) (Lesobre, 2015).

$$F(t) = P(T \leq t) = \frac{\Gamma(\alpha t, L\beta)}{\Gamma(\alpha t)} \quad (1)$$

$\Gamma(\alpha t, L\beta) = \int_{L\beta}^{\infty} u^{\alpha t - 1} e^{-u} du$ and $\Gamma(\cdot)$ is the Gamma function. The failure probability for a mission lasting t_m is equal to $F(t_m)$.

Operational environment

The vehicle evolves in a varying environment. Indeed, it is supposed to complete missions that may have different durations and different severities. The deterioration process is impacted by these variations that are captured in the model by a change in the Gamma process parameters. Each mission is then characterized by its duration t_m and the shape and scale parameters α_m and β_m for the deterioration process when the vehicle is completing the mission.

However, a mission to mission deterioration model is difficult to use as missions are grouped into blocks separated by maintenance operations. The operational environment can then change from mission to mission inside the same block. In this context, as maintenance operations are directly related to the vehicle health state at the end of the blocks, it is necessary to model the deterioration evolution in each block. An equivalent deterioration process approximation (Pierrat and D'Aubigny, 2004; Lesobre, 2015; Robert et al., 2018) can be given by a Gamma process whose parameters are based on the missions deterioration parameters and their durations. The equivalent Gamma process average value and variance are respectively the weighted means of the Gamma processes average values and variances associated to the missions in the block. The weighting coefficients are the ratio between the missions durations and the block duration.

Maintenance cost criterion

To make a decision regarding the best schedule, a criterion for the schedule π is defined (Robert et al., 2018):

$$Cost(\pi) = \sum_{k=1}^{N_b} (C_0 + C_f \mathbb{P}_f(k)) \quad (2)$$

with N_b the number of mission blocks in the schedule and $\mathbb{P}_f(k)$ the failure probability for the block k .

It takes into account the deterioration evolution.

As there are several missions in a block, the failure probability in a block can be computed based on the stochastic deterioration evolution in the block.

Finding the best schedule then corresponds to a balance between filling the blocks and the blocks number. It also depends on the ratio between C_0 and C_f . The next part introduces two strategies to jointly and optimally schedule the missions and the maintenance activities using the deterioration model.

3.2 Joint mission and maintenance scheduling

Both static and dynamic methods are integrated strategies because the preventive maintenance operations and the missions are simultaneously scheduled.

Static scheduling

A static method to schedule both the missions and preventive maintenance operations has been developed (Robert et al., 2018). This method uses a genetic algorithm to obtain a schedule minimizing a maintenance cost based criterion. The genetic algorithm functions are adapted from the ones used for a deterministic deterioration (Ladj et al., 2016).

The schedule is composed of blocks separated by maintenance actions and a similar deterioration model as the one explained in the section 3.1 is considered. However, no deterioration or on-line information are used to update this schedule. To try to compensate this limit, the defined criterion does not only considered the probability to have one failure by block but also the probabilities to have multiple failures. The maintenance cost criterion for the static strategy is defined (Robert et al., 2018):

$$C_{sp}(\pi) = \sum_{k=1}^{N_b} \left(C_0 + C_f \sum_{i=1}^{N(k)} \mathbb{P}_f(k, i) \right) \quad (3)$$

with N_b the blocks number in the schedule, $N(k)$ the maximum number of considered failures for block k and $\mathbb{P}_f(k, i)$ the probability to exceed the failure threshold for the i^{th} time in the block k , i.e. after $(i-1)$ renewals in the block. It is assumed that $N(k)$ is incremented as long as the n^{th} failure probability is greater than 1%.

A maximum failure probability \mathbb{P}_{max} is defined to condition the blocks filling. If the probability to have one failure $\mathbb{P}_f(k, 1)$ in the block k exceeds this limit, the block is not feasible because too risky. The genetic algorithm is steered in the right direction while reducing its computation time.

