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Managerial decision making for complex service systems optimisation

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Abstract - The present paper deals with managerial decisions for Predictive Maintenance (PrdM) of complex service systems. We propose a Multi-Criteria Decision-Making (MCDM) approach aimed at sorting those failure modes potentially involving critical components into risk classes for interventions prioritisation and maintenance control. In this context, the sorting technique ELimination Et Choix Traduisant la REalité (ELECTRE) TRI is applied to support in finding the root causes that can be eliminated for failure prevention and/or minimization. This methodology presents the advantage to not rely on comparisons (as well as on their transitivity) between pairs of elements, simplifying computations for complex systems. To be sorted, decision elements are indeed compared with single reference profiles and the final assignment may constitute a valid alternative to the traditional ranking of failures achievable by other MCDM techniques and, among others, consistency-based methodologies. The proposed approach will be eventually applied to a case study from the industrial reality.

1 Introduction and objectives

Predictive Maintenance (PrdM) is one of the strategies used to predict failures based on inspection, condition monitoring, past failures, maintenance and other types of data. Numerous studies have been undertaken in literature in this field and different PrdM models and processes have been developed in the context of industry 4.0. Developments have been made on the basis of Artificial Intelligence (AI), Machine Learning (ML), Statistical Process Control, Deep Learning (DL), Internet of Things (IoT), Big Data, cyber physical system and cloud environment, providing useful directions for future work. These methods enable failure prediction on the basis of data collection from various resources. However, failures are corrected by firefighting without addressing the true underlying causes [1]. Hence, it has been concluded from literature that there is still the need to develop approaches valuable in predicting failure and identifying related causes for pursuing core systems optimisation.

The present paper proposes a Multi-Criteria Decision-Making (MCDM) approach for complex service systems whose core components are subjected to PrdM interventions. In particular, we aim to sort potential failures modes of components, along with their related root causes, to ordered risk classes by means of the MCDM method ELimination Et Choix Traduisant la REalité (ELECTRE) TRI. The application of such a technique enables to highlight which failures are associated to higher risk conditions, then requiring higher priority of interventions by optimising the monitoring process for the whole system. This application allows to sort failures without performing judgments of preference between pairs of relevant decision-making elements nor checking their consistency, as required by other MCDM methods. The paper is organised as follows. Section 2 provides a comprehensive literature review about the main topics of research. Section 3 reminds to the ELECTRE TRI technique and section 4 presents and solves a real case study. Conclusions are discussed in section 5 along with possible future developments.

2 Literature review

Manufacturing equipment failures are crucial in those industries posing enormous losses in terms of maintenance cost and operations stoppage. In manufacturing industries, the primary objective of maintenance and reliability managers is to enhance the availability of assets [2]. It is not worthy to repair equipment once they have failed since failures should be predicted and controlled even before their occurrence, by identifying related underlying causes. According to Omshi et al. [3] various maintenance and replacement methods have been proposed so far, varying from simple age-based to condition-based maintenance. Further, Lundgren et al. [4] review numerous maintenance models and found that their applications are limited in industry to quantify the effects of maintenance. PrdM is one of the maintenance policies used to predict failures by using equipment condition monitoring, inspection, sensors, life cycle, process data, systems and past failures data.

Such a policy discourages routine and preventive maintenance interventions, by promoting a more proactive maintenance approach. A lot of research has been conducted on PrdM till date. Cheng et al. [5] identify that reactive maintenance is unable to inhibit failures and preventive maintenance cannot predict the future condition in advance so assets can be repaired earlier in order to extend their life. They use a PrdM approach with advanced technologies to avoid such limitations. Hashim et al. [1] propose a customised PrdM model to minimize the maintenance cost of centrifugal pump in chemical plant. Miller and Dubrawski [6] review literature on PrdM from system point of view and differentiated failure risk forecasting and condition estimation abilities, presently used for simple components and needed to solve critical assets. Gohel et al. [7] develop a ML algorithm to carry out PrdM of nuclear infrastructure. Daniyan et al. [8] use AI for PrdM and developed training modules to train maintenance personnel to monitor and analyse data from IoT and other sources in order to predict the condition and potential failure of a rail-car wheel bearing. Hsu et al. [9] use statistical process control and ML to detect faults of wind turbine and indicate maintenance predictions. Moreover, Jimenez-Cortadi et al. [10] review different maintenance approaches and presented the process to be adopted for implementation of data driven PrdM in machine decision making as well as data collection and processing. Fernandes et al. [11] propose an infrastructure deployed for failure detection in boilers, making possible to forecast faults and errors. Their paper also presents initial PrdM models based on the collected data. Namuduri et al. [12] review the DL algorithms used for PrdM and present a case study of engine failure prediction. Their study also discusses the current use of sensors in the industry and future opportunities for electrochemical sensors in PrdM. Peters et al. [13] explore a few typical ML techniques and also develop a novel one. Sang et al. [14] look at how to support PrdM in the context of Industry 4.0. Especially, the application of RAMI4.0 architecture supports the PrdM using the FIWARE framework.

