Impact of the Decision Horizon on Railway Systems Maintenance and Service Scheduling

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Prognostics and health management (PHM) has, recently, gained a lot of attention in the rail transportation context. However, most works in this field focus on the prognostic process. However, prognostics is not the end of PHM in itself, its results have to be used to better manage the life cycle of systems. PHM decision phase is applied to plan action in both operational and maintenance ways based on the current condition and the estimated RUL. One important parameter of this phase is the length of the scheduling horizon. In this paper, we propose a methodology to set the suitable values of this main parameter. In this paper, we also study the influence of some rolling stocks application parameters on the value of the decision horizon. As a result, we obtain a range of values for the decision horizon that optimizes the maintenance and service policies.

Keywords: Prognostics and Health Management, Post-Prognostic Decisions, Decision-Making, Railway System, Decision Horizon, Mission Assignment, Predictive Maintenance.

1. Introduction

Prognostics and health management (PHM) is an emergent technology that aims to study and analyze the behavior of a system, predict its end of life, estimate its remaining useful life (RUL), and manage its health states. PHM can be summarized into three phases: (i) observation, (ii) analysis, and (iii) decision support. Recently, this methodology became the focus of many works in the railway context. Several works have proposed an adaptation of the PHM framework to the railway systems applications, one can cite for example works of Galar et al. (2013) and Brahimi et al. (2016). Most of the works in this domain have focused on the observation and analysis phases. by proposing and comparing sensors configuration Camci et al. (2016), or by acquiring, processing, and analyzing the sensors data Cao et al. (2018). One can find several works studying railway assets health assessment and prognostics Guclu et al. (2010); Eker et al. (2011); Mishra et al. (2017). However, fewer works have focused on post-prognostics decision-making. These works can be divided into two categories based on the considered system: (i) stationary systems like rail infrastructure, rail switch, and traction power supply and (ii) moving systems like trams, metros, and trains.

Prognostics-based decisions for stationary systems have focused mainly on defining the maintenance dates. Villarejo et al. (2016) developed a hybrid PHM framework to optimize maintenance planning of rail infrastructure. Letot et al. (2016) used the estimated future degradation level to schedule tamping interventions on rail tracks. Durazo-Cardenas et al. (2018) conceived a maintenance decision support system for railways based on big data fusion and systems engineering. Camci (2014) developed a genetic algorithm and a particle swarm optimization algorithm to determine a maintenance schedule that minimizes the expected failure, maintenance, and the travel costs for rail switches. Verbert et al. (2017) designed a two-level maintenance strategy optimization for railway networks (i.e., tracks and switches). Traction railway power supply is another system that has been studied in a PHM context. Lin et al. (2016) used a partially observable Markov decision process to plan maintenance interventions for a traction power supply based on its remaining useful life. In the same context, Feng et al. (2017) developed a framework that combines PHM and active maintenance to optimize maintenance activities.

Although one can find several works that optimize the operations Turner et al. (2016) and the maintenance Yun et al. (2013) of rolling stocks, the prognostics information are not yet included in these works. To our knowledge, only the paper of Herr et al. (2017) presented a method to optimize jointly task assignment and the maintenance scheduling of trains given a predefined train timetable and the equipment's RUL.

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However, most of the works on post-prognostic decision-making in general and on the railway system, in particular, have focused on solving the maintenance and/or the operational problems and have deliberately omitted some of the PHM framework parameters. One important parameter of the decision-making process is how far ahead can we plan maintenance and/or operations, also known as the decision horizon. This parameter is responsible for defining the frequency at which one updates the schedule of actions. Several characteristics of the considered problem can influence the definition of this duration. The focus of this paper is to study the optimal decision horizon duration. Artificial intelligent techniques are used to solve this kind of problem under different conditions. We propose to study the influence of the problem size, the number of sub-systems, and the components characteristic on the decision horizon duration.

This paper is structured as follows; in section 2 a definition of maintenance and operation joint problem is proposed. The section 3 presents a description of the used genetic algorithm. In section 4, a case study is proposed and the obtained results are discussed. This work is finally concluded and some future perspectives are given in section 5.

