Proposition of a Generic Decision Framework for Prescriptive Maintenance

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Paper 01

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Abstract: The digitalization of the economy in the past decades has made data availability grow and become more important. From the maintenance point of view, clients are more demanding, wanting systems that will not have breakdowns while reducing exploitation costs. This challenging scenario has pushed companies in the direction of more intelligent maintenance solutions that involve choosing the best course of action in terms of system availability. Nowadays, these solutions are usually called prescriptive maintenance. This term is vaguely defined and its use is often unjustified. In this article we will discuss what really characterizes prescriptive maintenance, review some of the work published with this term and propose a generic framework to guide the development of such solutions. In the end, we will illustrate the use of the generic framework in a practical case.

1 Introduction

In the competitive and technological scenario of contemporaneous industry, the importance of efficient maintenance solutions has become a key factor of success. [1] has estimated that, in industrial firms, maintenance cost varies from 15% to 40% and even in simpler systems, such as industrial vehicles, this source of expense is far from neglectable. The National Road Committee (CNR) of France estimated that the maintenance costs of a long-haul truck accounted on average for 8.2% of the total expenses. For trucks in particular, not only this cost cannot be overseen but the importance of effective maintenance is crucial in the transportation business. Internal reports conducted with Volvo trucks clients suggest that when a truck undergoes a breakdown, all the annual revenue generated by this vehicle is compromised.

Since maintenance is so important in all sort of different domains, it is only natural that it has been the center of interest of several researchers. In recent years, academic works on new maintenance solutions have been published and terms such as condition-based maintenance (CM) [2], predictive maintenance (PdM) [3] and more recently prescriptive maintenance (PsM) [4] have gained some popularity.

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One of the main issues of employing the term prescriptive maintenance is that there is no clear definition for it. The boundaries between predictive and prescriptive maintenance are not well defined, and we have to be careful when employing those terms to avoid confusion. A rigorous definition of prescriptive maintenance is important to guide and frame future work on the area and to develop the necessary tools to design and implement solutions that really achieve reliability maximization and cost minimization in industrial applications.

In this paper, after a discussion on the use of the term prescriptive maintenance, a modeling framework that highlights the differences between predictive and prescriptive maintenance will be presented. This framework will help to guide the development of generic decision-making algorithms for up-time maximization and avoid the unjustified use of jargon.
Therefore, this document is organized according to the following structure: Section 2 will highlight the vagueness of the definition of prescriptive maintenance, briefly reviewing some of the work published using this term. A generic framework of PsM will be detailed in section 3 - hopefully its use will avoid ambiguity and guide future work in the area. Finally, through section 4, a practical example of PsM applied to the automotive domain will be given.

2. Prescriptive maintenance

2.1 Prescriptive Maintenance in the Literature

In recent years, a few authors have employed the term prescriptive maintenance in their works [4-6]. It appears that, even if these works focus on discussing conceptually PsM, they do not always present a formal definition of the term, but base their definition on the broad idea of choosing the correct course of action for a system. This general understanding of PsM seems to be an extension of the concept of prescriptive analytics, which focus on prescribing the best decisions in order to take advantage of the predicted future utilizing large amounts of data [**7**].

Hence, one can think of prescriptive maintenance as the use of prescriptive analytics to maintenance. According to this definition, a PsM solution should use failure predictions or, data-driven degradation models, to quantitatively give the best course of action in terms of up-time maximization. Some of the works published on PsM do not fit this definition perfectly.

For example, the authors in [5] developed a prescriptive maintenance solution built on a threshold-based rule, meaning that an action will be taken on the system only when a quality indicator overpasses a threshold. The second issue is that PsM should quantitatively assesses what is the best action to take. To that end, it is crucial to have an objective measure of the impact of different actions. However, in [5], actions are chosen based on previous engineering knowledge, working as thumb rules.

The main problem when using this rudimentary notion of PsM as the simple application of prescriptive analytics to maintenance is that it does not help to distinguish between PsM, PdM and CM. For example, [4] uses the term prescriptive maintenance to provide a solution that chooses the best maintenance and inspection schedule for a system subjected to degradation. Similar problems were addressed by different authors before [8], without using the term prescriptive maintenance. In fact, a big part of research conducted on PdM could be classified as decision-making and therefore as an application of prescriptive analytics, which makes this notion insufficient to make the distinction between PdM and PsM .