With a particular relation to the decision-making field, MCDM methods are an effective tool involving both subjective and quantitative elements. Various MCDM policies and methodologies have been recommended in literature over the recent years to select the options representing the best trade-off according to a set of evaluation criteria, and this is one of the broadly used decision making approach in such different fields as production, business, energy, economy, environment, sustainability, supply chain management, tourism, manufacturing systems, material, safety and risk, operations research, quality, technology, project management and so on. Mardani et al. [15] present various studies that show the vitality of the approach and stated various methodologies proposed in the literature. One of the MCDM methods widely used is ELECTRE TRI. The ELECTRE TRI method has emerged from the ELECTRE method after a series of versions including ELECTRE I, II, III, IV, IS. This is a multi-criteria sorting and decision aiding method used to deal with ordinal classification problem and allocates alternatives to predetermined categories [16, 17]. Various ELECTRE TRI applications have been found in literature in different areas and organizations. Fontana and Cavalcante [18] use ELECTRE TRI method for storage location assignment issues. Norese and Carbone [19] use it to evaluate and assign each airport to a sequential category in Italian Airports. Becker [20] applies the technique for ICT technology in enterprises. Trojan and Morais [21] use this method for reduction of losses in water distribution networks, maintenance of power distribution networks [22], and maintenance of water distribution network [23]. Certa et al. [24] use ELECTRE TRI in the project risk management field. Further, Brito et al. [25] apply this method for assessing risks in natural gas pipelines. Moreover, Trojan and Marçal [26] use ELECTRE TRI method for sorting maintenance types by multi-criteria analysis to clarify maintenance concepts in production and operations management. Almeida-Filho et al. [27] develop a decision support system based on MCDM for an electrical power distribution company to support maintenance planning. De Almeida et al. [28] provide MCDM models to categorize and allocate maintenance priorities for more effective maintenance planning. From the study of the existent literature, it is possible to conclude that many real case applications of ELECTRE TRI method has been related to the maintenance field. However, applications of this method in PrdM are limited, so that we propose the mentioned methodology for complex systems subjected to PrdM interventions. The main purpose consists in providing analysts with a tool capable to assist in potentiating failure control processes without pairwise comparing all the elements of analysis, simplifying calculations for complex systems.

3 Materials and method

ELECTRE TRI can be implemented by developing two phases in sequence. The first phase consists in defining outranking relations between pairs of alternatives and reference profiles by means of the calculation of concordance and discordance indices. The second phase consists in assigning alternatives to classes on the basis of the outranking relations established during the previous phase. The previous definition of ordered classes without any intersection among the related reference profiles is required, as well as the collection of the following input data:

- set of criteria $B_k, (k = 1, \dots, K)$ and criteria weights w_k, expressing the mutual importance of the aspects considered as relevant for the analysis;
- set of reference profiles $P_j, (j = 1, \dots, J)$ corresponding to specific evaluations for each criterion;
- number $J + 1$ of classes C_h determined by the J reference profiles;
- set of alternatives $A_i, (i = 1, \dots, I)$ and related evaluations $B_k(A_i)$ under each criterion;
- cutting value λ, that is a threshold value ranged in the interval $[0.5, 1]$;
- indifference, strong preference and veto thresholds characterising outranking relations, respectively indicated by the notations I_k, S_k, and V_k.

Once accomplished the input data collection, an exhaustive description of the method can be consulted in [29].

