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An integrated methodological approach for optimising complex systems subjected to predictive maintenance

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ABSTRACT

The present paper addresses the relevant topic of maintenance management, widely recognised as a fundamental issue involving complex engineering systems and leading companies towards the optimisation of their assets while pursuing cost efficiency. With this regard, our research aims to provide companies with a hybrid methodological approach based on Multi-Criteria Decision-Making (MCDM) capable to deal with the main failures potentially involving complex systems subjected to predictive maintenance. Such an approach is going to be integrated within the framework of traditional Failure Mode Effects and Criticality Analysis (FMECA), whose strengths and weaknesses are considered. In particular, the ELimination Et Choix Traduisant la REalité (ELECTRE) TRI is suggested to sort failure modes into risk priority classes while the Decision Making Trial and Evaluation Laboratory (DEMATEL) is proposed to highlight the most influencing failures within each risk class. The approach is applied to a real service system, whose critical components are monitored by sensors and subjected to predictive maintenance. Final results clearly demonstrate as highlighting the elements impacting the occurrence of other failures within specific risk classes is a significant driver towards the implementation of effective maintenance, maximising the whole level of performance of the analysed system over its lifecycle.

1. Introduction, research goal and structure

A complex system can be defined as an entity composed of multiple parts and components, for which relations of dependency may be completely unknown or difficult to be modelled [1]. Failure of complex systems or assets could strongly impact performance and poses enormous losses in terms of maintenance cost and operations stoppage if appropriate monitoring and alarming system is not implemented. The primary objective of maintenance and reliability managers is to enhance the availability of systems and making important decisions on how scheduling maintenance when it is required [2,3]. Currently, maintenance of complex systems is a key challenge for such industries as aerospace, automobile, oil and gas, chemicals, manufacturing, transport and so on. Adopting an optimal maintenance policy is indeed vital for industries [4], playing a significant role in effectively avoiding system failure meanwhile enhancing operational performance [5].

Such complex systems as for instance processing plants, pipelines, power plants, airplanes, ships, chemical plants or railway tracks, integrate various subsystems endowed with software, electrical, mechanical or electro-mechanical components. Throughout their lifecycle, these elements can show different behaviour so that maintenance decisions need to integrate theoretical reliability estimations and data monitoring [6]. When dealing with maintenance of complex systems, various functions have to be identified to execute and achieve the main maintenance goals [7]. The core of the manufacturing process is typically complex machinery with such features as complex product assembly, various parts, multidisciplinary technology and a long product lifecycle. Functioning conditions of systems can be assured and energy efficacy can be increased by implementing technical and appropriate maintenance [8]. For large plants, failure or breakdown of complex equipment can cause complete shutdown phenomena, so that an integrated condition monitoring system is desirable to save productivity and profit losses, ensure maximum availability and reliability of systems, as well as optimise economical and operational aspects [9]. Many organisations operating with complex systems face the challenge of keeping them running for long periods of time with minimum possible cost without losing safety and reliability. Of course, implementing proper maintenance actions is the best solution to optimise these objectives, in conflict

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with each other. These issues can be indeed managed by means of structured approaches of asset management. The first criterion refers to the collection of precise and up-to-date information about systems' states. Predictions and maintenance actions should be undertaken based on this information. An effectively integrated asset monitoring and maintenance system can have a positive impact on the main organisational aspects as well as improve asset uptimes, minimise maintenance expenses, maximise profits, and enhance reputation of companies with customers. Incorporating suitable decision-making tools within asset management systems improves efficiency and carefully planning both inspections and maintenance activities is essential [10].

Therefore, an accessible condition monitoring system should be implemented on assets for improving maintenance abilities of complex systems and making sufficient useful information available, with the purpose of analysing which types of maintenance actions are needed. These systems are organised through heterogeneous and hybrid elements, or even symmetric components performing the same function [5], needing structured methodologies to monitor their condition.

In this context, the goal of the present research consists in providing companies with an integrated methodological approach capable to deal with the main failures potentially involving complex systems subjected to predictive maintenance (PrdM). The general goal refers to the achievement of the following intermediate objectives:

- identifying core components of systems and characterising/assessing the potential failure modes;
- classifying the identified failures into risk classes expressing priorities of intervention;
- analysing the existence of relations of dependence to highlight the most influencing failures.

These objectives will be pursued by exploiting the advantages of decision-making theories and applications to analyse the impact of relevant aspects connected to maintenance and risk management. An important element of analysis will regard the study of dependency relationships among relevant failure modes to minimise their propagation. The proposed approach makes use of three different techniques, that are Failure Mode Effects and Criticality Analysis (FMECA) for identifying and assessing failures, ELimination Et Choix Traduisant la REalité (ELECTRE) TRI for sorting failures to risk classes and Decision Making Trial and Evaluation Laboratory (DEMATEL) for evaluating relations of dependence. To the best of the authors' knowledge, it is the first time that such an integration is proposed in the existing literature to deal with the problem of reference. After testing our approach, final results show the benefits derived from the study of dependence among failures within risk classes, something that can be assumed as significant maintenance driver.

The paper is organised as follows. Section 2 provides a detailed overview about the current state of the art by discussing maintenance policies of interest, existing techniques for failure analysis and advantages of current decision-making approaches. The description of the proposed methodological approach is developed in Section 3, whereas Section 4 discusses and solves a real case study on a complex service system whose core components are subjected to PrdM. Lastly, Section 5 closes the work by detailing a few lines for future developments.

2. Literature review

2.1. Preventive/predictive maintenance

Poor maintenance affects manufacturing operations and poses significant economic, social and environmental losses [11]. Maintenance can be reactive, i.e. fixing a problem after its occurrence, or proactive, i.e. predicting failure before its occurrence. In the vast majority of cases, repairing equipment after failures is not worth it, since failures should be ideally predicted by identifying relevant underlying causes. Various maintenance and replacement methods have been proposed till date, varying from simple age-based to condition-based maintenance [12]. However, their applications are limited in industry to quantify the effects of maintenance [13].

Preventive maintenance (PM) is a traditional industrial maintenance policy in which maintenance actions are planned based on a review of past failure data and system analysis. PM does not consider current health conditions of systems, so this strategy is not entirely effective in avoiding unforeseen system failures, something that may result in excessive costs related to the execution of some unnecessary interventions. However, these issues can be addressed by installing a network of sensors throughout the system. PrdM is one of the policies used to predict failures using equipment condition monitoring, inspection, on-board sensors, lifecycle, process data, systems and past failures data. It discourages routine and PM interventions by promoting a more proactive maintenance approach. PrdM is a type of strategy in which one can actively track performance, productivity or other significant factors to estimate the ideal period for leading maintenance on a given system. This is done on the basis of the particular features of systems and on the specific wear behaviour of the main critical components, instead of merely relying on statistical data. The cost of maintenance is greatly reduced if PrdM is strategically used.

Both PM and PrdM policies aim to prevent failures by retaining system operational state until they occur. At the analysis stage, the most significant distinction between the two strategies can be found in the granularity of analysis contributing to the maintenance function. PM focuses indeed on the sets of system that are characterised by the same features and attempts to figure out those metrics that can improve maintenance planning. PrdM, alternatively, considers each particular system as if it was a single component, attempting to derive those parameters describing the current state of health of components in order to determine the expected time of failure [7]. On the whole, PrdM promotes the reduction of problems by predicting systems' condition [11]. Although several efforts have been recently made for transitioning towards PrdM, integrating maintenance strategies is beneficial and is expected to be still needed for successful management. Reactive maintenance is somehow useful because certain systems will still malfunction unexpectedly, and PM is a valuable approach since it represents a sort of safety measure if the features required for PrdM are unavailable [7]. However, on the one hand reactive maintenance is certainly unable to inhibit failures and, on the other hand, PM cannot predict future conditions and cannot support in early restoring assets in order to extend their life [14]. PrdM is instead an effective strategy to minimise the level of PM as well as the frequency of failure contributing to reactive maintenance, thus generally increasing uptime and lowering global maintenance costs [7]. Moreover, systems and assets can be more easily protected from failure by implementing PrdM, which also ensures that the planned operations can be conducted throughout their lifecycle. It also pursues efficiency by avoiding high costs connected to corrective maintenance.

Previous research has found that, when PrdM is used wisely, the system's average reliability, availability, and maintenance operating expense are the lowest. Moving from reactive to PrdM greatly enhances system maintenance planning, especially for complex systems with huge economic value [15]. However, there are major practical barriers to the application of a PrdM approach because it demands innovative tracking technology, robust data collection processes and the implementation of complex supervision and prognosis architectures [16]. Some aspects are currently limiting the effective application of PrdM for complex assets. Monitoring and analysing all possible failure modes for the target complex equipment would put considerable financial and technological strain on individual organizations. Furthermore, categorising any possible failure mode related to single assets is impossible, and a single sample of data about failures is always insufficient, keeping prediction accuracy at a low level. As a result, accurate and timely maintenance scheduling information is needed and, to such an aim, enhancing the adaptability of PrdM decision-making in a complex manufacturing context is essential [8].

System models are commonplace because they automate prognostics and can accurately track complex systems in real time, as well as provide signs of potential risks. There are many approaches to PrdM, each one with its own combination of advantages and disadvantages [17]. PrdM can only be applied if online information about system status is accessible, which is now possible thanks to the implementation of suitable monitoring sensors. To date, a lot of research has been led on predicting system's remaining useful lifespan, focussing on a single component or on the complete system with deterministic reliability structures. Various studies can be found in the literature about PrdM for complex systems.

