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► To cite this version:

Ferhat Tamssaouet, Khanh Nguyen, Kamal Medjaher. System Remaining Useful Life Maximization through Mission Profile Optimization. Asia-pacific conference of the prognostics and health management society, PHM Society, Jul 2019, Pékin, China. hal-02800796

HAL Id: hal-02800796

<https://hal.science/hal-02800796>

Submitted on 5 Jun 2020

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System Remaining Useful Life Maximization through Mission Profile Optimization

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ABSTRACT

In the last two decades, prediction of the remaining useful life (RUL) of critical components and more recently of systems (SRUL) received an increasing attention. Indeed, this prediction allows scheduling predictive maintenance actions in order to avoid damages caused by unexpected failures. A major part of the studies related to failure prognostics reported in the literature considers the mission profile as a static parameter when evaluating RUL/SRUL. However in practice, operating parameters can be adjusted according to the system health state for extending the SRUL while satisfying the performance requirements. Therefore, this paper addresses the issue of adjusting the mission profile of a multicomponent system in order to maximize its SRUL. To do this, a variant of the inoperability input-output model is used to represent the system degradation and take into account the interactions between its components. Then, the mission profile parameters (load levels and durations) are optimized using a genetic algorithm-based method to maximize the SRUL. The proposed method is finally applied to a mechatronic system to demonstrate its effectiveness.

1. INTRODUCTION

Prognostics and Health Management (PHM) systems aims to monitor the degradation status of a component or a system. More specifically, the purpose of prognostics is to estimate the remaining useful life (RUL) of a given system in order to take adequate decisions to keep it under acceptable performances. For that reason, the topic of prognostics has become a full-blown research framework in the last two decades, with a profusion of papers covering numerous of scientific problems and various fields of applications (Atamuradov, Medjaher, Dersin, Lamoureux, & Zerhouni, 2017).

Despite the notable progress and convincing results, generally, prognostics studies were approached from a component-level view, assuming independent degradation processes in components. Nevertheless, engineering systems may present complex interactions among components. Indeed, the combination of small degradation levels observed in different components may cause a system failure event, depending on the interactions among these components (Daigle, Bregon, & Roychoudhury, 2012). Hence, for complex engineering systems, it is necessary to study the concept of failure prognostics at system-level, by considering the mutual interactions between its elements, in order to enhance the effectiveness and the relevance of the post-prognostics decisions (Bougacha, Varnier, Zerhouni, & Hajri-Gabouj, 2018).

Considering Post-Prognostics issues, the works reported in literature focus on the maintenance decisions (Bougacha et al., 2018), and do not investigate the operational decisions such as the definition of the appropriate mission profile. In reality, the way in which a system is used significantly impacts the future evolution of its degradation (Goebel et al., 2017). Therefore, the optimization of the mission profile (MP) is an essential aspect that should be carefully studied to extend the system life time.

In order to address the practical requirements and fill the literature gaps already mentioned, this paper develops two main original contributions: i) the proposition of a variant of the inoperability input-output model (IIM) to evaluate the system residual life time (SRUL), and ii) the optimization of the MP parameters to maximize the SRUL.

Regarding the first contribution, the IIM proposed in this work allows tackling the issues related to the system-level prognostics such as modelling the interactions between the system components and the mission profile effect. Furthermore, one of the challenges of the modelling issue, that is how to identify the appropriate parameters to capture the mutual interaction between the system components, is also addressed in this paper.

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As for the second contribution, a variant of the genetic algorithm (GA) is developed to optimize the MP parameters (load levels and durations) when handling multiple operational constraints.

The remainder of the paper is organized as follows. Section 2 briefly presents the proposed methodology while its main steps are described in Sections 3, 4 and 5. In detail, Section 3 presents the inoperability input-output model. Next, Section 5 describes the method of estimating the parameters of the IIM. The problem of the mission profile optimization is addressed in Section 5. Section 6 deals with a practical example and, finally, Section 7 concludes the paper and gives some future works.