4 Case study

The present case study shows the application of the described ELECTRE TRI methodology to a real complex system subjected to interventions of predictive maintenance. Specifically, the complex system is a vehicle deputed to the street cleaning service. The reliability diagram of the system was elaborated in previous research [30] as well as the related block diagram detailing the system structure [31]. This last research specifically identified a set of three critical components to be monitored with priority to lead interventions of predictive maintenance. These three elements are three hydraulic pumps, fundamental to guarantee the functioning of the most important sweeping elements along with the loading-up and emptying systems. Acceleration had been established as a parameter correlated to the wear state of pumps to be measured by a proper network of sensors.

We are going to analyse the three hydraulic pumps. The list of possible failures and root causes involving these elements is provided in Table 1, which also shows the potential effects of failures on the whole system functioning.

TABLE 1. Failures, root causes and criteria evaluation

ID	Failures	Causes	Effects
A_1	Pump I: fault distribution system	No power supply; fluid characteristics; failure of valves or other elements.	Compromised functioning of hydraulic circuit and hydraulic actuators; work position not taken; brush and roller rotation not allowed.
A_2	Pump I: mechanical fault	Wear of the elements (journal boxes, bearings, etc.); wear of the sealing elements.	Compromised functioning of hydraulic circuit and hydraulic actuators; work position not taken; brush and roller rotation not allowed.
A_3	Pump II: fault distribution system	No power supply; fluid characteristics; failure of valves or other elements.	Compromised functioning of the loading and unloading system; work position not taken; waste not loaded; tank not emptied.
A_4	Pump I: mechanical fault	Wear of the elements (journal boxes, bearings, etc.); wear of the sealing elements.	Compromised functioning of the loading and unloading system; work position not taken; waste not loaded; tank not emptied.
A_5	Pump II: fault distribution system	No power supply; fluid characteristics; failure of valves or other elements.	Compromised functionality of the elevator plant; difficulty in the interaction between the elevator plant and the collection tank; loading of waste in the tank not carried out; stopped elevator plant.
A_6	Pump I: mechanical fault	Wear of the elements (journal boxes, bearings, etc.); wear of the sealing elements.	Compromised functionality of the elevator plant; difficulty in the interaction between the elevator plant and the collection tank; loading of waste in the tank not carried out; stopped elevator plant.

By analysing Table 1, there are two types of possible failures that have been identified for pump I (deputed to the sweeping system), pump II (deputed to the loading system) and pump III (deputed to the emptying system). Although failures are related to the same root causes, they may lead to significantly different effects depending on the different distribution of the three pumps throughout the system. The ELECTRE TRI application is indeed aimed at finding those specific root causes on which a priority of action is required. To such an aim, the six failures (i.e. alternatives of the MCDM problem) are going to be sorted in the following three ordered risk classes: C_1, low priority; C_2, medium priority; C_3, high priority. The assignment procedure is carried out according to three main evaluation criteria: B1, execution time; B_2, execution modality; B_3, frequency. The first two criteria refer to the execution of maintenance interventions whereas the third criterion refers to failure occurrence. Criteria have been evaluated by means of a decision-makers' panel and their values (Table 2) posteriorly translated to a numerical scale (Table 3) of values ranged within the interval $[1, 5]$.

TABLE 2. Evaluation of alternatives under criteria

ID	B_1	B_2	B_3
A_1	4.00	3.00	3.00
A_2	4.00	3.00	3.00
A_3	2.00	3.00	2.00
A_4	3.00	3.00	2.00
A_5	2.00	3.00	2.00
A_6	3.00	3.00	2.00

TABLE 3. Evaluation scale

Criteria	Evaluation	Value
B_1, B_2	Low	1.00
	Medium-Low	2.00
	Medium-high	3.00
	High	4.00
B_3	Remote	1.00
	Occasional	2.00
	Probable	3.00
	Frequent	4.00