Hashim et al. [18] proposed a customised PrdM model to minimize the maintenance cost of centrifugal pumps in chemical plants. Miller and Dubrawski [19] reviewed the literature on PrdM from a system point of view and differentiated failure risk forecasting and condition estimation abilities. Gohel et al. [20] developed a machine learning algorithm to carry out PrdM of nuclear infrastructure. Daniyan et al. [21] used Artificial Intelligence (AI) for PrdM and developed training modules to train maintenance personnel to monitor and analyse data from the Internet of Things (IoT) and other sources in order to predict the condition and potential failure of a railcar wheel bearing. Hsu et al. [22] used statistical process control and machine learning to detect faults of wind turbine and indicated maintenance predictions. Moreover, Jimenez-Cortadi et al. [23] reviewed different maintenance approaches and presented the process to be adopted for implementation of data driven PrdM in machine decision making. Additionally, Fernandes et al. [24] proposed a PrdM model for failure detection in boilers. Namuduri et al. [25] used PrdM with Deep Learning algorithm for engines. Peters et al. [26] applied PrdM and ML for aircrafts and Hoffmann et al. [27] in medium voltage switchgear. Ruiz-Sarmiento et al. [28] executed PrdM in steel industry and Wang et al. [29] implemented PrdM for wind turbines. An integrated PrdM approach of Discrete Time Markov Chain (DTMC) and Bayesian Network (BN) for complex systems used by [1] and PrdM incorporating Proportional Hazard Models (PHM) method for aircraft components is presented in [30]. Further applications of PrdM in complex systems can be seen in [31–40].

2.2. Overview about FMECA strengths and weaknesses

FMECA is one of the earliest failure analysis techniques. It is a design approach using inductive logic to check the health and safety of equipment [15], to systematically analyse possible part failure modes of process or product. Identifying risks related to these failure modes as well as the resulting consequences on system functions leads to the optimisation of the stability of complex systems or components [15,41,42]. A ship and other transportation structures, power plants, chemical sectors, and oil and gas industries are typical examples of complex systems with a vast variety of subsystems and parts [43]. FMECA technique can mitigate this difficulty by first concentrating on systems' criticality. However, this method does not ensure that all the essential components have been detected [44]. FMECA is used in conjunction with condition monitoring to assess system criticality [41]. It is used to highlight and, more specifically, to define systems' elements in order to find the most appropriate factors to be analysed and monitored, so that a PrdM strategy can be effectively implemented [45]. Even if a PrdM-based approach could be a desirable strategy for a given complex system, in some cases it may not be compatible with all the components of that particular system. FMECA can be adopted to classify appropriate components. However, when implemented at the component level for critical assets, traditional FMECA-based approaches could become more exhaustive and time consuming. In these situations, it would be beneficial to find alternatives capable to decrease the efforts required by maintenance [44].

FMECA application for complex systems are considered as effective in integration with PrdM and presented in various case studies such as, for example, maritime systems [43], aircraft, production [46], Computer Numerical Control (CNC) lathe machines [45], dynamical evolving systems [16], super thermal power plant [41], wind turbine assemblies [47], and so on. Moreover, there are many papers addressing the application of FMECA for complex systems, as it can be seen in [42]. FMECA is a really flexible tool, but is characterised by various advantages as well as disadvantages/limitations in terms of applicability, cause and effects representation, risk analysis and problem solving [48]. Some of the advantages are herein discussed.

- It supports the identification of underlying causes of failure and the development of corrective measures.
- It aids to identify failure modes that may compromise operations safety, and to detect failures that may have undesirable or major consequences for system operation.
- It assists in recognizing the need of cost-effective design approaches for reliability enhancement, such as product selection and redundancy, by interfering at initial stages in the development process.
- It offers a way for evaluating the likelihood of system failures and the criticality analysis.
- It aids to resolve safety and system liability issues as well as regulatory non-compliance, by showing that anticipatable risks have been recognized.
- It supports in ranking different failures based on the Risk Priority Number (RPN).
- It facilitates the implementation of an efficient quality management, monitoring, and production process control system and aids to select a maintenance policy by providing a basis for scheduling maintenance.
- It is extremely rigorous and receptive to siege methods of system analysis, can improve design, selection of component as well as system reliability and is suitable to identify single points of failure [49].

Despite of its many advantages, FMECA suffers from significant weaknesses.

- It analyses the impact of single failures and, as a result, it is ineffective when it comes to offer a metric of system reliability, while being a valuable element for decision making.
- It relies on the independence among failure modes as a key hypothesis and is ineffective when portraying relationships among different failure modes.
- It deals with complex assets, what can be extremely challenging and time consuming [49] due to the multiple failure modes to be considered. In addition, the amount of specific system knowledge that must be investigated is huge, especially if we have a variety of possible operation modes, repairs and maintenance strategies to cope with.
- It is essentially a reductionist tactic, and the consequences of coexisting failures are not taken into proper account. Variations in the environment may affect the presumed reliability of elements. Moreover, human mistakes and hostile situations are often ignored and, in general, it is impossible to fix system problems [49].
- It is only applicable during the design stage and solely failure modes are taken into account, without considering their mutual relationships. Failure rates are not all the same and many combinations of multiple elements culminate in the same RPN index, what results in duplication or even misleading evaluations [50].

2.3. Review on MCDM approaches in the field

Integrating traditional failure analysis for complex systems with Multi-Criteria Decision-Making (MCDM) approaches can be strategic to overcome the underlined weaknesses. In such a context, MCDM involving both subjective and quantitative elements is considered as a

Table 1
Synthesis of the literature analysed with relation to the three proposed techniques.

Technique	Description	References
FMECA	Works detailing the wide application of FMECA for dealing with a large array of engineering fields. The key role played by such a technique for complex systems optimization is underlined in terms of criticality evaluation for components.	[15,42–44]
	Works proposing the practical application of FMECA for systems subjected to predictive maintenance, underlining the effectiveness of such an integration.	[16,41,43, 45–47]
	Works exposing the main advantages and disadvantages of FMECA technique highlighting as, despite its flexibility, FMECA should be prudentially used.	[48–50,88]
ELECTRE TRI	Works underlining the suitability of the methodology for solving a wide plethora of categorization problems with respect to other existing MCDM techniques.	[53–55,82]
	Works developing the practical application of ELECTRE TRI to face problems of different management areas, showing a gap in the predictive maintenance field.	[56–62,80]
DEMATEL	Works explaining the usefulness of DEMATEL for evaluating the existence of cause-effect relationships within a set of decision-making elements.	[63,64]
	Works applying DEMATEL in integration with other techniques and, in particular, with risk assessment analyses, other MCDM methods, probability-based approaches, structural modeling, and so on.	[11,65, 68–74]
	Works extending DEMATEL to its fuzzy version to treat input data uncertainty.	[75–79]

valuable approach. Various MCDM policies and methodologies have been recommended in literature over recent years to select the options representing the best compromise under various evaluation criteria. Similar approaches have been broadly used in different fields, such 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 [51]. Mardani et al. [51] presented various studies showing the vitality of MCDM approach and stated various methodologies proposed in the literature. One of the MCDM methods widely used is ELECTRE TRI [52]. This technique emerged from the ELECTRE family of methods after a series of versions including ELECTRE I, II, III, IV, IS. ELECTRE TRI is a multi-criteria sorting and decision aiding method used to deal with ordinal classification problems and allocate alternatives to predetermined categories [53–55]. The suitability of ELECTRE TRI for solving this kind of problems is the reason why this technique has been chosen for developing our methodological approach. Various ELECTRE TRI applications have been proposed in the literature to face different management areas. Fontana and Cavalcante [55] used ELECTRE TRI method for storage location assignment issues. Norese and Carbone [56] used it to evaluate and assign a set of airports to a sequential category in Italian Airports. Silveira et al. [57] applied the ELECTRE Tri-nC for ship collision risk assessment. Trojan and Morais [58] used this method for supporting reduction of losses in water distribution networks, maintenance of power distribution networks [59], and maintenance of water distribution networks [60]. Wang et al. [61] adopted an empirical classification approach based on this method for assessing safety criticality of energy production systems. Moreover, Trojan and Marçal [62] used ELECTRE TRI method for sorting maintenance types by multi-criteria analysis and for clarifying maintenance concepts in production and operations management. Various real applications of ELECTRE TRI method related to the maintenance field can be found in the literature, even if the application is limited for PrdM, for which a fundamental issue is certainly represented by dependency bounding potential failure modes.

With this last regard, the DEMATEL approach is more effective than other MCDM applications to illustrate the structure of complex causal interactions by means of suitable matrices and graphical charts. The DEMATEL approach is a trendy topic in the world of industrial engineering because it may be used to identify important elements in complex systems. As already underlined, an exhaustive analysis of dependence relations is particularly important to achieve exhaustive results in our particular field of application. Despite the fact that a lot of effort has been dedicated to enhance this aspect, there is still the absence of an objective perspective [63]. DEMATEL was initially designed and used to resolve complicated and interrelated group components or systems [64–67]. It is a systematic structural modelling methodology, particularly effective for creating and evaluating cause-effect relationships (dependency) among system components. DEMATEL could be used to investigate and solve difficult and interconnected issues by confirming interdependence among elements and assisting in building a diagram to depict related connections within components. It aids to identify cause and effect variables by highlighting the causative elements that can be prioritised towards to the prompt and effective resolutions of key problems, resulting in general improved performance [64–68]. The DEMATEL approach does not just transform interdependency links into cause and effect groups by using matrices. It also uses an impact-relation diagram to determine aspects of relevant importance for complex systems. This technique has received much interest over the last decade because of its benefits and flexibility of application, and many academicians have used it to solve complex system issues in a variety of fields. Furthermore, since many complex systems contain inaccurate and uncertain data, DEMATEL has been enhanced for improving decision-making in various situations [66]. The most of decision-making approaches established are on idealistic theories for example, risk contributing factor in a complex system and factor independence. There is indeed a robust connection between the risk factors and the information sources employed in the decision-making process. A decision-making strategy reflecting the interdependence between risk variables and data source is still required [69].