The static scheduling problem can then be formulated as:

$$\begin{aligned} \min_{\pi} \quad & C_{sp}(\pi) \\ \text{s.t.} \quad & \forall k \in \llbracket 1; N_b \rrbracket, \mathbb{P}_f(k, 1) \leq \mathbb{P}_{max} \\ & \forall k \in \llbracket 1; N_b \rrbracket, \mathbb{P}_f(k, N(k)) \leq 0.01 \end{aligned} \quad (4)$$

As for every meta-heuristic method, the obtained solution can be sub-optimal. On 200 scenarii of $n = 6$ missions, only 0.4% of the schedules towards which the genetic algorithm converges are not the optimal solution obtained by an exact method testing every possible missions arrangement. For the same scenarii with $n = 6$ missions, the computation time reduction is about 16% when compared with the exact method.

Static planning is only a first step to jointly schedule both maintenance and missions but it does not consider all the possible available monitoring data.

Dynamic scheduling: considering on-line information

The dynamic scheduling problem is defined as follows:

$$\begin{aligned} \min_{\pi} \quad & Cost(\pi) \\ \text{s.t.} \quad & \forall k \in \llbracket 1; N_b \rrbracket, \mathbb{P}_f(k) \leq \mathbb{P}_{max} \end{aligned} \quad (5)$$

Dynamic scheduling implies a schedule update when information related to the deterioration or a failure are available. The initial planning is obtained by using the static method with the criterion defined in Eq.(2). During its implementation, different events can trigger a possible update:

- A failure occurs during a mission (case 1). A corrective maintenance operation, incurring a cost C_f , is necessary. A rescheduling is applied on the remaining missions, assuming that the first mission to plan is the undone part of the unfinished on-going mission. An adaptation of the genetic algorithm is performed to consider this condition.
- A deterioration information is available at the mission end. It is then possible to update the schedule. According to the mission position in the block, different decisions can be made:
 - The mission is at the end of a block (case 2). A preventive maintenance is then planned just after. A new planning is computed based on the deterioration information and the remaining missions. If the maintenance cost difference between the new and current schedules, based on the remaining missions, is greater than the rescheduling limit condition ΔC_{min} , the new schedule is adopted. In this process, the preventive maintenance that was supposed to occur can be delayed. But if ΔC_{min} is not exceeded, the current planning is kept.
 - The mission is located in a block. The first question to answer is whether the vehicle is able to finish the block knowing the current deterioration level. Two situations come out:

- ▶ The block can be completed (case 3). The test explained just above regarding the possible maintenance cost gain with a new planning is applied.
- ▶ The probability to have a failure in the block is greater than the maximum failure probability \mathbb{P}_{max} (case 4). The remaining missions are rescheduled.

The rescheduling resolution method is also based on a genetic algorithm. Note that the criterion used for scheduling or rescheduling only considers the probability to have one failure in each block (Eq.(2)) which is justified by the rescheduling after each failure.

4. NUMERICAL EXPERIMENTS: PERFORMANCE EVALUATION AND ANALYSIS

This section illustrates the dynamic scheduling behaviour and compares the scheduling results with the ones for the static scheduling method. For the examples, the mission sets are composed of $n = 6$ missions but experiments have also been lead on sets with high mission number ($n = 20$).

4.1 Synthesis of the simulated data

Different parameters have to be defined to simulate both methods behaviours.

- The preventive maintenance cost: $C_0 = 1000\text{€}$.
- The corrective maintenance cost: $C_f = 3000\text{€}$.
- The maximum failure probability: $\mathbb{P}_{max} = 10\%$.
- The failure threshold: $L = 100\%$.

Two datasets of $n = 6$ missions are generated (Tables 1 & 2) to represent two scenarii. Each mission is characterized by its duration, the parameters associated with the deterioration process (shape and scale parameters α_m, β_m).

