Dynamic sequential decision making for missions and maintenances scheduling for a deteriorating vehicle

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Abstract: This article proposes an approach to define sequentially a schedule for both missions and maintenance operations for a deteriorating vehicle. Both activities are jointly scheduled to adapt to the real vehicle usage and improve the hauler productivity by integrating the constraints directly in the decision-making process. The monitoring information regarding the vehicle health state, the failure occurrences and the new missions to integrate in the schedule are considered as opportunities to update the initial schedule. The method is composed of three steps: a stochastic modelling of the vehicle deterioration evolution integrating the missions effects, a definition of the maintenance policy and schedule structure and the dynamic scheduling algorithm to define and update the schedule.

Keywords: Stochastic deterioration, maintenance planning, mission scheduling, dynamic sequential scheduling approach.

1. INTRODUCTION

1.1. Context and background: motivation for the work

To deliver satisfying transport solutions, the manufacturers of commercial heavy vehicles have understood the necessity to increase their offers in terms of services. The development of an efficient maintenance management system has become a key for success to enhance the solution quality. The main objective is to guarantee the vehicle availability for the missions to be performed. Therefore, optimizing the maintenance planning according to the vehicle usage is a way to reach this goal.

The customers for the different brands of the Volvo Group can subscribe to a maintenance contract for the vehicle. This contract is based on the vehicle configuration and the operating conditions specified by the purchaser. From these information, a maintenance planning is created. Maintenance intervals and the different operations to do at each planned stop are defined to improve the vehicle availability and guarantee its performances at a specified level. This maintenance planning is static because the maintenance intervals are never updated during the vehicle life. Moreover, as the vehicle health state is never considered, the total maintenance cost is impacted by unplanned stops generating high immobilization costs.

In this framework, some research works have been led in the Volvo Group to improve the maintenance planning by integrating the components deterioration in the decision-making process and grouping the maintenance operations in a relevant way to reduce the maintenance costs [1]. A maintenance policy has also been developed to ensure, at some risk, the autonomy of a multi-component system on given operation periods [2]. However, none of these approaches consider the variability of the hauler activity with the different missions the vehicle has to perform.

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For many haulers, mission scheduling and maintenance planning are independently defined. It can lead to non-optimal schedules insofar as the maintenance planning is not adapted to the real usage of the vehicle. Jointly optimizing the maintenance and missions scheduling becomes relevant to improve the haulers productivity while adapting to their operational constraints. By doing so, the preventive maintenance operations are scheduled and completed without impacting the vehicle availability and the missions execution order is adapted to the constraints. The generated schedule can evolve with time according to the occurring disruptions such as new missions to schedule, monitoring information regarding the vehicle health state or a failure.

1.2. State of the art

Scheduling both missions and maintenance operations at the same time while considering the possibility to have planning update according to disruption occurrences raises two main challenges: the way to generate a schedule integrating both activities and the rescheduling strategy.

The literature identifies two classes of static approaches to jointly schedule maintenance and production. The first one is a two-stage strategy that schedules the production tasks at first and uses it as a constraint to integrate preventive maintenance operations in the schedule. Benbouzid et al. [3] develop an approach that firstly schedules the production tasks and uses the production tasks order as a constraint to integrate periodic maintenance slots in the initial schedule. The objective is to find the best maintenance periodicity to balance the maintenance cost and the risk of the machine unavailability. Cassady et al. [4] suggest a similar method to schedule jobs and maintenance operations for a single vehicle to minimize the total expected completion time to perform the jobs. The second class deals with an integrated strategy that simultaneously schedules both activities. Feng et al. [5] propose an integrated strategy to minimize the costs generated by jobs tardiness and maintenance operations, either preventive or corrective. In a previous contribution [6], a method was developed to jointly schedule both activities to minimize the total maintenance cost.

Among all the existing approaches, two solving methods are applied. It is either an exact method [4] that tries out every scheduling possibility or a heuristic method such as genetic algorithm [3], [5], [6]. Larger size scheduling problems justify the emergence of heuristic methods as considering all the possible schedules is impossible in a satisfying computation time.