2. PROBLEM STATEMENT AND PROPOSED METHODOLOGY

Let us consider a system whose components are subject to different intrinsic continuous degradation processes that evolve (from a healthy state to failure) in the absence of maintenance actions. In practice, a component fails when its degradation level exceeds a fixed failure threshold. In this paper, the intrinsic degradation process and the failure threshold of each component are assumed to be known. However, the interdependencies between the components are hidden and are also interesting subjects to be further investigated and estimated. Besides, the system works under different operational conditions. These operational conditions may be related to the number of cycles to be executed, the operating time or the performances to be achieved (load, speed, torque, etc.). Their impact on the system is assumed to be known thanks to previous practical experimental studies. Considering the system health state and the operational constraints it must meet, an important question raised here which is: how to plan its appropriate future usage (i.e. mission profile) to maximize its useful lifetime?

In order to address the above question, firstly, it is necessary to model the system degradation while taking into account the component interactions and the MP impact. In the paper (Tamssaouet, Nguyen, & Medjaher, 2018), the PHM-adapted-IIM is proven as a promising solution for this first task. Its parameters, that characterize the component interdependencies, are estimated using a generalized linear model (GLM). Secondly, the IIM with its identified parameters is used to evaluate the SRUL corresponding to every mission profile under which the system works. These SRUL values are used as evaluation criterion for identifying the best appropriate MP parameters that maximizes the system life time. This procedure is illustrated in Figure 1.

3. INOPERABILITY INPUT-OUTPUT MODEL

The inoperability input-output model (IIM) is an extension of the Input-Output model developed by Leontief Wass-

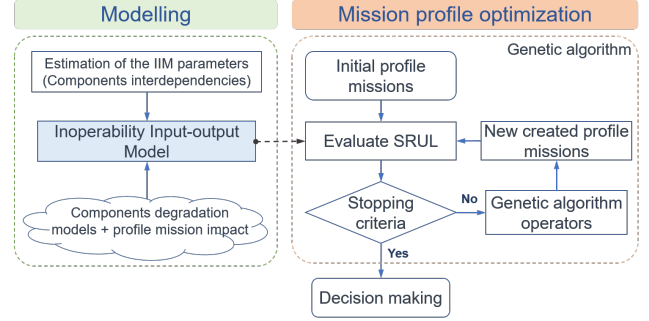


Figure 1. Methodology for optimizing the mission profile.

ily in 1936 (Leontief, 1936). The IIM and its variants are usually used to investigate the global effects of negative events on highly interdependent infrastructures or multi-sector economies (Santos & Haimes, 2004). This is achieved by using the concept of inoperability, which is defined as the inability of a system to perform its intended functions. In addition, the IIM capacity to take into account mutual interactions between numerous elements offers a promising perspective when applying this model in PHM domain.

The IIM adapted to prognostics was proposed in (Tamssaouet et al., 2018) as follows:

$$q(t) = K(t) \cdot [A \cdot q(t-1) + c(t)] \quad (1)$$

where:

- $q(t)$ is a vector representing the overall inoperability of the system's components at time t . Each component of this vector is a value between 0 and 1, where $q_i(t) = 0$ corresponds to a healthy component and $q_i(t) = 1$ to a faulty component.
- A is a matrix representing the interdependencies between the system's components. Each element a_{ij} of the matrix corresponds to the influence of the inoperability of a component j on the inoperability of a component i . The bigger a_{ij} is, the greater is the influence of j on i . The signification of a_{ij} values is presented in Table 1.
- $c(t)$ is a vector representing the internal inoperabilities of the system's components at time t , i.e. the intrinsic degradation of the components due to wear, corrosion or any other failure mechanism. The parameter $c_i(t)$ can be obtained by normalizing the health indicator of the component i to its failure threshold (Tamssaouet et al., 2018).
- $K(t)$ is a diagonal matrix representing the factors influencing the inoperabilities of the components at time t in relationship with the system mission profile. Each element $k_i(t)$ is specific to only one component i . The meaning of k_i values is presented in Table 2.

As one can notice in (1), the degradation of a component i , characterized by an inoperability $q_i(t)$, depends on its inher-

ent natural degradation mechanisms expressed by $c_i(t)$ and the degradation induced by the interactions with other components through the term $A.q(t)$. This makes it possible to estimate the health state of a system more accurately.