2. Problem Statement

In this paper, the problem of jointly assigning tasks from predefined time-schedule to trains and scheduling maintenance activities is considered. The problem consist in assigning a set $\mathcal{P}$ of periodically defined tasks to a set $\mathcal{M}$ of trains, with $Card(\mathcal{P}) = P$, $Card(\mathcal{M}) = M$, and $P < M$. The objective is to minimize the total cost, which includes assignment costs and maintenance costs. Each task (or mission) p is defined as a sequence of trips in which the start and the finish points are in the same depot. Thus, a mission p is characterized by the distance d_p to be covered by the train, and a coefficient of severity s_p. The severity coefficient can represent different aspects of the task, (e.g. the environment, the line characteristics, ...). This severity coefficient is used to differentiate the influence of different tasks on the degradation of the train's components.

2.1. *Train Model*

In this application, a train m is defined as a series of K predictive components and L preventive components i.e. if one component fails the whole system fails. The predictive components are subject to condition monitoring, health assessment and prognostics to assess their current condition and estimate their remaining useful life. Thus, for any given train m, a predictive component k is characterized by its type and its health state variable $H_{m,k} \in [0, 1]$ for $(1 \leq k \leq K)$. Where $H_{m,k} = 0$ indicates that the component k is as good as new and if $H_{m,k} = 1$ indicates that the component is completely deteriorated and failed. In this work, the degradation of the components is assumed to monotonously increases over time as an accumulation of small positive independent increments. Stochastic processes have been wildly used in literature to model degradation process van Noortwijk (2009).Therefore, $\{H_{m,k}(t), t \geq 0\}$ is assumed to be a homogeneous Gamma Process $\Gamma(\nu_k(t), \mu_k)$ with shape parameter $\nu_k(t) = \alpha_k * t$ and scale parameter μ_k and has following properties:

- $H_{m,k}(t' = 0) = 0$
- $H_{m,k}(t)$ has independent increments
- For $t > 0$ and $h > 0$ during which the tram m is serving a trip p with a severity s_p, $H_{m,k}(t + h) - H_{m,k}(t)$ follows a gamma distribution $\Gamma(\nu_k(t+h) - \nu_k(t), s_p \times \mu_k)$ with shape parameter $(\nu_k(t + h) - \nu_k(t))$ and scale parameter $s_p \times \mu_k$

We denote $\Delta_k \in [0, 1[$ the failure threshold of component k. This threshold is defined for security measure to avoid actual failure of the component and thus avoid putting passengers in risk.

The preventive components are subject to systemic periodic replacement based on the traveled mileage since the last maintenance. Therefore, the preventive components are characterized by the mean time to failure (MTBF) expressed in miles that depends on the type of the component l. Let us note $\theta_{m,l}(t)$ for $K \leq l \leq K + L$ and $1 \leq m \leq M$ the mileage traveled by component l of unit m from its last replacement up until instant t and $\Theta_l = f(MTBF_l)$ the mean time to failure of this component.

2.2. *Task Assignment Problem*

The task assignment problem aims to find a suitable train m for each mission p of a predefined timetable. This assignment is built while considering the health state of the vehicles and their ability to fulfill missions.

We consider the problem of vehicle scheduling over a rolling decision horizon noted DH with duration $DH = I \times \Delta\ T$ with $\Delta\ T$ is the time unit (a day for instance) and I is the number of time units. For each time unit, denoted i with $1 \leq i \leq I$ the set $\mathcal{P}$ of missions should be fulfilled by the set of trains $\mathcal{M}$.

A machine learning-based prognostic algorithm provides the degradation rate noted $\delta_{p,k} \in [0, 1[$ that describes the amount of additional degradation of component k caused by fulfilling a mission p. We generated some simulated degradation evolution under different conditions. This simulated data is used to train the machine learning algorithm that provides the prediction of the $\delta_{p,k}$. This degradation rate varies from one component to another and from one mission to another. Assigning mission p to a train m during period i should guarantee that the degradation level of every predictive component k of the train m after achieving the mission is lower than the failure threshold (see Eq. (1)).

$$H_{m,k}(i) + \delta_{p,k} < \Delta_k, \quad i = 1..I, k = 1..K \quad (1)$$

Moreover, the assignment of a mission should also take into consideration the mileage traveled of preventive components. Therefore, assigning mission p to train m should also guarantee that the mileage covered by any preventive component l after achieving the mission is lower than its MTBF (see Eq. (2)).