Various DEMATEL applications can be found in the literature, and some of them are herein presented. Rolita et al. [65] suggested an integration between DEMATEL and Analytic Hierarchy Process (AHP) in order to improve the performance of airport safety management system. Authors investigate on contributory relations among the related criteria for effective decision-making based on related analysis. Maduekwe and Oke [70] used the DEMATEL technique in the food processing industry to identify and rank maintenance system KPIs. Karuppiah et al. [71] integrated DEMATEL and Fuzzy AHP (FAHP) to recognise, investigate and evaluate a set of Faulty Behaviour Risks (FBRs) potentially causing workplace injuries and accidents. Karuppiah et al. [11] combined Interpretive Structural Modelling (ISM) and DEMATEL methodology for implementing sustainable PrdM. Moreover, an integrated model based on Failure Modes and Effects Analysis (FMEA) and DEMATEL approach for photovoltaic cell manufacturing industry is proposed in [68], and an integration of DEMATEL with Best-Worst Method (BWM) and Bayesian Network (BN) was carried out for safety management in the high-tech industry [69]. Other examples of DEMATEL applications are a hierarchical DEMATEL process for complex systems [72], a DEMATEL-ANP risk assessment model in oil and gas construction projects [73], an integrated method of Dynamic Quantitative Risk Assessment based on DEMATEL and BN for oil and gas leaks on offshore platforms [74]. The DEMATEL has been extensively applied also in its fuzzy version to deal, for instance, with household appliances assembly [75] or with supply chain in automotive industry [76]. Fuzzy DEMATEL has been combined with such other methods as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to assess the comprehensive risk of hydrogen generation unit [77], or also with cloud models [78] and FMEA analyses applied for turning machines [79].

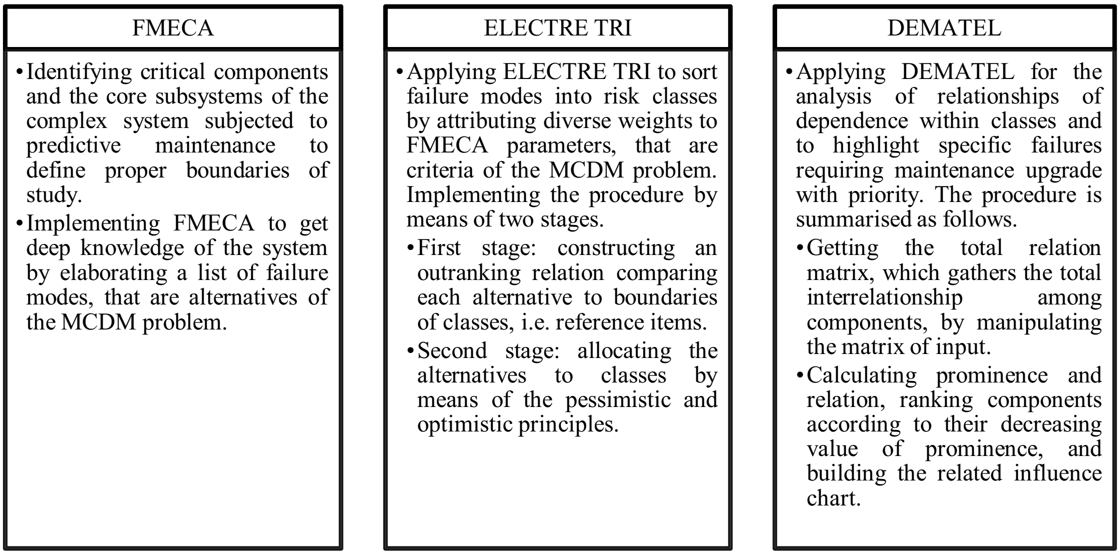


Fig. 1. Diagram exemplifying the proposed procedure for complex systems.

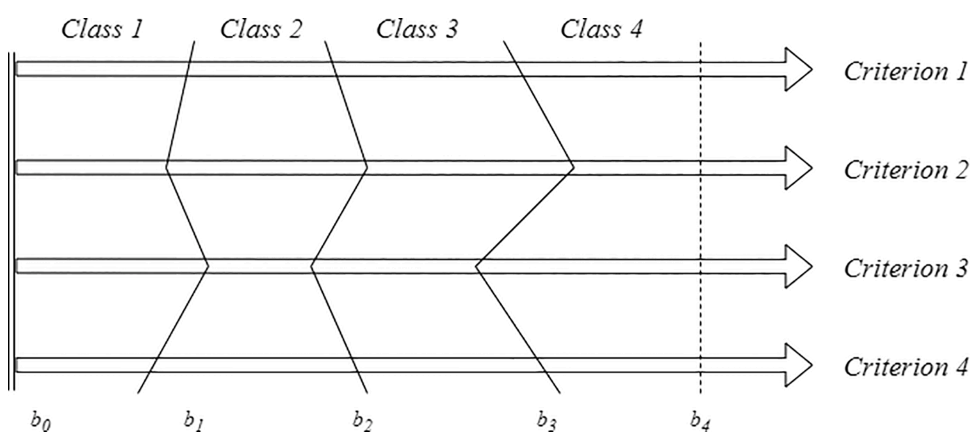


Fig. 2. Classes and reference profiles representation for each criterion adapted by [82].

Table 1 reports a brief general overview on the current state of the art related to the three techniques herein combined (FMECA, ELECTRE TRI and DEMATEL), by also discussing gaps in the field as well as advantages potentially deriving from methodological integration.

3. Proposed methodological approach

After having analysed weaknesses, strengths and common applications of FMECA, ELECTRE TRI and DEMATEL, we herein propose the combination of these three techniques for optimising the management of failures for systems subjected to PrdM. In particular, this approach extends a previous conference paper [80], where ELECTRE TRI was suggested for failure classification. The reasons why the combination of these three specific techniques is proposed to the field of study are formalised as follows:

1 FMECA is herein used as a tool to identify all the potential failures involving systems subjected to PrdM as well as to evaluate the criticality of failure modes according to the risk parameters of interest;
2 ELECTRE TRI is applied to sort the highlighted failures to ordered risk classes on the basis of their common features and, above all, to show those specific sets of failures having associated higher risk levels and conditions;
3 DEMATEL is implemented for highlighting, within each class, those specific failures showing higher degrees of interdependence with other failures belonging to the same risk category.

The proposed integrated framework intends to contribute in making more effective decisions in industry and to further plan effective actions of risk management. The goal consists in identifying, for each risk class, those failure modes having a stronger impact on the systems and also on the occurrence of other failures. Managing those particular aspects would indeed imply also the prevention of the other dependent failure modes. This would lead to optimise the maintenance and risk management processes on the whole as well as the general functional state for systems. A diagram representing step-by-step the approach is reported in Fig. 1 and the description of the methodologies is presented through the following subsections.

3.1. *FMECA for quantitative failure assessment*

As specified by the CEI EN 60812 standard, FMECA is an organized approach to analyse a system in order to recognise potential failure modes, identify causes and their effects on performance of a system. Being a modified and extended version form the FMEA technique, FMECA facilitates ordering and highlighting failure modes on the basis of their criticality. Specifically, three risk parameters Severity (*S*),

Table 2
Components and subsystems functional description.

Component/ Subsystem	Description
1 Integral PTO	Component 1 allows the connection of the hydraulic pumps to the main engine by means of a suitable power take-off system. The regular functioning state of the entire system is directly dependent on the functionality of this component, being the pumps the main critical components through which the movement of vehicle is guaranteed and all the diverse sweeping working phases are carried out.
1 Oil Tank	Component 2 is the first element of the entire hydraulic circuit and aims to ease the dissipation of the heat generated during the operations of the vehicle. This is the reason why the oil tank is partially integrated inside the water tank and connected to it by means of an external flange. It is essential to monitor the oil level as well as its temperature through the appropriate level indicator and temperature sensor.
1 Moving System	Subsystem 3 guarantees the advancement of the vehicle during the working phases and is made of start-up pump (3.1), start-up engine (3.2) and electronics control (3.3). The start-up pump has variable capacity and controls the hydraulic traction engine. In particular, by varying the pump displacement, the rotation speed of the hydraulic motor and therefore the advancement of the vehicle are modified. The hydraulic transmission enables to move the vehicle at a lower speed for sweeping (vehicle speed is determined by the flow of oil from the pump). The electronics control manages all the equipment, in particular the integral PTO and the hydrostatic transmission.
1 Sweeping and Funnelling System	Subsystem 4 integrates the sweeping activity with the conveyance of waste to the loading system. It is made of water spray system (4.1) and hydraulic circuit and sweeping elements (4.2). The spray system acts upstream of the sweeping and conveying activities, and consists of a water tank, a water pump and spraying nozzles. The main function of subsystem 4.1 consists in spraying water to compact powders and avoid their dispersion in the air, making the action of side brushes and side rollers more effective. Subsystem 4.2 is made of pump I, deputed to the movement of the sweeping elements belonging to the circuit itself, that have been grouped into the right-side system and the left-side system, based on their position.
1 Loading-up and Emptying System	Subsystem 5 integrates and regulates waste loading-up and tank emptying activities. It is made of pump II (5.1), loading-up system (5.2) and emptying system (5.3). Pump II controls the hydraulic engine for the rotation of the rear roller, the cylinders acting on the roller structure, the cylinders deputed to the overturning of the tank and the releasing cylinder of the elevator plant. The loading-up system, ruled by pump III, consists of rear roller and chained elevator plant, responsible for waste collection until the collection tank is filled. Wastes are first loaded from the rear roller to the elevator plant and then from the elevator plant to the collection tank. Once the elevator plant is released through the action of proper cylinders, the emptying working stage takes place by overturning the tank through its support structure, so that the sweeper can be ready for executing cleaning activities again.