Table 1. Degradation influence between multiple components.

case	Description
$a_{ij} = 0$ and $a_{ji} = 0$	Component j and i are independently subject to gradual degradation.
$a_{ij} > 0$ and $a_{ji} = 0$	Component j influences unilaterally the degradation behavior of component i .
$a_{ij} > 0$ and $a_{ji} > 0$	Components j and i influence each other.

Table 2. Meaning of the influence factor k_i .

	Inoperability	Meaning
$k_i = 0$	q_i is stationary	The component does not degrade.
$k_i > 0$	q_i varies over time	$k_i = 1$: normal case when a system operates in a normal conditions with a normal work load. $0 < k_i < 1$: when a system operates in a favorable environment or with a low work load, its degradation process is slower than the normal case. $k_i > 1$: accelerated degradation due to a hostile environment or a high work load.

4. IIM PARAMETERS ESTIMATION

One of the principal barriers when deploying a mathematical model in practice is to identify its parameters corresponding to the case study. For the proposed IIM, the component intrinsic degradation models $c(t)$ and the MP impact K on the system are assumed to be known in advance. This can be achieved by the investigation of the component failure mechanisms, the system physical characteristics and through run-to-failure tests. Therefore, identification of the component interdependencies A can be considered as the most challenging task. This section aims to deal with this task.

Firstly, the run-to-failure experiments are performed under nominal operation conditions to obtain the overall inoperabilities of the systems components $q(t)$. Note that the nominal operation conditions are defined as the normal case when the system operates with a normal work load. In this case, K is an

identity matrix $n \times n$, where n is the number of components. Secondly, assuming that the component intrinsic degradation models $c(t)$ are known, the interdependence matrix A is estimated based on $q(t)$ and $c(t)$.

In detail, from the equation (3), under the nominal operating conditions, the degradations that are due to interactions between the components are enclosed in the term $A.q(t - 1)$ and given by:

$$Aq(t - 1) = q(t) - c(t) \quad (2)$$

where $q(t)$ and $q(t - 1)$ are the component inoperability values obtained through the run-to-failure experiments while $c(t)$ is the theoretical intrinsic inoperability.

More specifically, $A.q(t - 1)$ is a linear combination of unknown parameters A and the measured inoperability values $q(t)$. In the literature, there exists numerous methods to estimate A . As the main contribution of this paper is to optimize the mission profile for maximizing SRUL, we do not focus on the development of the estimation method for A . Therefore, we propose to use the generalized linear models (GLM), one of the most common and popular method for linear regression. This method allows overcoming the drawback of the ordinary linear regression that is based on the assumption of the normal distribution for the response variable.

In GLM, the variance of the outcome, that is expressed in this paper as the difference between the overall and the intrinsic inoperability $q(t) - c(t)$, is assumed to follow a distribution of exponential family. Then, the expected value of $q(t) - c(t)$ can be expressed as:

$$E(q(t) - c(t)) = g^{-1}(A.q(t - 1)) \quad (3)$$

where $g(\cdot)$ is the link function.

Using the GLM, the unknown parameters of the matrix A are estimated with maximum likelihood.

5. MISSION PROFILE OPTIMIZATION

In literature, several studies have already been carried out on the optimization of maintenance activities for prognostics but not on the optimization of the operational decisions to postpone the system degradation. (Bougacha et al., 2018) proposed a classification of operational decisions into three categories:

- **Mission profile:** it consists in defining the good fitting between the tasks that should be realized and the system degradation levels.
- **Automatic control:** if the system is controllable, one can monitor and modify the control parameters to adapt the system usage.
- **Logistics:** it consists in determining the right amount of

row materials and/or spare parts according to its capacity to produce or its need to be maintained.

In this paper, we will focus on post-prognostics decisions regarding the mission profile. Indeed, a mission profile can accelerate or decelerate the degradation of system components. Therefore, it is necessary to identify the most appropriate mission profile that maximizes the SRUL while respecting the operational constraints.