$$\begin{aligned} &\theta_{m,l}(i) + d_p < \Theta_l \\ &i = 1..I, l = K+1..K+L \end{aligned} \quad (2)$$

In addition, we assume that a given mission p could be assigned to at most one train m during a period i (see Eq. (3)). And that a train m could be assigned to at most one mission p during a period i (see Eq. (4)). Therefore, let us denote the variable $\beta_{p,m}(i) \in \{0,1\}$. When mission p is assigned to train m, we have $\beta_{p,m}(i) = 1$. Otherwise, it is equal to zero.

$$\sum_{m=1}^{M} \beta_{p,m}(i) \leq 1 \quad i = 1..I, p = 1..P \quad (3)$$

$$\sum_{p=1}^{P} \beta_{p,m}(i) \leq 1 \quad i = 1..I, m = 1..M \quad (4)$$

Furthermore, we assume that all trains are identical. Meaning, that assigning any mission p to train m or train m' has the same cost. Therefore, we excluded the cost of the mission assignment of this work. Eq. (3) implies that for a certain period i a mission p could be not assigned to any train. Thus, this mission will be missed during period i which will consequently cause a penalty cost noted $C_{lost,p}$. It is assumed that all missions have the same priority, thus they have the same missing penalty $C_{lost,p} = C_{lost} \forall p \in \{1, ..., P\}$. We define the assignment cost over a period i, noted $C_O(i)$ as the sum of missed missions penalties (see Eq. (5)).

$$\begin{aligned} C_O(i) = C_{lost} \times \sum_{p=1}^{P} (1 - \sum_{m=1}^{M} \beta_{p,m}(i)) \\ i = 1..I \end{aligned} \quad (5)$$

2.3. *Maintenance Problem*

Let us denote $\sigma_{m,x}(i) \in \{0,1\}$ with $x \in \{1, ..., K+L\}$ the variable that describes if component x, whether it is a predictive or a preventive one, of train m is scheduled for maintenance during period i. $\sigma_{m,x}(i) = 1$ when the component is scheduled for maintenance and it is equal to zero otherwise. Consequently, we note $\omega_m(i) \in \{0,1\}$ the variable that describes if a given train m is scheduled for maintenance during period i. If train m is scheduled for maintenance during period i then $\omega_m(i) = 1$ otherwise $\omega_m(i) = 0$ (see Eq. (6)).

$$\omega_m(i) = min(1, \sum_{x=1}^{K+L} \sigma_{m,x}(i)) \quad i = 1..I \quad (6)$$

Let us also denote CR_x the replacement cost of component x for $x \in \{1, ..., K+L\}$. Any component x, whether it is predictive $x \in \{1, ..., K\}$ or preventive $x \in \{K, ..., K+L\}$, has a maintenance cost composed of two terms. The first term is the replacement cost. The second term is a penalty on the early maintenance of the component. This penalty has a different formula depends on the type of the component, i.e., for predictive components, the penalty is computed by multiplying a penalty coefficient LP_k by the difference between the current state of the component $H_{m,k}(i)$ and the components end of life threshold Δ_k, while for preventive components it is obtained by multiplying a penalty coefficient LP_l by the remaining miles to Θ_l. Eq. (7) and (8) present the maintenance cost of any predictive component k respectively any preventive component l of a given train m during a given period i with $m \in \mathcal{M}$ and $i \in \{1, ..., I\}$.

$$\begin{aligned} C_{m,k}(i) = \sigma_{m,k}(i) \times [CR_k \\ +(\Delta_k - H_{m,k}(i)) \times LP_k] \end{aligned} \quad (7)$$

$$\begin{aligned} C_{m,l}(i) = \sigma_{m,l}(i) \times [CR_l \\ +(\Theta_l - \theta_{m,l}(i)) \times LP_l] \end{aligned} \quad (8)$$

The objective behind using PHM technology is to maximize the usage of an asset while avoiding its failure. In other words, we aim at using the components while minimizing their wasted RUL. However, this can cause the system to fail due to the uncertainties of the RUL predictions. Therefore, we denote $f_m(i) \in \{0,1\}$ the variable that describes if train m failed during period i. If train m failed during period i (i.e., $f_m(i) = 1$), its failure causes disturbance of the timetable schedule (e.g., a delay for all scheduled missions on the same line, and efforts to move the failed rolling unit to a spare track, ...). Consequently, an extra cost is generated due to the failure and its corrective maintenance. This corrective maintenance cost noted C_{corr} is assumed to be much more expensive than the cost of missing a mission (i.e., $C_{corr} >> C_{lost}$).