The variety of approaches comes from the chosen hypotheses in terms of optimization criterion, maintenance policy and deterioration model. The optimization criteria are either cost-related by considering maintenance and/or production costs [5], [6] or time-related when considering the completion times to do the jobs [3], [4]. Multi-objective optimization is also applied to optimize both maintenance and production costs as well as the completion time [7]. The preventive maintenance strategy differs from one approach to another. It can either bring the system back to an as good as new state [4], [6] or consider that a maintenance operation can be imperfect [5]. Finally, the deterioration affects the system in different ways i.e. its age [5] or its health state [4], [6]. The time to complete a task can also be influenced due to the deterioration state [4]. However, the possibility to update the schedule or reschedule the remaining tasks according to real time information or events is never considered.

Rescheduling consists in updating an existing schedule in response to disruptions or other changes. It includes new jobs, machine failures and machine repairs [8]. Vieira et al. [8] define the scope of rescheduling research in production according to three axes: the rescheduling environment, the strategy and the methods. The environment is either static with a finite set of jobs to do or dynamic. The rescheduling strategies are divided into two groups: the dynamic and predictive-reactive strategies. For the dynamic strategy, there is no schedule but dispatching rules or a control strategy to dispatch the tasks while for the predictive-reactive strategy, a schedule is generated and updated in response to disruptions. Finally, the methods are either to generate a schedule or to repair it. The schedule repair methods are in fact only needed in predictive-reactive approaches.

There are two major challenges when initiating rescheduling. It is necessary to estimate if the rescheduling is worth it or if doing a schedule update will be too expensive in terms of resources and changes. Then, thinking about the strategy to trigger rescheduling is unavoidable. By doing periodic rescheduling, the events occurring between two rescheduling points are ignored. If it is combined with an event-driven rescheduling method to consider the disruptions that are significant enough, the rescheduling approach can be attractive [9]. The rescheduling problem is mostly studied without considering maintenance. Hoogeveen et al. [10] consider the rescheduling problem to schedule sets of jobs to reduce the production costs and limit disruptions by avoiding too many schedule updates. The few researches investigating the rescheduling problem while considering maintenance often use simple maintenance strategy. Wang et al. [11] study the rescheduling problem in response to the arrival of new jobs in a single machine layout where preventive maintenance should be determined. The objective is to optimize both the total completion time to do the jobs as well as the maintenance and production costs. The processing time of each job is affected by the deterioration and the allocation of more resources on a job can reduce its processing time. However, only one maintenance slot has to be scheduled. Its effect on the machine deterioration varies according to its duration.

1.3. Contribution of this paper

The previous contributions detailed in section 1.2 either limit the joint missions and maintenance scheduling problem to a static one or consider rescheduling options but only in a limited framework either with just the jobs to do and the new ones to add or without the maintenance strategy to adapt the production scheduling to the system health state.

In this paper, a predictive-reactive approach is proposed to jointly schedule the available missions and the maintenance operations for a deteriorating vehicle. An initial joint schedule is generated based on the available missions at the initial stage. To do so, the deterioration properties of the vehicle as well as the maintenance and production costs are considered to determine the best schedule. Then, different events such as failures, health state information or new missions can trigger schedule updates.

The approach encompasses three parts. The first one is the stochastic modelling of the vehicle deterioration evolution that integrates the different deterioration effects from the different missions. The second part deals with the definition of the maintenance policy and the schedule structure. The final part explains the dynamic scheduling strategy to optimize the initial static schedule defined with the missions characteristics and the vehicle state. Sequential rescheduling occurs according to the available information: a failure or a vehicle deterioration measurement or a new mission to add to the mission pool. Numerical examples are then presented to illustrate the behaviour and performance of the method. The results show the benefits of using a sequential approach that takes into account all the available on-line information on the vehicle state and operating requirements.

2. PROBLEM STATEMENT

A vehicle has an initial set of missions to complete. The severity of the missions differs from one to another because the operational conditions change. Indeed, the topography, the road type and quality have a direct impact on the deterioration evolution and it has to be considered when modelling the vehicle usage.

As the vehicle deteriorates over time, maintenance operations have to be integrated when scheduling the missions execution. From there, a joint schedule for missions and maintenance operations is initially defined. This schedule evolves according to the events occurring during the schedule completion. A failure of the vehicle, an information regarding its current health state or additional missions that have to be integrated in the schedule justify the necessity to update the initial schedule.

The objective is then to develop an approach to use the different event and real-time information to define sequentially a schedule for both missions and maintenance activities for a deteriorating vehicle.