As a mission profile is characterized by numerous parameters (such as load levels and durations) and also specified by different operational constraints, the identification of the best MP can be expressed as the optimization of multiple variables when handling various problem constraints. This optimization issue can be solved using different techniques like exact methods (such as linear programming, branch and bound procedure) or heuristic approaches (such as evolutionary algorithms). Among heuristic approaches, the genetic algorithm (GA), one of evolutionary algorithms, is a mature method utilizing heuristic rules to produce improved approximations of the objective function over a number of iterations. Even though GA does not guarantee the global optimum solution, it is a commonly used method giving one of the best results (Pandey, Chaudhary, & Mehrotra, 2014). Possible solutions are evaluated with the fitness function, and the best solutions are utilized to produce other possible solutions, while the bad solutions are eliminated through natural selection. The process of producing new solutions based on best solutions on hand is called crossover & mutation.

Thanks to the evolutionary mechanism, the GA allows handling numerous optimization variables, investigating a wide range of solutions and supporting heterogeneous constraints (equality and non-equality). Therefore, it offers an adequate solution for the MP optimization problem investigated in this paper. In detail, a variant of GA to adapt the MP optimization problem is described in Algorithm 1.

Note that corresponding to every MP, the SRUL is evaluated based on the IIM with its estimated parameters. This SRUL value is used as the evaluation criterion for the possible solutions. The details of the SRUL evaluation according to the system architecture can be found in (Tamssaouet et al., 2018).

In addition, for MP optimization, the proposed GA must well handle different constraints. As basic GA is not specifically dedicated to solve constrained optimization problem, researchers have developed several methods to fill this gap. Among these methods, one can cite: the penalty function method, the Lagrange multiplier method, and the complex search method (Deb, 2000). In this paper, a death penalty method is used because of its simple implementation. Indeed, this method consists in assigning a very high cost when one of the solutions does not satisfy the constraints, and thus, in next generation, these solutions are effectively eliminated through natural selection. However, in the case of a strict constraint,

Algorithm 1. PM optimization based on a variant of Genetic Algorithm

1. **INITIALIZATION**: randomly generate an initial population of N PM.
Verify if an individual PM satisfies the constraints. If not, regenerate it.
2. **while** generation number $< N_G$ **do**
 - **EVALUATION** : evaluate the population.
Calculating SRUL corresponding to every PM by the IIM.
Handling constraints: penalize individuals which do not satisfy the constraints by adding a cost.
 - **MATING SELECTION**: select parents to reproduce offsprings.
 - **CROSSOVER**: apply crossover operator to the mating pool to generate offsprings.
Offsprings are added to parents to recreate the population.
 - **MUTATION**: mutate the offsprings at different positions by genetic mutation operator.
Some of the parents are not affected by mutation.
Generate some new individuals which satisfy constraints and add them to the population.
3. **end while**
4. **SOLUTION SELECTION**: select the PM having highest SRUL in the last generation.

natural selection makes the feasible space very small compared to the entire search space. To address this problem, the GA operations should be modified in order to create and mutate chromosomes with some local search optimization that fulfill the equality constraints. Finally, to maintain a diversity inside a population and avoid a premature convergence, a part of the population is created and added to the population resulting from mutation and crossover (Pandey et al., 2014).

6. CASE STUDY

In this section, the performance of the proposed method is highlighted through a case study. Firstly, the mechatronic system, which emulates the operation of a subway, will be presented in Subsection 6.1. Secondly, the effect of the interactions between its component is estimated in Subsection 6.2. Finally, in Subsection 6.3, the mission profile is optimized in order to maximize the system remaining useful life.

6.1. System description

A subway, also known as underground, tube or metro, is a type of high capacity public transport generally found in urban areas. Unlike buses or trams, subway systems are electric railways that operate on exclusive right-of-way. The motion power is provided by a separate locomotive where the electric motor is situated.

In this paper, because of the complexity and lack of data, the subway is simplified to a mechatronic system. This latter was

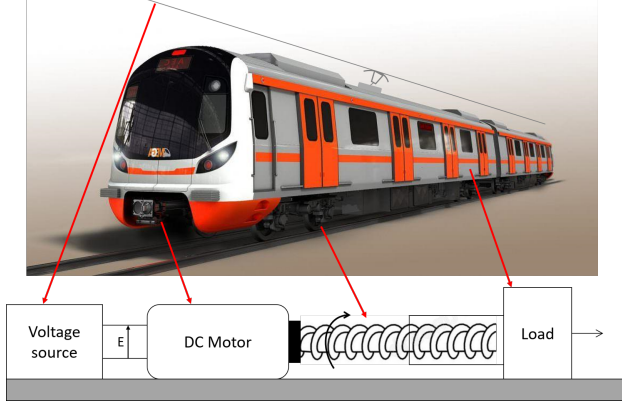


Figure 2. Scheme of the studied system.