2.2 Defining Prescriptive Maintenance

An attempt of differentiating PsM from PdM is given in [9]. According to the author, a crucial difference lies in the fact that PsM takes into account all the functionalities of the system, by extending the notion of maintenance to the one supported by the Prognostics and Health Management (PHM) community. Thus, the objective of PsM is to provide the best course of action to minimize the overall cost of systems exploitation. These actions may include use mode recommendations, tasks management, parameters reconfiguration, etc.

Many research works are increasingly interested in developing one or many of these actions in addition to maintenance scheduling. In [10] for example, the authors focused on finding the best moment to perform maintenance while managing spare parts. Another example is given in [11] where a dynamic method was developed to jointly schedule missions and maintenance operations while taking into account the system's deterioration, in order to minimize the maintenance costs.

It is worth noticing that most of the previous actions will have an impact on the system's usage and on the degradation process, which should in turn affect the choice of the next actions to be applied. Therefore, PsM should take this notion into account by following a closed-loop structure, meaning that algorithms should be robust, deal with uncertainty and assess the effect of the decisions chosen on the system to adapt them as often as required.

In the next section, a PsM framework that relies on the concept of closed-loop decision process will be proposed.

3 A generic framework for prescriptive maintenance

One key aspect of PsM is the notion of closed loop, as represented in Fig. 2. Due to the randomness of degradation processes, the outcome of previously chosen actions must always be monitored. As the system evolves through time, actions may be chosen considering previous unexpected behavior, as well as new inputs.

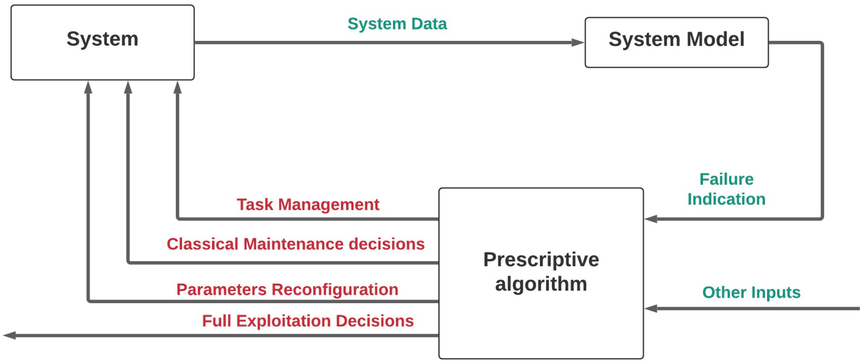

Fig. 2. Example of PsM algorithm

To arrive at such structure, which characterizes PsM, a generic framework is proposed. It is composed of three main steps: system modeling, action modeling and optimization.

3.1 System modeling

To quantitatively decide between different actions, it is necessary to understand how the system behaves and how it fails. Actions may affect the remaining useful life (RUL) of a system and quantifying this effect is crucial for choosing how to exploit it. Since the PsM solution may prescribe changes in usage conditions and environment, it is crucial to model the degradation process of the system in a way that all different operational conditions are considered. To this aim, data availability is not enough. It is also important to ensure that the variables which have the biggest impact on the degradation process were identified and monitored, and that the degradation model took them into account.

In the following sections, three classes of techniques, which are the most common in the literature for modeling the behavior of the system in terms of RUL, are presented.

3.1.1 Degradation Modeling

Degradation models are usually developed based on degradation data combined with the understanding of the physics of the process. These models can be deterministic or stochastic, with the latter usually presenting more flexibility and robustness.

In the literature, several stochastic degradation models have been used. For PsM, models with covariates may be used to handle applications where several different factors affect the degradation. As an example, one can cite the variance gamma process combined with Markov chains [12].

It is important to highlight that in some simple cases, where the possible actions to be applied affect only one variable, or where the degradation process is well defined by only one stress factor, classical models such as the gamma [13] and the wiener processes [14] can be used.