Let us denote $C_M(i,m)$ the maintenance cost of a given train m during period i with $m \in \mathcal{M}$ and $i \in \{1,...,I\}$ (see Eq. (9)).

$$C_M(i,m) = \sum_{x=1}^{K} C_{m,k} + \sum_{x=K}^{K+L} C_{m,l} + f_m(i) \times C_{corr} \tag{9}$$

Furthermore, maintenance resources are assumed to be limited. In other words, the maintenance workshop can only support a maximum number of trains per period (noted ML_T) due to the limited number of tracks and the maintenance workshop due to the available workforce can only maintain a limited number of components per period (noted ML_C) (see Eq. (10) and (11)).

$$\sum_{m=1}^{M} \omega_m(i) \leq ML_T \quad i = 1..I \tag{10}$$

$$\sum_{m=1}^{M} \sum_{x=1}^{K+L} \sigma_{m,x}(i) \leq ML_C \quad i = 1..I \tag{11}$$

2.4. *The Joint Problem*

The objective of the joint problem is to find a suitable match between trains and missions while minimizing the total cost including maintenance cost and missing task cost over the duration of a simulation horizon noted SH. This simulation horizon is covered by N steps of decision-making over the rolling horizon DH. The number of steps, noted N, is defined in a way that verifies $SH = N \times I \times \Delta T$.

The minimization of the cost over the simulation horizon can be approximated by minimizing the cost of each of the N steps over the decision horizon. Thus the objective function of this problem can be written as in Eq. (12).

$$min \sum_{i=1}^{I} [C_O(i) + \sum_{m=1}^{M} C_M(i,m)] \tag{12}$$

Moreover, any train $m \in \mathcal{M}$, during any period i, can either be in maintenance ($\omega_m(i) = 1$), assigned to a task p ($\beta_{p,m}(i) = 1$), or at rest (i.e., no mission is assigned to it). Let us denote $\pi_m(i) \in \{0,1\}$ capture if rail vehicle m is at rest during period i (i.e., $\pi_m(i) = 1$ if m is neither in maintenance nor in operation). Therefore, the state of any train $m \in \mathcal{M}$ during a period i can be limited with constraint (see Eq. (13)).

$$\pi_m(i) + \omega_m(i) + \sum_{p=1}^{P} \beta_{p,m}(i) = 1 \qquad i = 1..I \tag{13}$$

If a solution of this problem proposes a joint schedule that satisfies all constraints defined in Eq. (4), (3), (13), (10), and (11), it is considered as a valid solution. Valid solution can be applied to the system but with a high risk of failure to the railway vehicle during their operations. Moreover, if this solution, also, satisfies Eq. (1) and (2), it is feasible in a way that the failure risk is almost eliminated.

3. Genetic Algorithm

In optimization problems, the aim is to find the best of all feasible solutions in the solution space. Each point in the search space represents one possible solution. Every possible solution is characterized by its fitness (or cost) for the problem. Genetic algorithm (GA) is a well used, mature artificial intelligent method based on heuristic rules to produce improved approximations of the objective function over a predefined number of iterations. Even though GA does not guarantee the global optimum solution, it is a commonly used method in cases of combinatorial, high instances or non-linear optimization problems. The objective of this paper is not to describe universally the proposed GA. Then, readers can refer to Davis (1991) for more details about GA. The overall GA is described in Algorithm 1. One should note that parents selection in case of crossover is done according to the roulette wheel method.

4. Results

In this section, first, a case study is presented to show the importance of studying the duration of the decision horizon. The obtained results are explained. Then, the influence of problem size (number of trains, components, and the components' characteristics) is investigated. Finally, the effects of train configuration are explored.