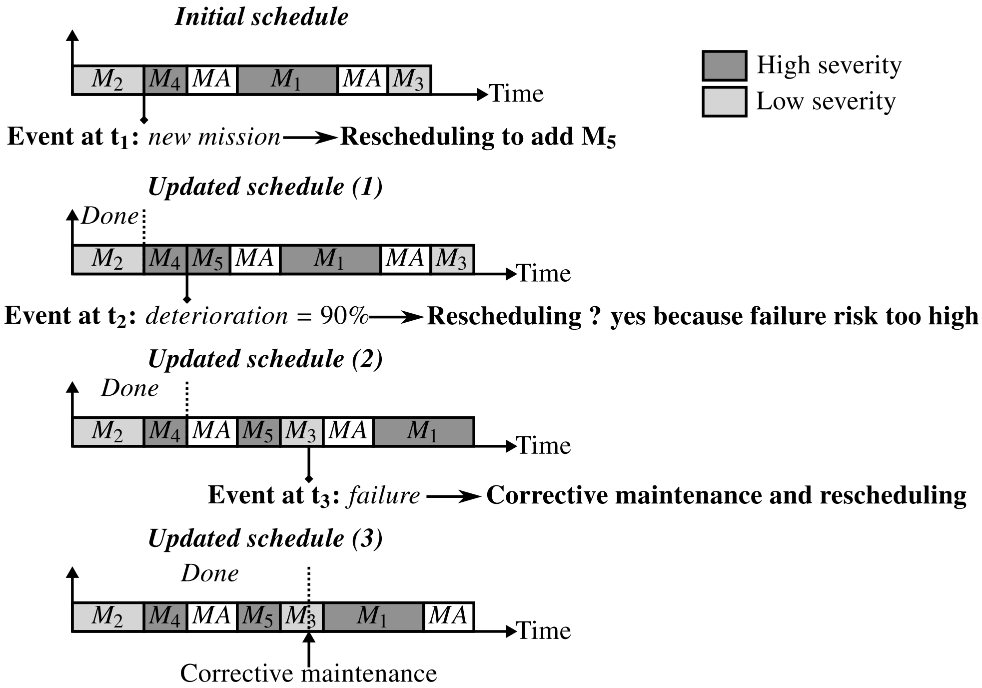

Figure 1: Principle to schedule missions and reschedule according to the occurring events (new mission M_5, deterioration measure, failure)

The main challenges lie in the way to reorganize the missions when new ones have to be added in the schedule and to evaluate if an event is significant enough to initiate a rescheduling. Figure 1 describes the reactive strategy when events occur. At the beginning, an initial schedule is set to schedule the missions M_1, M_2, M_3 and M_4 as well as maintenance operations MA. At t_1, a new mission M_5 is requested and has to be added to the schedule. A schedule update is generated to react to this event and M_5 will be performed after M_4. At t_2, a measurement of the current health state is available. The question is to know whether a rescheduling is needed. If the failure risk is too high before the next maintenance operation, it can be relevant to reschedule. An update is then set up and occurs at the end of M_4. Then, the missions M_5 and M_3 are performed but a failure happens during M_3. A corrective maintenance is necessary to repair the vehicle as well as a rescheduling. The maintenance operation MA scheduled at the end of M_3 in the updated schedule (2) is postponed after M_1.

3. METHODOLOGY

This section describes the dynamic sequential decision method to schedule the missions and maintenance operations operating for a deteriorating vehicle.

3.1. Deterioration modelling

The vehicle health state evolves over time according to its activity and the different usage conditions it is submitted to. The effect of the different missions can be related to the road type and road conditions as well as the driver type. It is then very difficult to quantify exactly how each of these parts affects the deterioration evolution. In the Volvo Group, usage severity levels are defined by the mix of several conditions of use as topography or activity type.

The deterioration phenomenon is assumed gradual and depends on the usage conditions. That is why, a stochastic process has been chosen to model the vehicle deterioration evolution. The Gamma process has been favoured due to its capacity to represent gradual deterioration phenomena for industrial systems [2], [12]. It is one of the most used process when it comes to model the deterioration of mechanical components. It has already been applied in a previous work [6].

Each mission is characterized by a mission duration, earnings when the mission is achieved, a starting deadline representing the date before which the mission must have started, a unitary delay cost and the influence on the vehicle deterioration. The unitary delay cost corresponds to the cost charged for each delay unit. It then reduces the final gain earned after the mission execution.