3.1.2 Reliability Distributions

In several real-world applications, the degradation process may be too complex to model, or there may not be enough data available to infer the parameters of degradation models. In these cases, other approaches, such as reliability distributions, may be used to directly estimate a failure probability in given usage conditions. In this case, the failure time of a system is modeled as a random variable with known distribution.

It is worth noting that most of the classical distributions, such as Weibull, Gamma and Exponential, do not account for covariables and hence they do not account for the possible effect of the chosen actions and for different usage conditions. Therefore, they may not be suitable for PsM applications. Some examples of reliability distributions that are relevant for PsM applications can be found in [15].

Moreover, it is important to highlight that, although reliability distributions can be useful for system modeling, they provide less insight on the system than degradation models. Indeed, the latter can always be used to derive distributions of the time to failure, but the opposite is not always true. Therefore, degradation models should be used whenever it is possible because they contain more information on the system.

3.1.3 Black Box Data Driven Approaches

Data driven approaches are an alternative to the model-based approaches discussed before. Black Box Data-driven approaches can infer patterns from data without prior hypothesis on the degradation process nature or on the failure time distribution and incorporate the effect of several different covariables.

Data-driven algorithms can be used to predict the failure time, estimate a failure probability, or classify systems in different categories according to the severity of their usage. Examples of data-driven approaches for prognostics can be found in [16]. However, it is important to highlight, that the accuracy of such models depend on data availability and quality, and an understanding of different failure modes and stress factors can be necessary to employ them satisfactorily.

3.2 Action Modeling

Once the system is modeled, the following step is to list and model all the actions that can be applied to it. It is important to keep in mind that each system is unique and that different classes of actions may apply in each case. In the following, different examples of actions are presented.

3.2.1 – Classical Maintenance Decisions

PsM solutions must account for the classical maintenance decisions that are usually found in PdM and CM literature. The vast majority of literature on decision-making for maintenance focuses on choosing the maintenance date, assessing how to make this decision under different circumstances, i.e. perfect and imperfect maintenance operations [17], perfect and imperfect information [18], etc.

Alongside maintenance date decision, one can find several articles interested in defining inspection intervals, such as [8].

Therefore, it appears that classical maintenance decision is the core of every intelligent maintenance policy. A PsM must take it into account and go beyond, exploiting other dimensions of the decision-making process.

3.2.2- Task management

Systems can be composed of more than one subsystem (e.g a fleet of vehicles). Some subsystems are more prone to failure than others and, therefore, the decision regarding which subsystem to use to perform a task must be made taking the different degradation levels into account. Similarly, different tasks may present different levels of severity, which makes the order in which they are performed impact the evolution of the RUL as well.

One example of task management considering degradation information can be found in [11], where the mission plan of a fleet of trucks is decided based on the severity of each displacement and the current health state of each vehicle.

3.2.3 – Parameters Reconfiguration

PsM relies on the fact that the actions applied on a system can affect its degradation process. The same actions could be used to, at some extent, control the degradation process directly. One example is the action related to parameter reconfiguration. Indeed, controlling the RUL of a system could be achieved by modifying, in a suitable way, the parameters of the system.

Two aspects should be considered when modeling this type of action: (i) the impact of the parameter reconfiguration on the degradation model (e.g., limiting the power of a machine via software change can postpone maintenance operations) and (ii) the impact of the parameter reconfiguration on the system performance (e.g., reducing the power of the machine will reduce productivity and the software change has a financial cost). On this topic, one can cite the article [19] where a wind turbine RUL is controlled based on its torque.

3.2.4 – Full Exploitation Decisions

As PsM considers a holistic vision of the system, it also addresses actions that do not impact the degradation process or the maintenance strategy but are rather affected by it. Indeed, not all decisions will result in an acceleration or a deceleration of the degradation process. One example is given in [20] where deterioration information is used to decide the inventory level, providing insight on the best spare part management strategy.

3.3 Optimization

Once every relevant aspect of the system is modeled, an optimization layer is necessary to prescribe the best course of action.

3.3.1 Cost function

To choose the best actions to apply, a metric has to be established so that actions and their expected outcomes can be quantitatively compared. The chosen actions are the ones that minimize this metric, generally referred to as the cost function.