4.1. *Case Study*

The use of the proposed genetic algorithm is illustrated on a numerical example in which the algorithm should optimize maintenance and operational scheduling for a set of $M = 18$ trains. Periods, in this application, are defined as days. During each period (day) i, there are $P = 15$ missions to assign. These missions are divided into three types according to their respective severity presented in Table 1. Each Train m is composed of $K = 13$ predictive components and $L = 4$ preventive components. Trains are configured as

Algorithm 1 GA for Train Task Assignment and Maintenance Planning

Create Initial_Generation
Input_Generation ← Initial_Generation
while $generation < Generation\_Limit$ **do**
  Evaluate all individuals of the Input_Generation
  Sort Input_Generation
  Select $X_{Surv}\%$ of the Input_Generation
  for $Individual \in Input\_Generation$ **do**
    Generate randomly a and $b \in [0, 1[$
    if $a < Mutation\_Probability$ **then**
      Do Mutation
    end if
    if $b < Crossover\_Probability$ **then**
      Do Order Crossover (OX)
    end if
  end for
  Evaluate the Mutation_Results
  Sort Mutation_Results
  Select $X_{Mut}\%$ of the Mutation_Results
  Evaluate the Crossover_Results
  Sort Crossover_Results
  Select $X_{Cros}\%$ of the Crossover_Results
  Input_Generation ← Output_Generation
  generation++
end while

presented in Table 6. Details about the components types and characteristics can be found in Tables 3 and 4 for predictive and preventive components. For this configuration, the maximum number of components to maintain per period is set to 4 ($ML_C = 4$) and the maximum number of trains to maintain per period is set to 2 ($ML_T = 2$). All costs are expressed in terms of u.m. (i.e., unit of currency).

The objective is to search for the best DH value or range of values that minimizes the overall cost as described in the objective function (Eq. (12)). Considering a simulation horizon of 300 days, the possible DH values are obtained in a way that $SH = N \times DH$ with $N \in \mathbb{N}$ and $N > 1$. The numerical values of other variables are presented in Table 2.

The GA is executed 10 times to include different initial conditions of the components and to add some uncertainties presented by the random evolution of the component's health state. The obtained results are then used to produce the box plot presented in Figure 1. One can notice, in this figure, that the DH influences the total cost of the joint schedule. The minimal value of the total cost is obtained for a decision horizon duration around 10-days to 25-days. For these same values of the decision horizon, the variation of the total cost is minimal from one execution to another. This proves that there is a need to search for the DH value that optimizes the objective function. Figure 2 presents the mean number of missed missions for this numerical example. One can note that for a DH between 10 and 25 days the missed missions are minimized.

Table 1. Characteristics of the Missions

Type	Severity (s_p)	Length (mi)
1	0.85	110
2	1	130
3	1.3	170

Table 2. The Values of the Numeric Application

Name	Significance	Value
SH	Simulation Horizon	300 Days
LP	Penalty on a lost mile	2 u.m
C_{lost}	Cost of Missing a Mission	10 ku.m
C_{corr}	Cost of Mission Failure	100 ku.m

Table 3. Predictive Components Characteristics

Type	α_k	μ_k	Δ_k	CR_k
T_A	0,00077	0.00178	0.95	150
T_B	0,00087	0.002	0.95	100
T'_A	0,00346	0.002	0.95	100
T'_B	0,0031	0.00178	0.95	150
T_C	0,01246	0.00166	0.95	75
T_D	0,00798	0.00208	0.95	100
T'_D	0,01663	0.00208	0.95	100

Table 4. Rolling Stocks Preventive Components Characteristics

Component Type	Θ_l(mi)	CR_l
T_E	187 250	100
T_F	155 250	100
T_G	63 000	100
T'_G	31 250	100
T_H	15 625	100
T'_H	7 500	100

4.2. *Different Problem Sizes*

In this section, the problem sizes are varied (number of trains M and the number of missions P) to see the effects of the problem characteristics over the decision horizon duration. Proportions between the number of trains, the number of missions per period, and the maintenance constraints

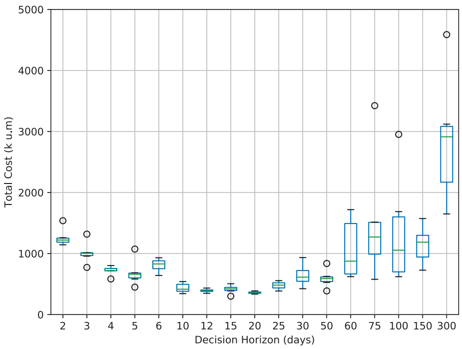

Fig. 1. Box plot of total cost variation for the GA.