proposed by (Medjaher & Zerhouni, 2013) and its main purpose is to position horizontally a load which is situated at the right side of Figure 2. The system is composed of a voltage source, which can be a battery, a DC motor providing a rotational movement and a screw transforming this latter movement to a translational one. The mechatronic system illustrated in Figure 2 can be likened to a subway as follows. The battery delivering a constant amount of energy can be considered, in the case of a subway, as an overhead line or a third rail. The DC motor represents the electrical traction motor. The screw is considered as the transmission chain. Finally, the load can be assimilated to the subway payload.

In this application, three components are considered: the stator, the rotor and the screw (respectively, component 1, 2 and 3). These components are subject to the following degradation phenomena: 1) a drift in the DC motor's winding (stator), 2) a deterioration of the DC motor's permanent magnet (rotor), and 3) a bending of the rotating shaft. The causes and the models of these degradations are explained below.

- For the electrical resistance (related to the stator), the degradations can be caused by the variation of the resistivity of the winding due to temperature changes inside the DC motor. The performance in this case can be monitored by measuring (or estimating) the electrical flux Φ of the inductance, which is linked to the resistivity of the winding, as expressed by the following equation:

$$\Phi(t) = \frac{R(t) \cdot U}{L} \quad (4)$$

where $R(t)$ stands for the winding resistance of the DC motor, L is the inductance and U is the voltage delivered by the battery.

Note that as the inductance of the winding is constant, as well as the voltage delivered by the battery, the electrical flux of the winding varies due to the variation of the resistivity. Therefore, the internal stator resistance is

assumed to vary according to the following model:

$$R(t) = R_0 \cdot (1 + \alpha \cdot t) \quad (5)$$

- The magnetic degradation in the mechanical part (rotor) concerns the diminution of the magnetic field generated by the permanent magnet of the DC motor. The performance of this mechanical part can be determined by the variation of the electromagnetic torque T_{em} . By considering a series excitation of the motor and by neglecting the electromagnetic losses, this torque can be expressed by the following equation:

$$T_{em}(t) = B_c(t) \cdot \Phi(t) \cdot I(t) = B_c(t) \cdot \frac{U^2}{L} \quad (6)$$

where $B_c(t)$ is a parameter which depends on the structure of the motor and $I(t)$ is the electrical current crossing the winding, which is equal to $\frac{U}{R(t)}$. Since the input voltage U and the inductance L are constant, the variation of the electromagnetic torque is due to the degradation of the internal structure of the motor expressed by the variation of $B_c(t)$ over time. This latter parameter can be represented by an exponential degradation model:

$$B_c(t) = B_{c0} \cdot e^{\beta \cdot t} \quad (7)$$

- Finally, the bending of the shaft can be induced by overloading the DC motor and by external perturbations which decrease the stiffness of the linking part between the screw and the mass. The inoperability of this linking part is determined by its stiffness B_s as follows:

$$B_s(t) = B_{s0} \cdot e^{\gamma \cdot t} \quad (8)$$

6.2. IIM parameters estimation

The component intrinsic degradation models given in the previous section do not take into account the interactions between the components. Considering the reference mission profile, under which the system works in normal conditions,

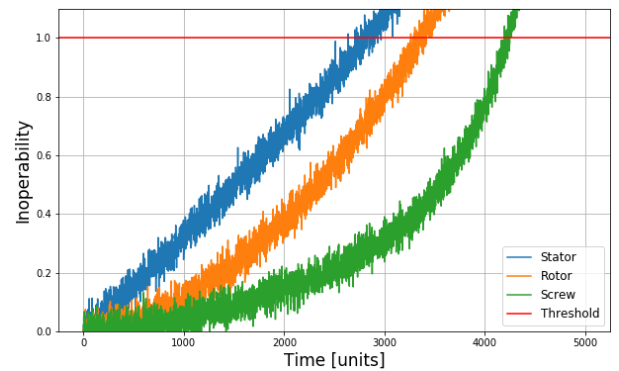


Figure 3. Component degradations following the reference mission profile.