To illustrate the different severity levels of the missions, it is assumed that the vehicle deterioration trend depends on the severity level. So, the Gamma process modelling the deterioration has varying parameters. Each mission is then associated with a pair of parameters to take into account the missions characteristics when estimating the vehicle lifetime. Thanks to this model, the developed maintenance strategy is adapted to the vehicle usage.

3.2. Maintenance model and schedule structure

The adopted maintenance model is a deterioration-threshold failure model [6]. When the deterioration exceeds a threshold L, the vehicle fails. The objective is then to avoid failures during missions by scheduling maintenance operations at the right time. Thanks to the deterioration model presented in the part 3.1, the failure probabilities and the remaining useful life can be estimated to decide whether the health state is enough to dispatch the vehicle on a mission or if a maintenance operation is needed. It is an essential information to consider when building a joint schedule for missions and maintenances as well as for the rescheduling strategy. It is assumed that each maintenance operation restores the vehicle to an ”as good as new” health state.

The schedule structure is defined as follows. Missions are grouped into blocks and the bocks are separated by a maintenance operation. To perform the 5 missions described in Figure 1, the final schedule is $\pi = \{(M_2, M_4)(M_5, M_3, M_1)\}$. It is composed of two blocks and at each block end, a maintenance is performed.

The maintenance strategy enable to know how to build the schedule. But, an optimization criterion is necessary to schedule at best missions and maintenance activities.

3.3. Optimization criterion

To schedule both missions and maintenance operations, the optimization criterion C has to consider the maintenance costs as well as the missions characteristics. It is then composed of two parts: the total maintenance cost C_m considering both preventive and corrective maintenance and the production gain generated by the missions achievement. For a schedule π composed of n missions, this criterion represents the operating incomes generated by π (Eq.1).

$$C(\pi) = \sum_{i=1}^{n} \big(g_m(i) - c_d(i)\big) - C_m \tag{1}$$

The raw gain and the delay cost generated by the mission i are respectively denoted $g_m(i)$ and $c_d(i)$. The production gain for the mission i is then equal to $g_m(i) - c_d(i)$.

The delay cost $c_d(i)$ for the mission i is based on the estimated delay time $t_d(i)$ and the unitary delay cost C_{ud} (Eq.2). This time represents the difference between the starting deadline $d_{max}(i)$ defined in the mission characteristics and $E\big(t_s(b)\big)$ the average time for the beginning of the block b containing the mission i (Eq.3). It is assumed that all the missions in the block b start at $E\big(t_s(b)\big)$. This assumption is sufficient to orientate the scheduling algorithm towards the schedule maximizing C and enables to save some computation time. If $E\big(t_s(b)\big)$ is smaller than the starting deadline, there is no delay in the mission execution.

$$c_d(i) = t_d(i) \times C_{ud} \tag{2}$$

$$t_d(i) = max\{0, E\big(t_s(b)\big) - d_{max}(i)\} \tag{3}$$

To estimate $E\big(t_s(b)\big)$, it is necessary to know the number of previous preventive maintenances, the missions scheduled before the block b and the average number of failures that could occur in the previous blocks.

$$E\big(t_s(i)\big) = t_0 + (k-1)d_p + \sum_{b=1}^{k-1} \left(d_c E\big(N_f(b)\big) + \sum_{i=1}^{N_m(b)} d(i) \right) \tag{4}$$

where t_0 is the initial time for the schedule, d_p and d_c respectively denote the preventive and corrective maintenance durations, $d(i)$ is the duration of the mission i, $E\big(N_f(b)\big)$ is the average number of failures in the block b and $N_m(b)$ is the number of missions in the block b.

The maintenance cost C_m (Eq.5) depends on the number of blocks N_b composing the schedule as well as the number of failures considered in each block b, denoted $N_f(b)$.

$$C_m = \sum_{b=1}^{N_b} \left(C_0 + C_f \sum_{i=1}^{N_f(b)} \mathbb{P}_f(b,i) \right) \tag{5}$$

A preventive maintenance, occurring at the end of each block, costs C_0 while a corrective maintenance costs C_f. C_f is assumed to be greater than C_0 to include the immobilization costs. $\mathbb{P}_f(b,i)$ is the probability to have at least i failures in the block b. While $\mathbb{P}_f(b,i)$ is greater than 1%, $N_f(b)$, the number of considered failures for the block b, is incremented.