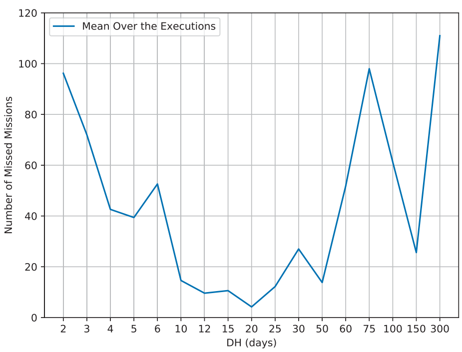

Fig. 2. Evolution of the mean number of missed missions.

are kept the same. These variables and the obtained mean total cost over the multiple executions for each test case are grouped in Table 8. These results are shown in Figure 3. One can notice that the mean cost over the executions of each of the test cases is minimal for the same range of decision horizon duration. Therefore, one can conclude that the decision horizon duration influences the total cost over a simulation horizon and that when using a genetic algorithm, the number of trains and missions (i.e., the size of the problem) does not influence the optimal duration of the decision horizon.

Table 6. Components Configuration

K=13		L=4	
Type	Number	Type	Number
T'_A	1	T'_G	1
T'_B	2		
T_C	2	T_H	3
T_D	8		

Table 8. Configurations of Different Problem Sizes

M	18	25	45	90
P	15	21	38	75
ML_T	2	3	5	10
ML_C	4	6	10	20

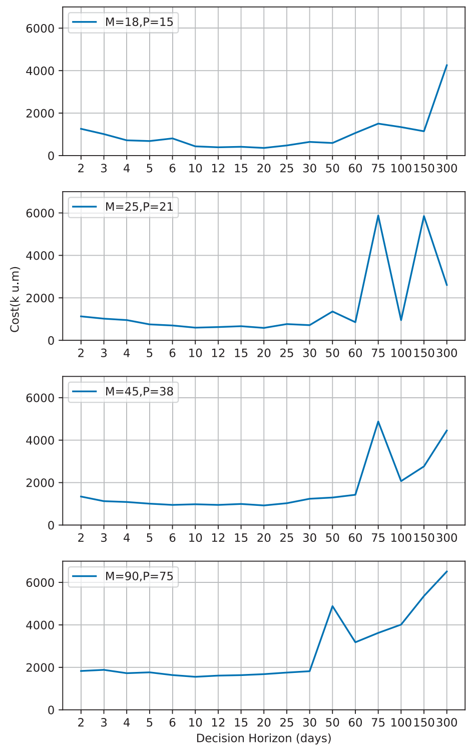

Fig. 3. Mean Total Cost Variation Under Different Problem Sizes

4.3. *Different Trains Configuration*

In this section, the configuration of the train is altered in the number of components per type and the characteristics of the components. The objective of this study is to see if the dynamics of the degradation of the components influence the duration of the decision horizon. In this section, all trains are composed of $K = 13$ predictive components and $L = 4$ preventive components. The dynamics of the component's degradation (mean traveled miles before the component's end of life) are varied through the variation of either the gamma process parameters (α_k, μ_k) for predictive components or the MTBF for preventive components. Three categories of components are considered: (i) rapidly deteriorating (T_C, T_D, T'_D, T_H, and T'_H), (ii) normally deteriorating(T'_A,

T'_B, T_G, and T'_G), and (iii) slowly deteriorating (T_A, T_B, T_E, and T_F). One can refer to Tables 3 and 4 for more information about these components characteristics.