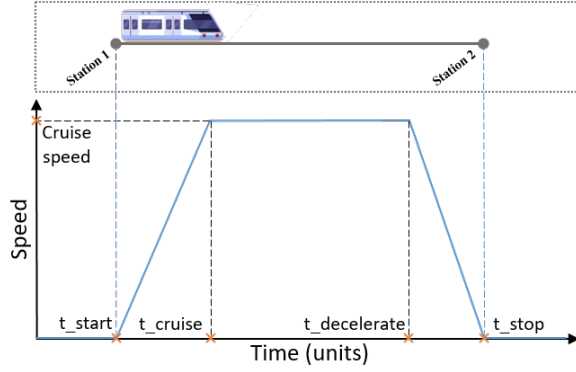


Figure 4. mission profile pattern of a subway.

the reference matrix K_{ref} is defined as an identity matrix as follows:

$$K_{ref} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Then, performing the run-to-failure experiments under the normal operating conditions, the overall inoperability of the system components can be obtained. However, in this paper because of the lack of real data, we propose to use the simulation data that are generated by the IIM with the following matrix A :

$$A = \begin{bmatrix} 0 & 0.2 & 0.1 \\ 0.1 & 0 & 0.3 \\ 0.06 & 0.26 & 0 \end{bmatrix}$$

Using the simulated data, shown in Figure 3, we try to reestimate the matrix A and then compare its estimated values with the theoretical ones. In detail, based on the difference between the overall and intrinsic inoperability of the system components, the interactions between the components are estimated by using the GLM leading to the following matrix:

$$A = \begin{bmatrix} 0 & 0.21 & 0.09 \\ 0.11 & 0 & 0.31 \\ 0.064 & 0.28 & 0 \end{bmatrix}$$

One can notice that the estimated values are close to the theoretical ones.

6.3. Mission profile optimization

Under different operating conditions (mission profiles), the degradation of subways, and generally of all systems, can be accelerated or decelerated. In the case of subways, it can be assumed that the components degradations are proportionally affected by speed. This is rather realistic, because one can imagine that, depending on the quality of the rails, an increase in the subway's speed will generate more vibrations and thus increasing the components degradations.

The mission profile of a subway, represented by its speed pro-

file, is shown in Figure 4. By assuming a linear relationship between the speed and the influence factor, the values of K are a function of speed. Besides, an example of a mission profile of the subway is described hereafter:

- From 0 to t_{start} time units (ut), the subway is at a standstill and therefore the degradation is not influenced by external parameters. However, as the engine continues to run in the station, the system continues to degrade naturally and therefore $k_i = 1$.
- From t_{start} to t_{cruise} , the subway's speed increases. Within this period, the degradation increases proportionally to speed.
- From t_{cruise} to $t_{decelerate}$, the subway reaches its maximum speed during a mission period. A maximum speed of 50 km/ut corresponds to $k_i = 2$, i.e. the component degradations are twice faster than when the subway is at a standstill.
- The system decelerates as it approaches a station at $t_{decelerate}$ and reaches a new station at t_{stop} .

By considering that the effect of velocity is the same on the subway's components and by assuming that the distance between the stations is constant, the optimization objective is to find the set of the mission profile parameters (t_{start} , t_{cruise} , $t_{decelerate}$, t_{stop} and v_{cruise}) that maximizes the SRUL while respecting these self-evident operating constraints:

- Distance between the stations is constant (1200 m).
- Cruise speed is less than 50 km/h .
- The subway's journey time between two stations is limited to 120 time units.

Using the proposed GA presented in Section 5, the MP parameters, that are presented in the form of chromosomes of five genes: cruise speed, t_{start} , t_{cruise} , $t_{decelerate}$ and t_{stop} , are optimized. The GA configuration is summarized in Table 3.

Table 3. Genetic algorithm parameters and rules.