The dynamic scheduling algorithm defines the missions and maintenance schedule by maximizing the criterion C.

3.4. Dynamic scheduling algorithm

The dynamic scheduling algorithm aims at populating the blocks of missions to optimize the operating incomes considering both the maintenance costs and the gains generated by the missions completion. It optimizes the initial schedule with the missions characteristics and the vehicle state. Then, sequential rescheduling occurs according to the available information such as a failure occurring in a block, a real-time deterioration measurement and new requested missions. The decision-making process happens at the end of each mission (Figure 2) as long as the number of missions done m does not exceed the total number of missions to schedule N_t.

An initial schedule is generated based on the genetic algorithm developed by Robert et al. [6]. It is a static method that schedules the missions initially available as well as the maintenance operations to optimize the criterion defined in the section 3.3. The deterioration model for the vehicle is considered to fill in the blocks and a maximum failure probability $\mathbb{P}_{max}$ is used as a condition on the block filling process. If the probability $\mathbb{P}_f(b,1)$ to have at least one failure in the block b is greater or equal to $\mathbb{P}_{max}$, the block is considered as not feasible because too risky.

This initial schedule is implemented and during its execution, different real-time event can occur and trigger possible updates (Figure 3:

- A failure happens during a mission. A corrective maintenance operation is performed to restore the vehicle health state to an as good as new state. Then, a rescheduling is initiated on the remaining missions. A corrective maintenance is a major event to consider when scheduling the next missions and preventive maintenance slots as it strongly affect the current vehicle health state. The first scheduled mission is the undone part of the unfinished mission. The static algorithm is then adapted to consider the unfinished mission position in the schedule.

- A new mission is requested. It has to be added to the schedule as soon as possible because of the starting deadline characterizing the mission. As a mission cannot be interrupted once it has started, a new mission can only available at the end of the already scheduled missions. A rescheduling is then applied to integrate the mission in the schedule. This rescheduling affects the remaining missions and the preventive maintenance slots already scheduled.

  ◇ If a deterioration measurement is available at the end of the mission completed just before the rescheduling order, this information is integrated in the rescheduling and conditions the first block filling for the new schedule.

  ◇ If there is no deterioration measurement available, the rescheduling is performed normally.

- No new mission is requested but a deterioration measurement is recorded.

  ◇ If the mission is at a block end, the possible gains generated by a rescheduling with respect to the current schedule are estimated. If they are greater than the rescheduling limit condition C_{lim}, the rescheduling is adopted. Otherwise, the current schedule is kept.

  ◇ When the mission is not at a block end, the first question is to know whether the block can be finished or if the failure risk is too high with respect to the maximum failure probability $\mathbb{P}_{max}$. If it is impossible to finish the block, a rescheduling is performed. Otherwise, the possible gains driven by a rescheduling are estimated. If they are significant enough, a rescheduling is applied.

The described strategy is represented by Figures 2 and 3. The way to fill in the blocks can slightly vary according to the information available. A failure during a mission, caused by an excess of the deterioration D with respect to the failure threshold L, implies that the first mission to do in the new schedule is the failed mission remaining part. When the deterioration level D is known, it conditions the way to compute the failure probability of the new schedule first block. The failure threshold not to be exceeded becomes $L-D$.

This method is a predictive-reactive one insofar as a schedule exists and is updated according to the occurring events. Sequential rescheduling enables to adapt at best the schedule to the vehicle health state and usage.