Occurrence (O) and Detection (D) are combined to compute the criticality of each failure mode. S is an estimation of how intensely the failure would potentially harm the system, O is the rate of occurrence within a specified time period of any failure mode, and D indicates the likelihood of identifying the failure. The RPN for each failure mode is obtained by multiplying the parameters S, O and D as presented in Eq. (1):

$$RPN = S{\cdot}O{\cdot}D \tag{1}$$

Generally, a discrete value in the range from [0, 10] is taken for each risk factor. The initial stage of FMECA consists in describing the identified system and building a systematic structure. To get a comprehensive description of the analysed system, it is primarily essential to collect sufficient information about the reliability relationship among the main components of the system as well as to substantially define them through their order and position (that is by outlining system boundaries and levels). It is noticeably recommended to exclude such components from the study that will neither be assessed nor considered in the analysis. The practical connections among components is developed and represented through a system block diagram. Additionally, it is vital to outline all the potential failure modes for every component, identify the failure causes and explain equally the failure effects. Collectively, all the obtained outcomes should be summarized and recorded in suitable worksheets that help the investigator in developing the phase of risk assessment, specifically the calculation of the RPN against each failure mode [81].

3.2. ELECTRE TRI for sorting failures into risk priority classes

ELECTRE TRI is an outranking-centred approach utilised to sort and categorize decision-making problems. An outranking relation highlights certain conditions existing among the sets of choices or, particularly in the ELECTRE TRI approach, among choices and reference items. This type of relation is basically centred on concordance/discordance rules, which respectively involve validating the concordance between criteria that a particular alternative outranks different option (or reference items) as well as the discordance between criteria that this statement may not be approved. A common relationship can highlight situations of indifference, preference, or incomparability. In the first case, an alternative outranks a reference item and conversely; secondly, an alternative outranks a reference item but not conversely; and lastly, such a divergence between alternative and reference item exists that they cannot be compared. Such situations are presented by setting up appropriate numerical thresholds.

Determining threshold values is a critical aspect for ELECTRE TRI, since it has a direct influence on the categorization of outcomes. As specified in [82], the analyst has to define cut-off values in order to calibrate the approach in accordance with the specific problem under investigation. Greater values can be modelled for thresholds by initially making different attempts and then gradually calibrate these values until they are identified as acceptable for each criterion.

ELECTRE TRI demands the prior specification of ordered classes that do not overlap with any of the associated reference item. Each reference item reflects the higher reference items for one class and the lower reference item for the next class at the same time. Reference item could be identified directly by a single expert or a team of decision makers, either via particular elicitation procedures allowing indirect preferred information. As a generic example, Fig. 2 defines four ordered classes delimited by three reference profiles with relation to four generic criteria. Considering these fundamental concerns about the ELECTRE TRI method and proceeding with the application, the below input data

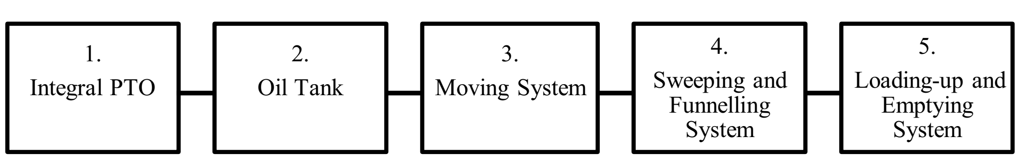


Fig. 3. Series of components and subsystems.

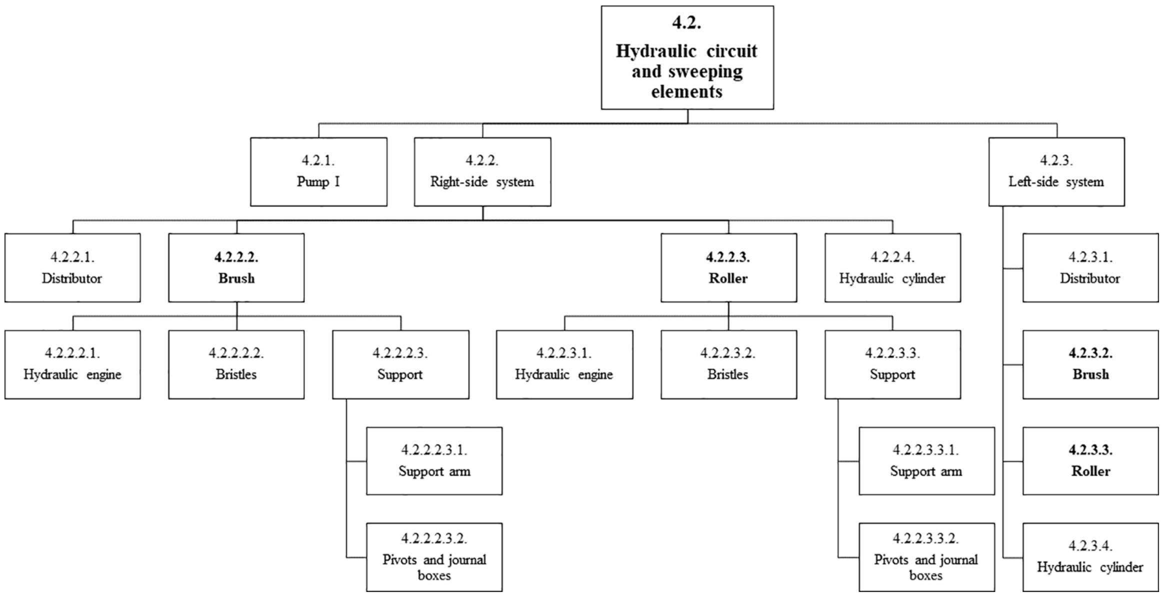


Fig. 4. Hierarchical structure of the subsystem ruled by pump I.

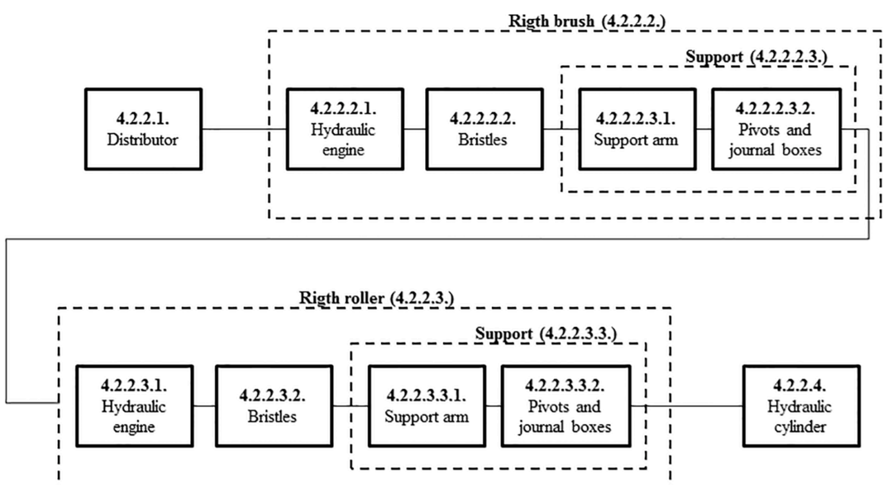


Fig. 5. Detailed reliability diagram of the "right-side system".

are required.

- Set of criteria g_j, (j = 1, …, J) pertinent to the decision-making problem under consideration, as well as criteria weights w_j indicating their relative importance.
- Set of reference items b_k, (k = 1, …, K) pertaining to particular assessments for each criterion j and bounded by values $b_0^{(j)} < \ldots < b_{K+1}^{(j)}$.
- Set of classes C_h, (h = 1, …, K+1) specified by the K reference items.
- Set of alternatives A_i, (i = 1, …, I) with their associated evaluations $g_j(A_i)$ under each criterion.
- Cutting value $\lambda \in]0.5, 1]$, a threshold value required to finish the first phase of the ELECTRE TRI process.
- Indifference, strong preference, and veto thresholds characterizing connections among sets of pairs are denoted by the notations q_j, p_j, and v_j, respectively.

Once we have gathered all of the essential input data, we will go over the two steps of the procedure, explained in the following.