Number of individuals	200
Number of parents	50
Selection type	Best fitness
Crossing type	One point
Mutation type	Uniform random selection with multiple mutations
Termination criteria	Generation: 200

Figure 5 shows the extension of the SRUL of the PM population through different generations. One can easily notice that the proposed algorithm converges after 175 generations. In fact, from this generation, the SRUL corresponding to different PM in the population are almost same, i.e. different solutions have the same objective function value. Some of the best

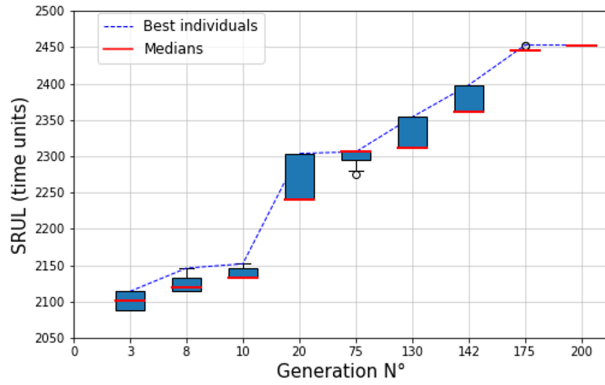


Figure 5. Population evolution through generations.

solutions obtained by the GA after 200 generations are shown in Table 4. They provide the best objective function value (i.e. the largest SRUL) that is equal to 2453 *ut*. All those solutions satisfy the operational constraints, i.e., the subway will make its journeys within the time limits and without exceeding its maximum speed, while reducing the degradations affecting its components. The existence of multiple solutions, that maximize the system life time, offers the ability to flexibly change the PM for adapting to real situations. Indeed, the planned mission profile may be modified along the way due to problems. For example, blocking the doors of the subway when they are closing induces a delay in the subway start. In this case, rather than choosing solution 1 in Table 4 (with start time at 10 *ut*), one can opt for solution 2 (with start time at 16 *ut*), and thus adapt the mission profile to the operational conditions while maximizing its lifespan.

Table 4. Solutions for the mission profile parameters optimization.

	Cruise speed	t_{start}	t_{cruise}	$t_{decelerate}$	t_{stop}
1	12.7	10.9	22.6	104.9	118.2
2	12.7	16.4	26.4	114	118.9
3	15.6	13.5	25.7	72.7	108.9

In Figure 6, the mission profiles obtained in the first and last generation of genetic algorithm are presented. One can no-

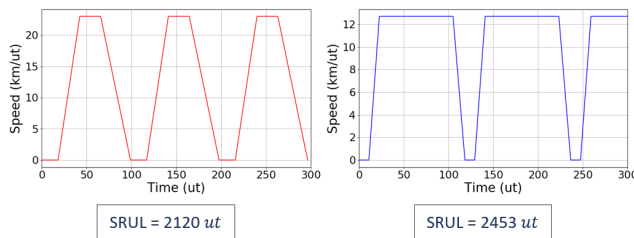


Figure 6. Profile missions before and after optimization.

tice that with the optimized mission profile (Generation 200), the subway SRUL is extended more than 15% compared to that one of the best solution obtained in the first generation. Indeed, for the non-optimized mission profile, the subway undergoes more setpoint changes, and therefore, degrades more quickly and requires more frequent inspection and maintenance. This is true for a very wide range of systems subject to highly varying operating conditions such as wind turbines (Zaher, McArthur, Infield, & Patel, 2009) and pneumatic actuators.

7. CONCLUSION

In this paper, a methodology for optimizing the mission profile and maximizing system residual life time is proposed. To that end, a new modelling approach was proposed for multi-component system prognostics, namely, the inoperability input-output model. This approach allows taking into account the mutual interactions between the system components and also the operating conditions impact on them. Furthermore, the assumption about the given component interdependencies, that is one of the main barriers when deploying the proposed model in practice, was released. In detail, the GLM is used to estimate these parameters based on the difference between the overall and intrinsic inoperabilities of the system components. The results showed that the estimated values are close to the theoretical ones. Then, the proposed IIM with its estimated parameters is used to evaluate the SRUL that is the objective function for optimizing the MP. An effective optimization approach based on genetic algorithm was developed to find the best appropriate mission profiles that satisfy different operating conditions.

As future work, we plan to apply the proposed methodology on a industrial application with real in-field data. The assumptions about the availability of the intrinsic degradation models and the relationship between the mission profile and the system degradations can be seen as a limitation of our methodology. These assumptions should be released in the future work by developing a more flexible and more effective estimation method that allows estimating different model parameters at the same time.

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