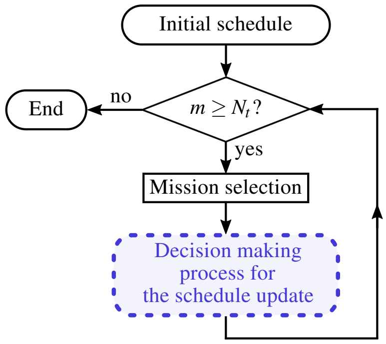

Figure 2: Dynamic sequential algorithm: way of working

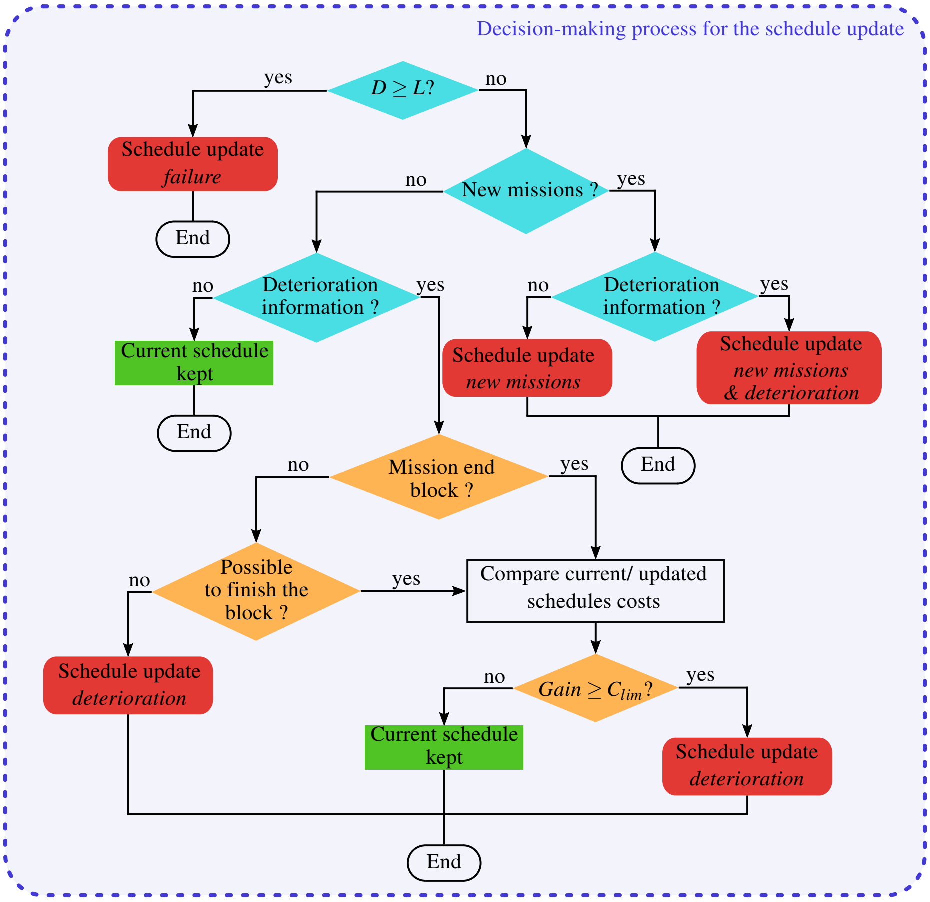

Figure 3: Decision-making process for the schedule update

4. APPLICATION EXAMPLE

The application example analyses the reactions of the dynamic sequential algorithm according to the occurring events. The obtained schedules are simulated to estimate the gains generated by the schedules and the results are compared with a static method for which no rescheduling can happen when a schedule is defined.

4.1. Parameters & missions definitions

The different parameter necessary for the simulations are defined in Table 1.

Table 1: Parameter definitions

Parameter	Definition	Value	Parameter	Definition	Value
C_0	Preventive maintenance cost	1000	C_f	Corrective maintenance cost	3000
d_p	Preventive maintenance duration	2	d_c	Corrective maintenance duration	4
L	Failure deterioration threshold	100	$\mathbb{P}_{max}$	Maximum failure probability	0.1

Table 2: Mission characteristics

Mission N^o	Duration (h)	α	β	Failure probability	Starting deadline
1	21	0.1335	0.1	0.0021	90
2	21	0.1837	0.1	0.0087	12
3	8	0.3959	0.1	0.0035	32
4	8	0.3285	0.1	0.0015	2
5	2	1.3254	0.1	0.0016	43
6	3	1.3206	0.1	0.0099	110
7	3	1.0150	0.1	0.0030	45
8	10	0.4216	0.1	0.0132	48
9	13	0.2465	0.1	0.0037	70
10	44	0.1041	0.1	0.0195	200
11	19	0.1937	0.1	0.0070	150
12	9	0.4043	0.1	0.0067	98
13	13	0.2077	0.1	0.0017	190
14	3	0.8863	0.1	0.0016	160
15	5	0.9130	0.1	0.0192	165
16	3	0.8177	0.1	0.0012	128
17	22	0.1303	0.1	0.0023	165
18	6	0.6972	0.1	0.0127	145

The initial list of missions is composed of 6 missions. The next 12 missions are progressively added in the mission pool and have to be integrated in the schedule. Table 2 describes the characteristics for the 18 missions to schedule. The shape and scale parameters for the deterioration Gamma process are respectively denoted α and β. The raw gain earned when a mission is completed without delay is $g_m = 5000$ and the unitary delay cost is $C_{ud} = 50$ for all missions.