1. First stage: constructing an outranking relation S by comparing each option to class boundaries, i.e. reference items. This level is broken down into four intermediary stages.
1.1. Calculating the concordance indices for every criterion. Each alternative A_i has to be pairwise compared with all of the defined reference items b_k, and concordance indices, denoted as $C_j(A_i,\ b_k)$, has to be computed for each criterion g_j using the following formula:

$$C_j(A_i,\ b_k) = \begin{cases} 1 \text{ if } g_j(b_k) - g_j(A_i) \le q_j \\ \dfrac{g_j(A_i) - g_j(b_k) + p_j}{p_j - q_j} \text{ if } q_j < g_j(b_k) - g_j(A_i) < p_j\,. \\ 0 \text{ if } g_j(b_k) - g_j(A_i) \ge p_j \end{cases} \tag{2}$$

The aggregated concordance index $C(A_i,\ b_k)$ will be obtained by using the previously calculated concordance indices for each criterion by accumulating and weighing the indices as mentioned below:

Table 3
Analysis of failure modes, causes and effects.

ID	Component	Failure Modes	Failure Causes	Failure Effects
4.2.1.	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.
		Mechanical fault	Wear of the elements (bearings, journal boxes, etc.); wear of the sealing elements.	Compromised functioning of hydraulic circuit and hydraulic actuators; Work position not taken; Brush and roller rotation not allowed.
4.2.2.1./ 4.2.3.1.	Distributor	Sweeping elements not lubricated	No oil supply; mechanical fault; wear of the contact elements.	Rotation of brushes and rollers not allowed; Waste not conveyed.
4.2.2.2.1./ 4.2.2.3.1./ 4.2.3.2.1./ 4.2.3.3.1.	Hydraulic engine	Stopped start-up engine	Pump I failure; overheated oil.	Stopped brushes; stopped lateral rollers; waste not conveyed.
		Mechanical fault	Bearing wear.	Excessive vibration.
4.2.2.4./ 4.2.3.4.	Hydraulic cylinders	Stopped hydraulic cylinders	Pump I and / or pump II failure; excessive friction; hydraulic circuit failure.	Translation of brushes / rollers not carried out (elements not adherent to the ground when working or not lifted during transportation).
		Mechanical fault	Wear of the sealing elements.	Irregular translation and loss of oil.
4.2.2.2.3.1. 4.2.2.3.3.1. 4.2.3.2.3.1. 4.2.3.3.3.1.	Support arms	Broken arms	Deformation due to impact with large waste or sidewalks.	Compromised functionality of brushes and side rollers.
		Stopped arms	Hydraulic system fault.	Failure in opening / closing side arms; changes in action range of conveyance system.
4.2.2.2.3.2. 4.2.2.3.3.2. 4.2.3.2.3.2. 4.2.3.3.3.2.	Pivots and journal boxes	Slackened pivots	Incorrect assembly / stress due to vibrations.	Excessive vibration; risk of detachment of the brush (s) or roller (s) from the holder.
		Worn journal boxes	Wrong assembly / action of pins inside the journal boxes.	Incorrect joint between arms and brushes or rollers.
4.2.2.2.2./ 4.2.2.3.2/ 4.2.3.2.2./ 4.2.3.3.2/	Bristles	Damaged brush or roller	Mechanical action of conveyed waste and road surface.	Inefficiency in waste collection; low adherence of bristles to the ground.

Table 4
List of failure modes for subsystem 4.2 and factors evaluation.

FAILURE MODES		ID	S	O	D
4.2.1. Pump I	Fault distribution system in Pump I	PI_1	2	2	2
	Mechanical fault in Pump I	PI_2	2	1	2
4.2.2. Right-side system	Sweeping elements not lubricated through right-side distributor	RSS_1	2	3	2
	Stopped right-side hydraulic cylinders	RSS_2	1	2	2
	Mechanical fault of right-side hydraulic cylinders	RSS_3	1	2	2
	Stopped start-up engine of right-side brush	RSS_4	1	2	1
	Mechanical fault of start-up engine of right-side brush	RSS_5	3	1	1
	Broken support arms of right-side brush	RSS_6	2	1	1
	Stopped support arms of right-side brush	RSS_7	2	1	1
	Slackened pivots of right-side brush	RSS_8	1	2	3
	Worn journal boxes of right-side brush	RSS_9	2	2	3
	Damaged bristles of right-side brush	RSS_10	1	3	2
	Stopped start-up engine of right-side roller	RSS_11	1	2	1
	Mechanical fault of start-up engine of right-side roller	RSS_12	3	1	1
	Broken support arms of right-side roller	RSS_13	2	1	1
	Stopped support arms of right-side roller	RSS_14	2	1	1
	Slackened pivots of right-side roller	RSS_15	1	2	3
	Worn journal boxes of right-side roller	RSS_16	2	2	3
	Damaged bristles of right-side roller	RSS_17	1	3	2
4.2.3. Left-side system	Sweeping elements not lubricated through left-side distributor	LSS_1	2	3	2
	Stopped left-side hydraulic cylinders	LSS_2	1	2	2
	Mechanical fault of left-side hydraulic cylinders	LSS_3	1	2	2
	Stopped start-up engine of left-side brush	LSS_4	1	2	1
	Mechanical fault of start-up engine of left-side brush	LSS_5	3	1	1
	Broken support arms of left-side brush	LSS_6	2	1	1
	Stopped support arms of left-side brush	LSS_7	2	1	1
	Slackened pivots of left-side brush	LSS_8	1	2	3
	Worn journal boxes of left-side brush	LSS_9	2	2	3
	Damaged bristles of left-side brush	LSS_10	1	3	2
	Stopped start-up engine of left-side roller	LSS_11	1	2	1
	Mechanical fault of start-up engine of left-side roller	LSS_12	3	1	1
	Broken support arms of left-side roller	LSS_13	2	1	1
	Stopped support arms of left-side roller	LSS_14	2	1	1
	Slackened pivots of left-side roller	LSS_15	1	2	3
	Worn journal boxes of left-side roller	LSS_16	2	2	3
	Damaged bristles of left-side roller	LSS_17	1	3	2

$$C(A_i,\ b_k) = \frac{\sum_{j=1}^{J} w_j \cdot C_j(A_i, b_k)}{\sum_{j=1}^{J} w_j}. \tag{3}$$

1.2. Computing the discordance indices for every criterion by means of below formula:

$$D_j(A_i,\ b_k) = \begin{cases} 1 \text{ if } g_j(b_k) - g_j(A_i) > v_j \\ \dfrac{g_j(b_k) - g_j(A_i) - p_j}{v_j - p_j} \text{ if } p_j < g_j(b_k) - g_j(A_i) \le v_j \\ 0 \text{ if } g_j(b_k) - g_j(A_i) \le p_j \end{cases}. \tag{4}$$

1.3. Calculating the outranking credibility indices using the below equation:

Table 5a
ELECTRE TRI results – pessimistic procedure.

	Scenario 1			*Scenario 2*			*Scenario 3*		
Failure ID	λ=0.70	λ=0.80	λ=0.90	λ=0.70	λ=0.80	λ=0.90	λ=0.70	λ=0.80	λ=0.90
PI_1	A	A	A	A	A	A	A	A	A
PI_2	B	B	B	B	B	B	B	B	B
RSS_1	A	A	A	A	A	A	A	A	A
RSS_2	B	B	B	B	B	B	B	B	B
RSS_3	B	B	B	B	B	B	B	B	B
RSS_4	B	B	B	B	B	B	B	B	B
RSS_5	B	B	B	B	B	B	B	B	B
RSS_6	B	B	B	B	B	B	B	B	B
RSS_7	B	B	B	B	B	B	B	B	B
RSS_8	B	B	B	B	B	B	B	B	B
RSS_9	A	A	A	A	A	A	A	A	A
RSS_10	B	B	B	B	B	B	B	B	B
RSS_11	B	B	B	B	B	B	B	B	B
RSS_12	B	B	B	B	B	B	B	B	B
RSS_13	B	B	B	B	B	B	B	B	B
RSS_14	B	B	B	B	B	B	B	B	B
RSS_15	B	B	B	B	B	B	B	B	B
RSS_16	A	A	A	A	A	A	A	A	A
RSS_17	B	B	B	B	B	B	B	B	B
LSS_1	A	A	A	A	A	A	A	A	A
LSS_2	B	B	B	B	B	B	B	B	B
LSS_3	B	B	B	B	B	B	B	B	B
LSS_4	B	B	B	B	B	B	B	B	B
LSS_5	B	B	B	B	B	B	B	B	B
LSS_6	B	B	B	B	B	B	B	B	B
LSS_7	B	B	B	B	B	B	B	B	B
LSS_8	B	B	B	B	B	B	B	B	B
LSS_9	A	A	A	A	A	A	A	A	A
LSS_10	B	B	B	B	B	B	B	B	B
LSS_11	B	B	B	B	B	B	B	B	B
LSS_12	B	B	B	B	B	B	B	B	B
LSS_13	B	B	B	B	B	B	B	B	B
LSS_14	B	B	B	B	B	B	B	B	B
LSS_15	B	B	B	B	B	B	B	B	B
LSS_16	A	A	A	A	A	A	A	A	A
LSS_17	B	B	B	B	B	B	B	B	B

$$\sigma(A_i,\ b_k) = \prod_{j\in F} \frac{1 - D_j(A_i,\ b_k)}{1 - C(A_i,\ b_k)}, \tag{5}$$

where $F = \{j : D_j(A_i,\ b_k) > C(A_i,\ b_k)\}$; $\sigma(A_i,\ b_k) = C(A_i,\ b_k)$ otherwise. If the veto threshold for any criterion is not specified, the credibility index $\sigma(A_i,\ b_k)$ equals the aggregated concordance index, $C(A_i,\ b_k)$. Following computation, a fuzzy outranking relation founded on reliability indices has to be converted into a crisp relation.