For each set, the scale parameters are identical for each mission. The second set (Table 2) is based on the same missions as the first one. For each mission, the expected value E is the same but the deterioration variance V is increased. Increased variance means a higher variability between the deterioration trajectories of the same deterioration process (Fig. 2.). It enables to see the variance variation impact on the optimal schedule.

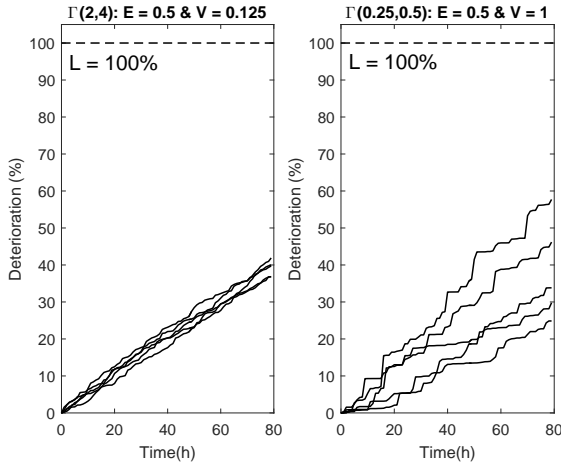


Fig. 2. Deterioration trajectories for two Gamma processes with the same E but different V

Table 1. Dataset n°1

Missions	Durations (h)	α_m	β_m	Failure probabilities
1	21	0.13	0.1	0.002
2	21	0.18	0.1	0.009
3	8	0.4	0.1	0.004
4	8	0.33	0.1	0.002
5	2	1.33	0.1	0.002
6	3	1.32	0.1	0.01

Table 2. Dataset n°2

Missions	Durations (h)	α_m	β_m	Failure probabilities
1	21	0.07	0.05	0.02
2	21	0.09	0.05	0.04
3	8	0.2	0.05	0.02
4	8	0.16	0.05	0.01
5	2	0.66	0.05	0.01
6	3	0.66	0.05	0.04

4.2 Comparison between the static and dynamic scheduling methods

Analysis of the maintenance costs for each dataset

A comparison between the maintenance costs generated by the dynamic and static schedules is drawn to study the possible cost gains. For each scenario, 1000 simulations are generated to study the maintenance cost convergence for each method. In this section, the rescheduling limit condition ΔC_{min} is fixed at $C_0/2$. It is only used in the cases 2 and 3 explained in part 3.2.2.

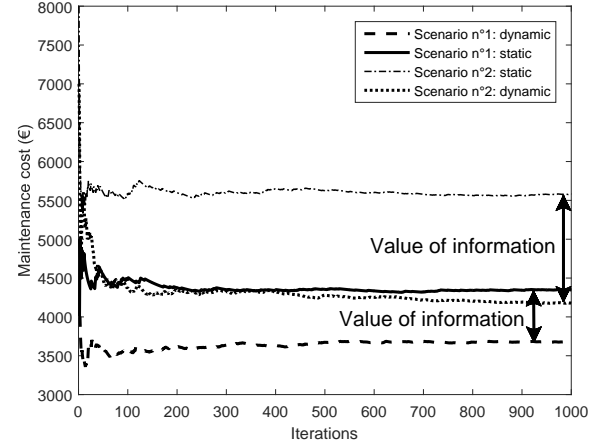


Fig. 3. Maintenance cost convergence for the scenarii n°1 and n°2: dynamic versus static

The static schedule for the scenario n°1 is $\pi_{s1} = \{(2) (3, 4) (1, 5) (6)\}$. For most simulations in the static case, the initial schedule is π_{s1} . The only difference can come from blocks permutations. Even if the criteria for the static and dynamic cases are different, the initial dynamic schedule remains π_{s1} . For the scenario n°2, the static and initial dynamic schedules are $\pi_{s2} = \{(5, 4) (6) (1) (3) (2)\}$.

Figure 3 shows that a dynamic schedule enables to make maintenance cost savings with respect to a static one. In the scenario n°1 and n°2, the savings respectively represent 15.4% and 25.1% of the maintenance costs.