For the static method with no rescheduling, the 6 first missions are scheduled to optimize the criterion defined in the section 3.3. Once, all these missions are performed, the 12 others are scheduled and performed.

Occurring events: 4 new missions are available at the end of the missions 1, 3 and 5 and deterioration information are available at the end of the missions 1, 2, 5, 6, 8, 10, 12, 13, 14, 17 and 18.

4.2. Results

The initial schedule based on the 6 first missions is identical for both methods. It is defined by $\pi_i = \{(4,2)(3)(5,1)(6)\}$. Permutations inside the blocks and between the blocks can happen. The only difference is in the final schedule. Indeed, with the dynamic sequential method, the schedule evolves according to the occurring events and the decisions are made as reactions to these events.

For each method, Monte-Carlo simulations are generated to compare both the operating incomes generated by the schedules and the computation time necessary to obtain the different schedules. Let π_{ds} (Eq.6) and π_s (Eq.7) be examples of final schedules respectively for the dynamic sequential method and the static one. The schedule π_{ds} only have 9 blocks while π_s have 13 ones. Then, π_s performs 4 more maintenance operations. It explains why the gains generated by π_{ds} are equal to 80550 while the ones for π_s are 67600.

$$\pi_{ds} = \{(4,2,5)(3,8,7)(6)(9,1,16)(12,18)(11,14)(15)(13,17)(10)\} \tag{6}$$

$$\pi_s = \{(4,2)(3)(5,1)(6)(7)(8)(9,16)(15)(12)(14,13)(18)(17,11)(10)\} \tag{7}$$

Figure 4 shows that the dynamic sequential method is more profitable than the static one by about 6200. The benefit represents the costs of two corrective maintenance operations. However, the dynamic sequential method is more time-consuming than the static method. Indeed, the static method requires about 10s to compute the schedule while the dynamic sequential one needs about 50s, namely 5 times longer.

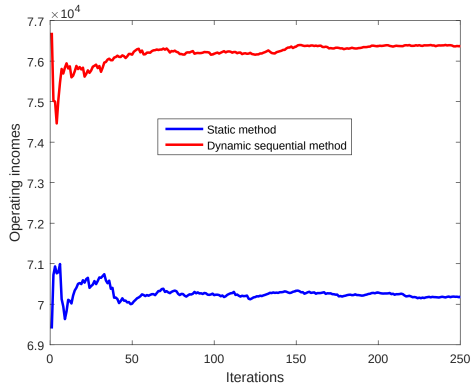

Figure 4: Convergence analysis of the operating incomes: static VS dynamic sequential

Figure 5 shows the distribution of the total rescheduling number n_t according to the simulations made with the dynamic sequential method. On average, 5 updates are performed to schedule the 18 missions. For each simulation, it can be divided into 4 parts according to the events causing the schedule updates. The parameters n_f, n_d, n_m and n_{md} respectively denote the rescheduling number caused a failure during a mission, an available deterioration information, new requested missions and a mix of both new requested missions and deterioration information. For each cause, the rescheduling strategy is different. The total rescheduling number n_t is then defined by:

$$n_t = n_f + n_d + n_m + n_{md} \tag{8}$$

Figure 6 illustrates the distributions of the rescheduling numbers n_f, n_d, n_m and n_{md}. Among the schedule updates, 2 always happen. It is due to new requested missions and deterioration information available at the end of missions 1 and 5. Likewise, one update always occurs owing to new requested missions. It takes place at the end of the mission 3.