1.4. The cutting level λ, typically falling within the range [0.5, 1], indicates the threshold value for $\sigma(A_i,\ b_k)$ to support the hypothesis that A_i outranks b_k, and is used to describe the particular type of outranking relationship. The values of $\sigma(A_i,\ b_k)$, $\sigma(b_k,\ A_i)$ and λ establish the preference relationship between A_i and b_k:

- $\sigma(A_i,\ b_k) \geq \lambda$ and $\sigma(b_k,\ A_i) \geq \lambda \Rightarrow A_i$ S b_k and b_k S $A_i \Rightarrow A_i$ I b_k;
- $\sigma(A_i,\ b_k) \geq \lambda$ and $\sigma(b_k,\ A_i) < \lambda \Rightarrow A_i$ S b_k and not b_k S $A_i \Rightarrow A_i$ P b_k;
- $\sigma(A_i,\ b_k) < \lambda$ and $\sigma(b_k,\ A_i) \geq \lambda \Rightarrow$ not A_i S b_k and b_k S $A_i \Rightarrow b_k$ P A_i;
- $\sigma(A_i,\ b_k) < \lambda$ and $\sigma(b_k,\ A_i) < \lambda \Rightarrow$ not A_i S b_k and not b_k S $A_i \Rightarrow A_i$ R b_k;

where S denotes the outranking relationship (particularly, A_i **S** b_k denotes that alternative *i* is at least as good as reference profile *k*) and I, P, and R denote indifference, strong preference, and incomparability, respectively.

2. Second stage: allocating alternatives to categories using pessimistic and optimistic principles.

2.1. Pessimistic (or conjunctive) procedure: alternative A_i is assigned to the class C_k for which the condition that A_i S b_k is validated, implying that alternative *i* is at least as good as reference profile *k*. The pessimistic procedure starts from the top value restricting reference profiles defining classes and is implemented by the two following steps:

- Progressively evaluating every alternative to the class boundaries, that is A_i is successively compared to profiles defining classes until verifying the previously expressed condition.
- Assigning alternative A_i to class C_{k+1}.

1.%2 Optimistic (or disjunctive) procedure: alternative A_i is assigned to the class C_k for which the condition b_k P A_i is verified, implying that reference profile *k* should be preferred above alternative *i*. The optimistic procedure starts with the lowest value restricting reference profiles establishing classes and is performed through the following steps:

- Comparing every alternative with the class boundaries. Alternative A_i is sequentially compared to profiles defining classes till the condition b_k P A_i is verified.
- Assigning alternative A_i to class C_k.

3.3. DEMATEL for analysing relationships of dependence within each class

This subsection discusses the technique used to define impact relationships among the critical components of a complex system. Decisions concerning complex systems need to consider the existence of mutual dependency among the core elements and this could be efficiently accomplished by using the DEMATEL method. Indeed, when

Table 5b
ELECTRE TRI results – optimistic procedure.

	Scenario 1			*Scenario 2*			*Scenario 3*		
Failure ID	λ=0.70	λ=0.80	λ=0.90	λ=0.70	λ=0.80	λ=0.90	λ=0.70	λ=0.80	λ=0.90
PI_1	A	A	A	A	A	A	A	A	A
PI_2	B	B	B	B	B	B	B	B	B
RSS_1	A	A	A	A	A	A	A	A	A
RSS_2	B	B	B	B	B	B	B	B	B
RSS_3	B	B	B	B	B	B	B	B	B
RSS_4	B	B	B	B	B	B	B	B	B
RSS_5	A	A	A	A	A	A	A	A	A
RSS_6	B	B	B	B	B	B	B	B	B
RSS_7	B	B	B	B	B	B	B	B	B
RSS_8	A	A	A	A	A	A	A	A	A
RSS_9	A	A	A	A	A	A	A	A	A
RSS_10	A	A	A	A	A	A	A	A	A
RSS_11	B	B	B	B	B	B	B	B	B
RSS_12	A	A	A	A	A	A	A	A	A
RSS_13	B	B	B	B	B	B	B	B	B
RSS_14	B	B	B	B	B	B	B	B	B
RSS_15	A	A	A	A	A	A	A	A	A
RSS_16	A	A	A	A	A	A	A	A	A
RSS_17	A	A	A	A	A	A	A	A	A
LSS_1	A	A	A	A	A	A	A	A	A
LSS_2	B	B	B	B	B	B	B	B	B
LSS_3	B	B	B	B	B	B	B	B	B
LSS_4	B	B	B	B	B	B	B	B	B
LSS_5	A	A	A	A	A	A	A	A	A
LSS_6	B	B	B	B	B	B	B	B	B
LSS_7	B	B	B	B	B	B	B	B	B
LSS_8	A	A	A	A	A	A	A	A	A
LSS_9	A	A	A	A	A	A	A	A	A
LSS_10	A	A	A	A	A	A	A	A	A
LSS_11	B	B	B	B	B	B	B	B	B
LSS_12	A	A	A	A	A	A	A	A	A
LSS_13	B	B	B	B	B	B	B	B	B
LSS_14	B	B	B	B	B	B	B	B	B
LSS_15	A	A	A	A	A	A	A	A	A
LSS_16	A	A	A	A	A	A	A	A	A
LSS_17	A	A	A	A	A	A	A	A	A

relations of interdependence are not exhaustively considered, outcomes of decision-making can be likely negatively affected. The DEMATEL approach is used in this paper to identify the impact of intensity of connections among components and decision-making of a complex system. To such an aim, the DEMATEL technique needs the assistance of an expert or a team of specialists in the subject in order to gain deeper knowledge about the problem under analysis. The major stages required to apply the procedure are outlined below [83].

- Gathering the non-negative input matrix, X, whose cells represent the relationships of impact x_{ij} of one component, i, over another one, j, using the given linguistic assessment scale: 0 (no influence), 1 (very low influence), 2 (low influence), 3 (high influence), 4 (very high influence). Because components have no impact on themselves, the main diagonal will be filled with zeroes.
- The previous phase is carried out by incorporating a decision-making team and requesting every specialist to complete their own input matrix, with the goal of treating the set of input data as evenly and reliably as possible. All of these matrices are then combined into one, the so-called direct relation matrix, A (input of the next step of the method). If only one expert is involved, matrix X will coincide with matrix A.
- Computing the normalised direct relation matrix N as:

$$N = sA, \tag{6}$$

s representing a positive integer slightly smaller than:

$$\min\left[\frac{1}{\max\limits_{1\le i\le n}\sum_{j=1}^{n} x_{ij}}, \frac{1}{\max\limits_{1\le j\le n}\sum_{i=1}^{n} x_{ij}}\right]. \tag{7}$$

Matrix N depicts the initial effect that components exert on and receive from one another. The next stage is to get a continuous decrease of indirect effects among variables in terms of consecutive powers of N.

- Getting the total relation matrix, T, which gathers the total interrelationship among components, including both direct and indirect impacts, which may be computed as the sum of the powers of the normalised direct relation matrix N, provided by:

$$T = N(I - N)^{-1}, \tag{8}$$

where I is the identity matrix. One has to observe as $\lim_{n\to\infty} N^n = 0$, since the spectral radius of N is less than 1 and is restricted by the maximum row and column sum. The power series of the normalised direct relation matrix converges to $(I - -N)^{-1}$. Furthermore, it should be noted that, while the main diagonal of matrix N is filled with zeroes since, as explained before, an element has no direct impact on itself, the main diagonal of the total relation matrix T gathers all of the non-direct impacts associated with the respective components.

- Describing the two vectors $\mathbf{r} = (r_i)$ and $\mathbf{c} = (c_j)$, denoting the $n \times 1$ and $1 \times n$ vectors of sums of the rows and the columns in the total relation matrix T. Considering these two vectors, one can compute

Table 6a
DEMATEL input matrix for high risk class A.

X	PI_1	RSS_1	RSS_5	RSS_8	RSS_9	RSS_10	RSS_12	RSS_15	RSS_16	RSS_17	LSS_1	LSS_5	LSS_8	LSS_9	LSS_10	LSS_12	LSS_15	LSS_16	LSS_17
PI_1	0	3	3	1	1	0	3	1	1	0	3	3	1	1	0	3	1	1	0
RSS_1	1	0	3	3	3	3	3	2	2	2	1	2	2	2	2	2	1	1	1
RSS_5	3	2	0	2	2	2	1	1	1	1	2	1	1	1	1	0	0	0	0
RSS_8	2	1	3	0	3	3	1	1	1	1	1	2	1	2	2	0	0	0	0
RSS_9	2	1	3	2	0	3	2	1	1	1	1	2	1	1	2	1	0	0	0
RSS_10	1	1	3	2	3	0	2	1	1	1	0	2	1	2	1	1	0	0	0
RSS_12	3	1	1	2	1	1	0	0	3	3	2	0	1	0	0	1	0	2	2
RSS_15	2	1	2	1	1	1	3	0	3	2	1	2	0	0	0	2	1	2	1
RSS_16	2	1	2	1	1	1	3	2	0	3	1	2	0	0	0	2	1	1	2
RSS_17	1	1	2	1	1	1	1	2	3	0	0	2	0	0	0	0	1	2	1
LSS_1	1	1	2	2	2	2	2	1	1	1	0	3	3	3	3	3	2	2	2
LSS_5	3	2	1	1	1	1	0	0	0	0	2	0	2	2	2	1	1	1	1
LSS_8	2	1	2	1	2	2	0	0	0	0	1	3	0	3	3	1	1	1	1
LSS_9	2	1	2	1	1	2	1	0	0	0	1	3	2	0	3	2	1	1	1
LSS_10	1	0	2	1	2	1	1	0	0	0	1	3	2	3	0	2	1	1	1
LSS_12	3	2	0	1	0	0	1	0	2	2	1	1	2	1	1	0	0	3	3
LSS_15	2	1	2	0	0	0	2	1	2	1	1	2	1	1	1	3	0	3	2
LSS_16	2	1	2	0	0	0	2	1	1	2	1	2	1	1	1	3	2	0	3
LSS_17	1	0	2	0	0	0	0	1	2	1	1	2	1	1	1	1	2	3	0

Table 6b
DEMATEL input matrix for medium risk class B.