When the mission variances increase, the savings are higher. Indeed, in case of high variances, the monitoring information carry more information on the consider item behaviour with respect to the average fleet behaviour. A dynamic maintenance decision based on these richer information will be all the more relevant.

Rescheduling limit condition effect on maintenance costs

The maintenance costs are influenced by the rescheduling limit condition. The maintenance costs evolution is studied for the scenario n°1 when the condition ΔC_{min} varies and compared with the static schedule maintenance cost.

Figure 4 presents the maintenance costs for the static and the dynamic methods with rescheduling limit condition values varying between $2C_0$ and $C_0/256$. Globally, the costs decrease just as ΔC_{min} decreases until the rescheduling becomes almost automatic after each mission. When $\Delta C_{min} \geq C_0$, the maintenance costs are quite similar for both methods. The dynamic method is then equivalent to the static one. A sharp drop occurs when ΔC_{min}

reaches $C_0/2$ and is followed by a softer decrease. For ΔC_{min} belonging to $[[C_0/16, C_0/256]]$, the maintenance costs variations are small enough to assume that there is a maintenance cost stabilization.

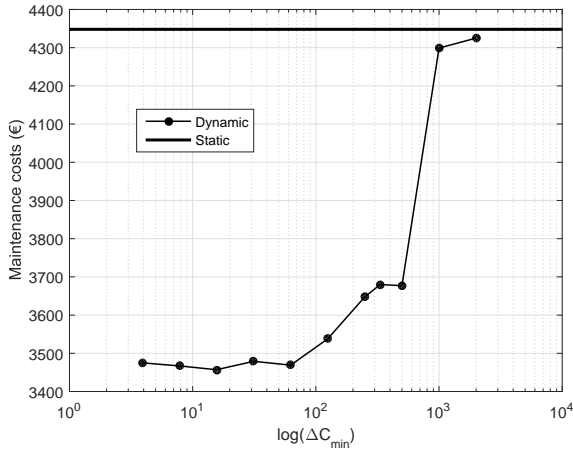


Fig. 4. Maintenance costs variations according to ΔC_{min} (dynamic versus static)

Table 3. Costs gain: dynamic vs static

ΔC_{min} (€)	Cost gain (%)	ΔC_{min} (€)	Cost gain (%)
C_0	1.1	$C_0/8$	18.6
$C_0/2$	15.4	$C_0/16$	20.2
$C_0/4$	16.1	$C_0/32$	20.0

The main cost gains (Table 3) show that encouraging rescheduling more often enables to minimize the maintenance costs. However, this study does not consider the rescheduling cost. By taking it into consideration, an optimal value of ΔC_{min} could identify a balance between the rescheduling costs and gains. With this optimal value, the final maintenance cost gain could be compared with the cost to retrieve the monitoring information.

5. CONCLUSION AND PERSPECTIVES

A dynamic method is proposed to schedule both missions and preventive maintenance operations for a vehicle using failures and deterioration information as opportunities to update the initial schedule. Then, the static and dynamic methods are compared to evaluate the possible maintenance costs gain when using on-line information. Thanks to numerical examples, two conclusions can be drawn. Integrating monitoring information on the deterioration help reducing the maintenance costs and these monitoring data become essential when the deterioration model uncertainty increases. The rescheduling limit condition ΔC_{min} also plays its part on the maintenance costs. With high values, static and dynamic schedules give the same maintenance costs results while with smaller values, rescheduling enables to reduce the maintenance costs.

The results presented in this article are promising and enable to identify some improvement axes. Further investigation on the on-line information usage, especially the part regarding the rescheduling cost to identify the optimal ΔC_{min} value and the comparison between the final gain and the cost to retrieve the on-line information, are to

be led. The dynamic approach can also be enhanced by considering adding new missions to the list during the scheduling completion. Finally, extending this approach to schedule the vehicle fleet activities would be interesting.

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