For this purpose, four configurations of trains are considered:

- $Config\_1$: each train is composed of only rapidly deteriorating components (T_C, T_D, T'_D, T_H, and T'_H).
- $Config\_2$: this is the configuration used in the numeric example. In this case, each train is composed of a variety of normally deteriorating components and rapidly deteriorating components.
- $Config\_3$: each train is composed of only slowly deteriorating components (T_A, T_B, T_E, and T_F).
- $Config\_4$: trains in this configuration are composed of components that have two times more slower degradation than those of $Config\_3$.

Figure 4 presents the mean total cost over different executions for each train configuration. One can note that the degradation dynamics of the components has a big influence on the total cost. For very slow degradation components, the cost is in the order of $75 ku.m.$. While for rapidly deteriorating trains, the cost is in the order of $10\ 000 ku.m.$. This is explained that rapidly deteriorating components will be more frequently changed over the decision horizon compared to components that deteriorate slowly. Moreover, rapid deterioration of components will cause the failure of several trains in action and the avoidance of failure will cause more frequent maintenance activities. Since the maintenance resources are limited, this causes the system to have a lot of trains unavailable to achieve missions and waiting for maintenance. One can also notice that for medium and slow degradation dynamics ($Config_2$ - $Config_4$) the decision horizon value is almost in the same interval ($10-25$days). However, this duration is different in the case of rapid degradation in which the more higher the decision horizon gets the lower the total cost is. This is explained by the fact that the genetic algorithm finds a way to schedule the maintenance of the predictive components in a systematic cyclic way. In this case, the cost generated by missing several missions is more expensive than the penalty of early maintenance. Thus, allowing the train to be maintained at the first opportunity regardless of the penalty that can be caused by this date of maintenance to guarantee its availability for the next period.

5. Conclusion

In this paper, we have investigated the effects of modifying the duration of the decision horizon

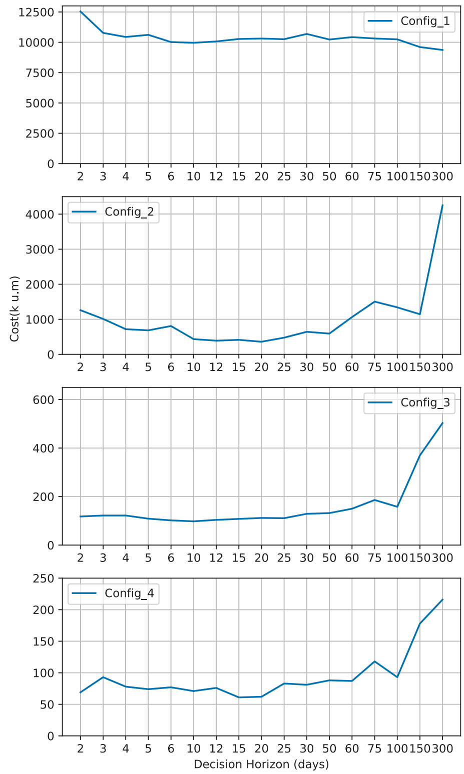

Fig. 4. Mean Total Cost Variation Under Different Trains Configurations

on the solution total cost. The results of this test show that for a planning horizon of duration between 10 and 25 days the total cost is minimized. These decision horizons are reasonable in terms of operational planning for trains that could be done over 1 to 2 weeks. These results are obtained in a numerical case study. Afterward, we varied the problem size through the number of trains, the number of missions per period and the maintenance constraints to capture the effects of these parameters on the solution and the decision horizon. We found that the decision horizon is optimal for the same duration independently from the problem size. Finally, we captured the effects of components' degradation dynamics on the results and the decision horizon. On the one hand, results show that the slower the degradation of components evolve the lower the total cost gets which is explained by the lower maintenance interventions and better trains availability. On the other hand, for rapid degradation dynamics, the optimal total cost is obtained for long decision horizons, while for other cases the decision horizon is optimal for the same previously obtained values.

Further investigations would be continued concerning these results. For instance, the effects of the slow deteriorating components could be more explored to find from which value of degradation speed the decision horizon duration is shifted. Moreover, one can explore the effects of other problem parameters such as the proportion of trains and missions, or the different cost parameters on the total cost and the optimal decision horizon.Finally, we assumed that all the components of the train are critical, in a way if one component fails the train fails. However, in real-life applications, some train components are not critical to the train operation. The proposed problem could be fine-tuned to model such a constraint to become more realistic.

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