X	PI_2	RSS_2	RSS_3	RSS_4	RSS_6	RSS_7	RSS_11	RSS_13	RSS_14	LSS_2	LSS_3	LSS_4	LSS_6	LSS_7	LSS_11	LSS_13	LSS_14
PI_2	0	4	4	3	1	3	3	1	3	4	4	3	1	3	3	1	3
RSS_2	2	0	2	2	1	3	2	0	0	0	1	1	0	2	1	0	0
RSS_3	2	3	0	3	2	3	3	3	3	2	0	2	1	2	2	2	2
RSS_4	2	2	1	0	2	3	2	1	1	1	0	0	1	2	1	0	0
RSS_6	1	2	2	1	0	3	3	1	1	1	1	0	0	2	2	0	0
RSS_7	2	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0
RSS_11	2	2	3	2	1	1	0	3	3	1	2	1	0	0	0	2	2
RSS_13	1	0	2	1	1	1	1	0	3	0	1	0	0	0	0	0	2
RSS_14	2	0	2	1	1	1	1	2	0	0	1	0	0	0	0	1	0
LSS_2	2	0	1	1	0	2	1	0	0	0	2	2	1	3	2	0	0
LSS_3	2	2	0	2	1	2	2	2	2	3	0	3	2	3	3	3	3
LSS_4	2	1	0	0	1	2	1	0	0	2	1	0	2	3	2	1	1
LSS_6	1	1	1	0	0	2	2	0	0	2	2	1	0	3	3	1	1
LSS_7	2	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1
LSS_11	2	1	2	1	0	0	0	2	2	2	3	2	1	1	0	3	3
LSS_13	1	0	1	0	0	0	0	0	2	0	2	1	1	1	1	0	3
LSS_14	2	0	1	0	0	0	0	1	0	0	2	1	1	1	1	2	0

Table 7
DEMATEL results.

Class A: HIGH RISK				Class B: MEDIUM RISK			
ID	$r_i + c_i$	$r_i - c_i$	Ranking position	ID	$r_i + c_i$	$r_i - c_i$	Ranking position
PI_1	6.8649	-0.5896	1st	PI_2	5.0521	0.6556	1st
RSS_1	6.5265	0.9876	3rd	RSS_2	3.5946	-0.0669	5th
RSS_5	6.5564	-1.1123	2nd	RSS_3	4.4026	0.4313	2nd
RSS_8	5.6600	0.0889	7th	RSS_4	3.6040	0.0098	4th
RSS_9	5.7838	-0.0397	5th	RSS_6	3.3846	0.3366	8th
RSS_10	5.5247	-0.1170	8th	RSS_7	3.5146	-0.6614	6th
RSS_12	5.9712	-0.3207	4th	RSS_11	4.0056	0.1520	3rd
RSS_15	5.1112	0.7988	9th	RSS_13	3.3186	-0.1777	9th
RSS_16	5.7361	0.1284	6th	RSS_14	3.4807	-0.3515	7th
RSS_17	5.0962	-0.1193	10th	LSS_2	3.5946	-0.0669	5th
LSS_1	6.5265	0.9876	3rd	LSS_3	4.4026	0.4313	2nd
LSS_5	6.5564	-1.1123	2nd	LSS_4	3.6040	0.0098	4th
LSS_8	5.6600	0.0889	7th	LSS_6	3.3846	0.3366	8th
LSS_9	5.7838	-0.0397	5th	LSS_7	3.5146	-0.6614	6th
LSS_10	5.5247	-0.1170	8th	LSS_11	4.0056	0.1520	3rd
LSS_12	5.9712	-0.3207	4th	LSS_13	3.3186	-0.1777	9th
LSS_15	5.1112	0.7988	9th	LSS_14	3.4807	-0.3515	7th
LSS_16	5.7361	0.1284	6th				
LSS_17	5.0962	-0.1193	10th				

the prominence as the sum $r_i + c_i$, which reflects the overall influence of element i on all the other elements, and the relation as the subtraction $r_i - c_i$, which aids in categorizing the elements as cause (if positive) or effect (if negative).

- Building the influence chart prominence-relation when required, and determining the final ranking of components according to their decreasing value of prominence.

4. Case study: a complex service system subjected to PrdM

The present case study aims to demonstrate the practical usefulness of coupling the FMECA technique with the proposed integrated MCDM approach for a core subsystem belonging to a complex service system subjected to PrdM. The ELECTRE TRI is going to be applied as an alternative way to traditional RPN, aiming at overcoming some of its drawbacks. Instead of merely ranking failures according to their RPN values, ELECTRE TRI will proceed by sorting failures into risk priority classes. In such a way, those set of failures in direct need of maintenance will be immediately highlighted according to their specific categories. This approach will promote a more efficient maintenance management by easing the execution of interventions. The discussed procedure will also permit to attribute diverse degrees of importance to the FMECA risk factors, something that it is not considered by the traditional procedure. Once failures have been assigned to classes, the DEMATEL technique will make use of opinions provided by the expert in charge of maintenance about relationships bounding pairs of failures. The purpose is to highlight, within each class, those failures associated with a higher degree of interdependence with the other ones, whose direct management can concur to minimise the probability of occurrence of other dependent failures. The main advantage of the proposed approach hence consists in finding, for each priority class, the failure modes characterised by higher prominence. Direct interventions on these specific failure modes contribute to the global enhancement of system conditions and to the optimisation of maintenance in integration with the PrdM policy applied for the system.

4.1. System description

The complex system herein analysed is a vehicle deputed to provide street cleaning services. The vehicle is made of five main elements, that are two components, 1) integral power take-off (PTO) and 2) oil tank, and three main subsystems, 3) moving system, 4) sweeping and funnelling system, and 5) loading-up and emptying system. An exhaustive functional description is provided in Table 2. The failure of even one of these five main elements would imply the failure of the whole system, so that reliability connections can be considered as in series (Fig. 3).

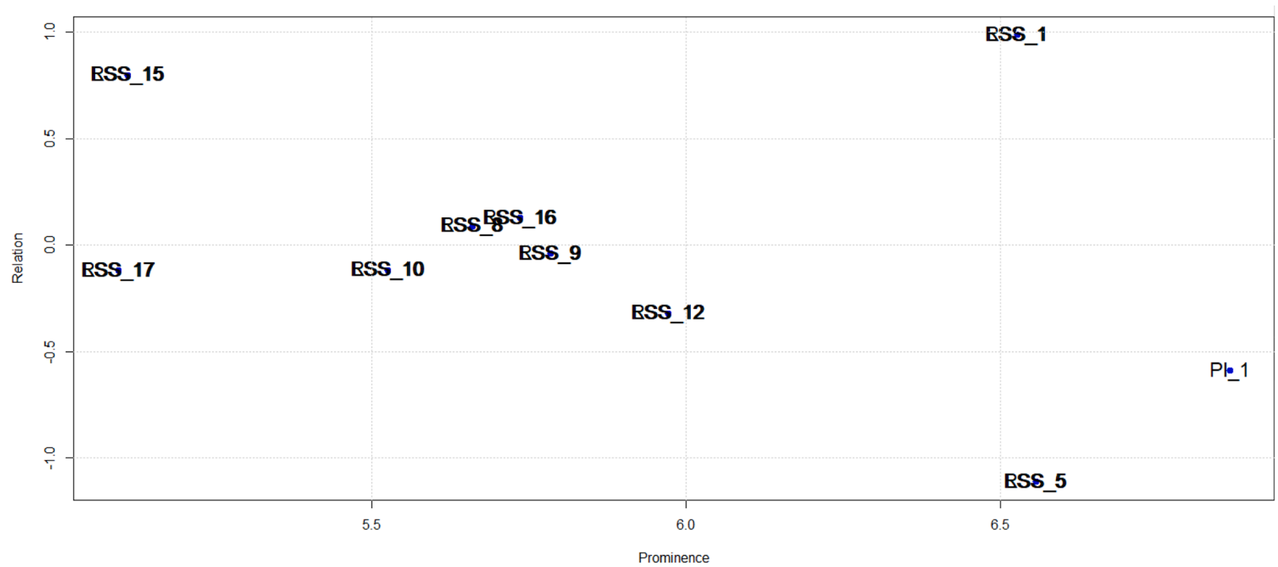
Complete block diagrams detailing the whole set of components and the structure of the system have been elaborated in previous works of research [84,85]. Three critical components to be monitored by sensors to lead interventions of PrdM have been specifically identified in [85]. These three elements are three hydraulic pumps (pump I, pump II, pump III), fundamental to guarantee the functioning of the most important sweeping elements along with the loading-up and emptying systems. Acceleration has been established as the parameter correlated to the wear state of pumps to be measured by a proper network of sensors. A further analysis carried out in [80] indicated as failures potentially involving pump I have associated higher degree of priority of intervention with respect to failures potentially involving pumps II and III.