The benefits generated by the dynamic sequential method comes from the schedule updates performed when events occur (failures, new missions) or information on the vehicle health state are retrieved. It is considered that failures and new missions necessarily involve updates of the current schedule. Indeed, a failure implies that the current schedule was not exactly well designed for the vehicle use. This event also enables to know that after the corrective maintenance, the deterioration state is back to 0 and it is a piece of information that can be used to schedule the remaining missions accordingly. Likewise, arrivals of new missions means that the schedule must be updated as soon as possible because each mission is characterized by a starting deadline that represents its priority. If a new top priority

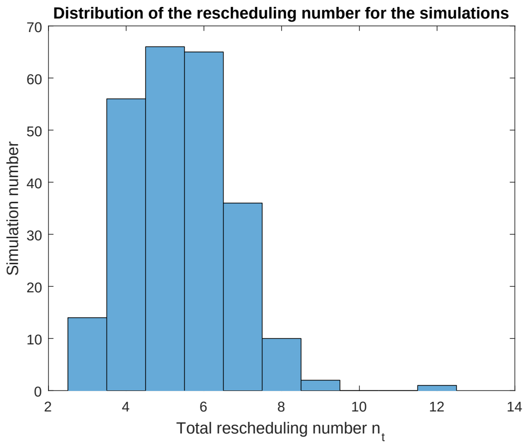

Figure 5: Distribution of the total rescheduling number n_t

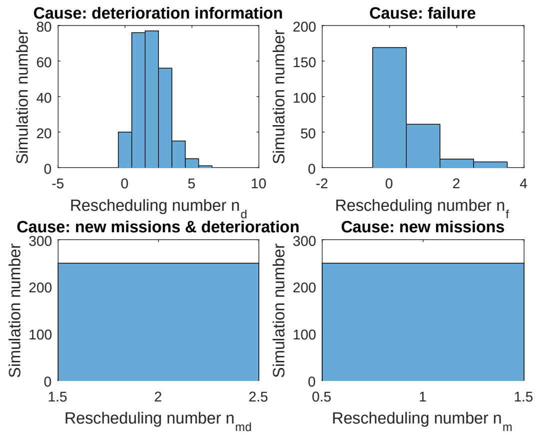

Figure 6: Distributions of the rescheduling numbers for each rescheduling cause (n_d, n_f, n_{md} and n_m)

mission is requested, it will be positioned in the schedule to maximize the criterion value. It is then a balance between the estimated gains, delay costs and maintenance costs. Nevertheless, rescheduling is compulsory to prevent potential delays on the new missions execution.

The only considered flexibility in terms of rescheduling is when an information regarding the vehicle health state is available. The notion of rescheduling limit condition is then introduced. This limit condition C_{lim} enables to decide whether or not a rescheduling is cost effective. If C_{lim} is not overstepped, no rescheduling is applied. C_{lim} is fixed at $C_0/2$ for the dynamic method results presented in Figure 4. The operating incomes increase when C_{lim} decreases (Figure 7). It is assumed that no cost is induced when a rescheduling happens. By considering it, a balance between the rescheduling costs and potential gains could be identified and these gains could be compared with the cost necessary to retrieve monitoring health state information. However, as the starting deadline is part of the mission characteristics, adding a rescheduling cost may not be relevant. The rescheduling impact is already considered in the operating incomes through the delay costs to limit the rescheduling disruption.

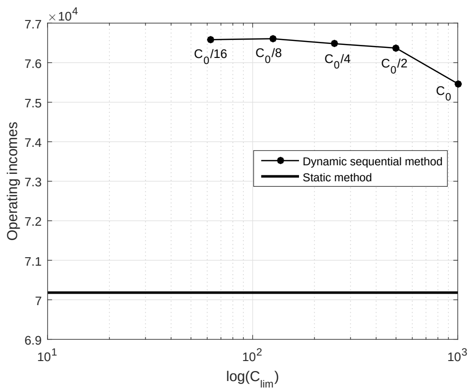

Figure 7: Operating incomes according to the rescheduling limit condition C_{lim}

5. CONCLUSION

This paper proposes a dynamic sequential method to schedule both missions and maintenance operations for a deteriorating vehicle. The schedule is updated when events such as failures or new missions occur and when deterioration information are available. The criterion to optimize the obtained schedules is based on the operating incomes considering the maintenance costs, the gains earned when the missions are completed and the delays when performing the missions. The interest of rescheduling according to the events is illustrated through a comparison with a method that do not update the initial schedule. Rescheduling improves the operating incomes at the expense of the computation time and the rescheduling limit condition also plays its part to increase the operating incomes.

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