The cost function has to capture the systems exploitation trade-offs. The example given previously in Section 3.2.3 illustrates this trade-off. If reducing machine power can postpone maintenance operations but will reduce productivity, the cost function has to be defined such that it is possible to compare those outcomes. The solution will then decide when and how to reduce machine power to minimize exploitation cost.

The cost function must also take into consideration other inputs such as operational constraints, e.g, availability of spare parts, deadlines, workload, etc.

The PsM solution should be built on a realistic cost function, that captures all the reality of system exploitation, considering trade-offs and constraints, in order to account for all the functionalities of the system.

3.3.2 Optimization Technique

Once the optimization criteria are chosen, different techniques can be employed in order to find the best course of action. The choice must be made based on the needed reaction time of the PsM solution and the complexity of the space of actions.

In cases where the choice of possible actions is limited, optimization methods that are guaranteed to reach the cost function minimum, such as dynamic programming, can be employed [20]. Whenever the space of actions becomes bigger or the dynamic of the system requires fast adaptability, meta-heuristic methods should be used [11].

4 PsM application

In this section, a closed-loop PsM solution for the joint maintenance and missions assignment of industrial vehicles is presented. The critical component chosen to illustrate the proposed framework is the brake-pad.

The main hypothesis are:

- Missions are defined as the deliveries that a vehicle has to make from one point to another. All the distances and durations from point to point are considered to be known, and are stored respectively in matrices D and T.
- A decision epoch P_k arises when a new set of missions has to be accomplished. For example, every day a fleet owner has to make deliveries and therefore,

decisions will happen at the beginning of each day, before sending vehicles from the headquarter.

- Only breakdowns related to the brake-pad are considered.

4.1 System modeling

Brake-pads failure is commonly caused by wear and tear with usage. The brake-pad must be replaced whenever its thickness falls under a critical threshold. Fig. 3 shows the thickness evolution of a real brake-pad.

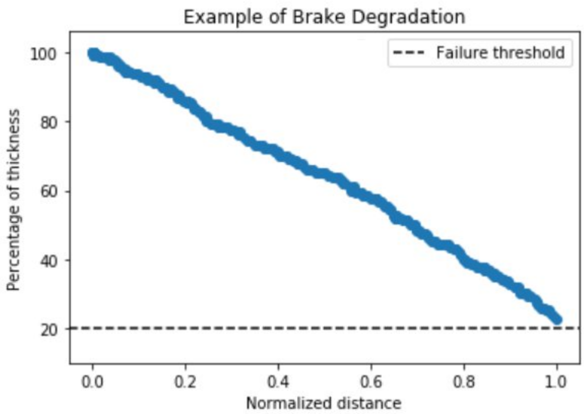

Fig. 3: Thickness Evolution

The brake-pad thickness evolution exhibits a mean trend close to be directly proportional to the traveled distance. The thickness degradation phenomena can be modeled with a Wiener process with a linear drift, as shown in the following equation:

$$Y(x) = Y_0 + \lambda x + \sigma_B B(x) + \varepsilon \quad (1)$$

where Y is the brake-pad thickness, Y_0 is the initial thickness, λ is the negative drift, x is the traveled distance, $B(x)$ is the standard Brownian motion, σ_B is its variance, and ε is the measurement noise considered to be white and Gaussian. Details on how to estimate those parameters from data can be found in [16].

4.2 Actions modeling

For this practical example, two types of actions are considered: classical maintenance and tasks management through missions scheduling.

4.2.1 Maintenance date decision

Vehicles come regularly to workshops to perform maintenance operations, such as oil change. To avoid extra workshop visits, brake-pad should only be replaced at those visits. The two next scheduled dates of workshop visit t_{wkp_1}, and t_{wkp_2} are known for each vehicle i. The maintenance decision comes down to choosing to replace the brake-pads at t_{wkp_1} or to postpone the change at least until t_{wkp_2}.

To decide the maintenance date, Monte-Carlo simulations are made based on equation 1 and the distribution of traveled distances, in order to compare the cost related to the possibility of a failure between t_{wkp_1} and t_{wkp_2} and the cost related to the expected amount of thickness wasted if a replacement occurs at t_{wkp_1}. If the cost associated to the failure probability is bigger than the one associated to the wasted thickness, the next workshop visit (t_{wkp_1}) is chosen to replace the brake-pad.