The preference and indifference thresholds have been respectively assumed as a half and a quarter of the width of classes, whereas veto threshold has been assumed as equal to the width of classes. Table 4 presents results derived from the both the pessimistic and the optimistic procedure. The pessimistic procedure begins from the upper value limiting reference profiles defining classes. It assigns the alternative A_i to the class for which the condition that A_i is at least as good as profile P_h is verified, that is class C_{h+1}. The optimistic procedure begins from the lower value limiting reference profiles defining classes. It assigns the alternative A_i to the class for which the condition that P_h is preferred to A_i is verified, that is class C_h. Readers are encouraged to consult [32] for further information. Since no divergence exists between the two procedures, we can affirm that no incompatibility relations exist within the set of evaluated elements. The assignment of each failure to the defined classes has been achieved under the assumption of equally weighted criteria and by fixing three values for the cutting level λ : $0.60, 0.70, 0.80$. Results have been eventually double checked and validated by means of the J-Electre-v2.0 software for multi-criteria decision aid (https://sourceforge.net/projects/j-electre/files/).

TABLE 4. Assignment of alternatives to classes

ID	$\lambda = 0.60$	$\lambda = 0.70$	$\lambda = 0.80$
A_1	C_3	C_3	C_3
A_2	C_3	C_3	C_3
A_3	C_2	C_2	C_2
A_4	C_2	C_2	C_2
A_5	C_2	C_2	C_2
A_6	C_2	C_2	C_2

We can derive various useful observations by analysing the results obtained through the ELECTRE TRI technique. All the three analysed pumps are considered as critical components for the complex system under analysis. Nevertheless, failures potentially involving pump I have been classified within the high priority class, whereas failures potentially involving pumps II and III have been assigned to the medium priority class. Such an output is important for organising the maintenance interventions on the system since it highlights the required maximum priority by means of a structured MCDM support.

Figure 1 shows the block diagram representing the subsystems of the vehicle directly depending on pump I functioning.

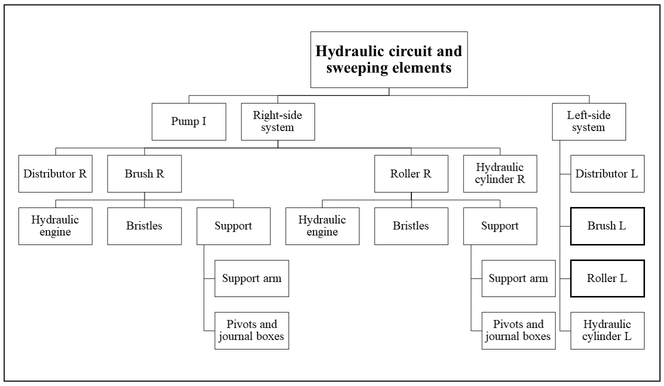

Figure 1. Block diagram of subsystems impacted by pump I

By minimising the root causes related to the potential occurrence of failures A_1 and A_2, it will be then possible to optimise the hydraulic circuit, actuators and such sweeping elements as brush and roller. Moreover, since a network of sensors is available to monitor pump I, II and III, the present application may also suggest a preferable allocation of sensors since failure root causes in need of higher priority have been associated to pump I. Results lastly confirm to be robust since no variations can be noted by varying the cutting level (Table 4).

5 Conclusions and future work

The main objective of the present research consists in assuming a MCDM perspective for maintenance management of service systems. In particular, we propose the application of the ELECTRE TRI technique for sorting failures potentially involving core components of systems subjected to predictive maintenance and related root causes. The main purpose is to highlight which root failure causes should be suppressed with priority by assigning failures to ordered priority classes. This application can be useful to support predictive maintenance management by assuring quick actions and operational readiness. We applied the proposed approach to a real world service system and, in particular, to sort common failures involving its core components. The application has been led by considering different values of cutting level to gain an overview about possible variations of results. An advantage of the proposed approach is that failures classification can be achieved without eliciting preference between pairs of alternatives, being elements pairwise compared just with reference profiles defining classes. This is certainly a more effective procedure when the number of core elements to be taken into account increases, enabling to manage complexity and potentially no transitive comparisons.

Possible future developments of the present research consist in extending the application to the whole system apart from the core components and in integrating the proposed method with a further MCDM technique to calculate criteria weights. This will be done to take into account the possibility that the main aspects of analysis may have different mutual influence on the final result. The aspect of dependence among criteria and alternative may be the object of further applications by contemplating again the potential presence of no transitive preference relations. Analysing the possible presence of dependency relations among the main elements of analysis will indeed be an important indicator to globally enhance predictive maintenance management.

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