4.2.2 Missions scheduling

The scheduler will receive the list of missions to be accomplished, alongside with the last available degradation measurement. It will then proceed to find the best schedule possible.

It is important to highlight that both maintenance date decision and mission scheduling affect each other. Indeed, the mission schedule will be followed by the fleet and new degradation measures will be collected. These measurements will be used as an input by the maintenance date decision maker which will decide if a vehicle will replace its brake-pads in the next workshop visit. Replacement dates are then updated and used to change the scheduler cost function.

4.3 Optimization

The cost function used by the scheduler, which is responsible for finding the optimal mission schedule, is presented below:

$$C = C_{dist} + C_{delay} + C_{deg} + C_{waste} \quad (2)$$

It integrates four costs. C_{dist} and C_{delay} capture the operational costs and are proportional respectively to the total distance of a schedule and to the delays. C_{deg} and C_{waste} are costs related to the brake-pad thickness. The first accounts for the expected amount of thickness that will be consumed when following a mission schedule. It only considers vehicles that have not established a maintenance date for the brakes. On the other hand, C_{waste} considers only vehicles that will replace brakes in the next workshop visit and accounts for the cost related to the surplus of thickness that may be wasted in that replacement.

This cost function was chosen so that the resulting schedule will reduce operational costs, minimize the brakes degradation and, at the same time, avoid wasting thickness.

4.4 Results

To validate the proposed solution, a comparison between the proposed PsM algorithm and a real client exploitation strategy, which focuses only on distance and delay costs, is made. The simulations emulate the exploitation of a fleet of vehicles that have to perform the same missions every week, scheduling missions and brake-pad replacements in different ways. The results showed that operational costs were identical for both strategies, meaning that the PsM scheduler was able to reduce distance and delay costs as well. On the other hand, maintenance costs were different, as can be shown in Fig. 4.

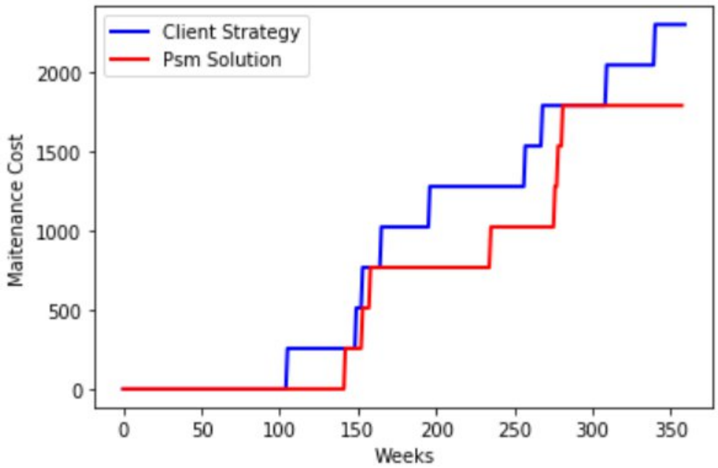

Fig. 4: Total Cost Comparison

The PsM algorithm performed better, postponing maintenance operations and avoiding waste while respecting operational constraints. This is due to the use of dynamic scheduling that accounts for maintenance dates and often uses more degraded vehicles to perform the least demanding missions.

5 Conclusion and future work

Maintenance is a key factor to ensure competitiveness and to minimize costs in many industrial systems. In the literature, maintenance has gathered a lot of attention from researchers who worked on maintenance solutions using concepts such as CM, PdM and more recently PsM. The term "prescriptive maintenance" has not been well defined in the literature. This lack of a robust definition represents an obstacle in the development of PsM solutions.

In this article, a discussion on the use of the term PsM in the literature and its differences regarding PdM was presented and key elements of a PsM structure were highlighted. A framework with three steps was proposed to guide future PsM solutions and avoid the unjustified use of the term prescriptive maintenance.

To illustrate the proposed approach, a practical example of PsM applied to the automotive domain was given, in which maintenance dates and missions are planned for a fleet of vehicles, minimizing the overall exploitation cost.
In future works, a deeper inquiry on the use of PsM in the literature can be conducted to improve the framework and applications involving more complex systems and components will be developed.

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