Given such a result, the present case study focuses on the core subsystem directly ruled by the functioning of pump I, that is subsystem 4.2 (hydraulic circuit and sweeping elements), whose hierarchical structure is reported in Fig. 4. Fig. 5 shows the detailed reliability diagram of the "Right-side system", being the "Left-side system" composed by the same type of components in a symmetrical way. It is immediate to observe as subsystem 4.2 is particularly crucial for avoiding any undesirable service shutdown.

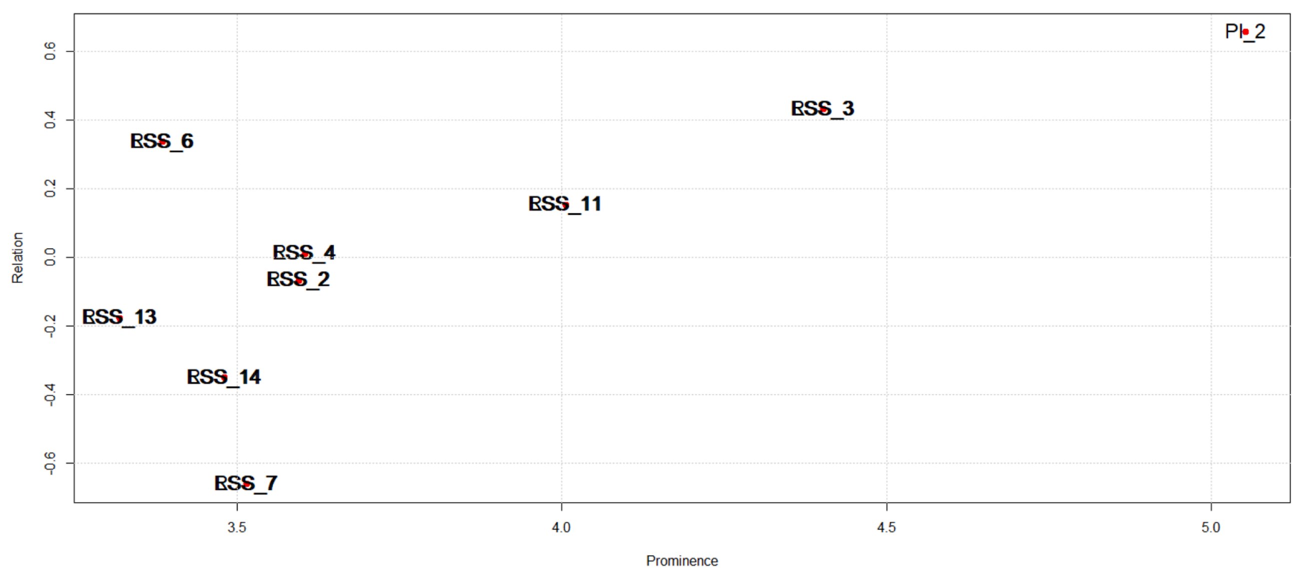
The next subsection is going to first carry out the FMECA analysis and secondly apply the integrated MCDM approach to treat the list of failure modes along with their evaluations.

4.2. FMECA analysis and integrated MCDM approach

Once all the components have been exhaustively identified, Table 3 analyses the failure of the elements located at the lowest levels of the structure of the analysed subsystem. The possible failure modes have been evaluated for each component along with their related failure causes and effects, the last ones referring both to single components and to the system level. Table 4 reports the quantitative evaluation of the three FMECA factors, established within the discrete range of values [1–3] thanks to the support of the technician in charge of the vehicle maintenance. In particular, the stage of input data collection has been organised by means of one-to-one meetings with the involved decision maker, that has been directly interviewed about the quantitative evaluations to be associated with the three FMECA factors for each failure mode. The expert has cooperated also to the definition of the scale of



a. DEMATEL chart with failure modes of class A (high risk)



b. DEMATEL chart with failure modes of class B (medium risk)

Fig. 6. (a) DEMATEL chart with failure modes of class A (high risk) (b). DEMATEL chart with failure modes of class B (medium risk).

values, agreeing about considering the interval [1–3] as suitable for the exhaustively represent the problem under analysis. Being in charge of the vehicle maintenance, the interviewed expert is aware of the main problematics frequently involving the system along with its core components as well as the main aspects referring to safety and security for operators.

Thirty-six failure modes have been identified and they constitute the set of alternatives for the hybrid MCDM application, while the three FMECA risk factors are herein assumed as evaluation criteria. For the sake of completeness, we herein specify that the following ELECTRE TRI application can be performed also by varying or expanding the set of criteria, for instance by taking into account such aspects referring to human factors and/or economic considerations. We are going to provide details about the evaluations of the parameters. Values of severity corresponding to 1 have been assumed for insignificant failures, that are when they may cause partial degradation of some functions without seriously affecting system and people. Values of severity corresponding to 2 have been assumed for marginal failures, that are when they may cause a drop in performance or even lead to the total degradation of some functions, without considerable damages for system and people. Values of severity corresponding to 3 have been assumed for critical failures, that are when they may seriously compromise primary operational functions and cause considerable damage to the system and its environment, with potential repercussions on people safety. Occurrence has been evaluated as 1 for remote failures, 2 for occasional failures, and 3 for probable failures. Lastly, detection has been evaluated from 3 to 1 representing, respectively, failures difficult to be detected (then concurring to higher risk conditions) and failures easily detectable (then indicating lower risk conditions).

Three classes of risk of equal width identified by two reference profiles ($b_1 = 1$ and $b_2 = 2$ for each criterion) have been taken into account for the ELECTRE TRI application, namely low (class C), medium (class B) and high risk (class A). Results of the ELECTRE TRI procedure have been double checked by means of the J-Electre-v2.0 software for multi-criteria decision aid developed by Pereira [86]. are reported in Table 5a (pessimistic procedure) and Table 5b (optimistic procedure), showing the assignment by considering different values of the cutting level λ and scenarios considering diverse weights for the risk parameter. In particular, scenario 1 attributes 50% weight to the factor of severity and the remaining 50% weight equally distributed between occurrence (25%) and detection (25%). Similarly, scenarios 2 and 3 attribute 50% weight respectively to occurrence and detection, and equal portion of 25% to the other parameters. Thresholds values have been set by leading different stages of application, until they have been considered as appropriate for the case study under analysis. The indifference threshold q_j has been assumed as equal to 0.5 and the strong preference threshold p_j to 1, while no veto threshold v_j has been taken into account for the present application. We specify that results coming from the optimistic procedure should be preferred, since it tends to assign alternatives to classes defined by higher profiles, as demonstrated in [82], which can be more effective in terms of risk evaluation and related interventions management.

In such a direction, we have considered the output of the optimistic procedure (Table 5b) as body of input information to carry out the DEMATEL application. Failure modes have been sorted into two classes, namely A and B, respectively representing high and medium risk conditions. No failure has been sorted into the low risk class C, according to the provided evaluations.

Two separated stages of DEMATEL, one for each class, have been carried out to identify the mostly influencing failure(s), potentially impacting the others. The first stage has been led by initially collecting pairwise evaluations of influence (Table 6a) from the involved expert about the set of nineteen failure modes sorted to class A. The second stage has been led on the set of the remaining seventeen failure modes sorted to class B (Table 6b). Table 7 reports the final ranking of failures within each risk class according to their decreasing values of prominence $(r_i + c_i)$. The values of relation $(r_i - c_i)$ are also reported to distinguish between causes and effects. Fig. 6a and b report the DEMATEL charts related to the two stages of the application, i.e. within each class.

4.3. Discussion of results and managerial implications

Obtained results are interesting under the practical managerial point of view and many useful considerations can be derived. First of all, FMECA representing a fundamental part of safety and risk analysis carried out by safety and risk engineers [87], suitable analyses have been led on the service system of interest. FMECA application first enables to carry out a deep system analysis, synthesising reliability relations and characterising the potential failure modes of the system, whose critical pumps I, II and III are monitored by sensors and subjected to PrdM.

Given the higher criticality of pump I emerged in the previous conference paper [80], we decided to study the portion of the system directly depending on the functioning of this component. A set of thirty-six failure modes (i.e. alternatives of the decision-making problem) has been identified by FMECA and the proposed hybrid MCDM has been applied to further optimise maintenance management. The thirty-six failure modes have been sorted into two risk classes expressing high and medium priority of intervention by means the ELECTRE TRI method. Sorting failure modes into ordinal classes permits decision-makers to swiftly access them [88] and, moreover, confirms to be an effective alternative procedure to the traditional ranking obtained by simply ordering RPN values. Sorting failures can indeed give meaningful information allowing to immediately visualise which failure modes require priority in terms of risk management. In particular, nineteen failures have been assigned to class A (high risk class) and seventeen failures have been assigned to class B (medium risk). The method considered a further class C (low risk class), but no failure mode has been sorted there according to the evaluations provided by the involved maintenance expert. This means that all the failure modes identified by FMECA are somehow crucial for the system. In other terms, quantitative evaluations attributed to FMECA parameters does not justify the possibility to associate a low level of risk for any of the identified failure modes. By further discussing such an aspect with the expert, he explained that this is a quite prudential assumption, since it is always better to consider worst scenarios when it comes to the risk assessment of the considered subsystem. We believe that this observation can be validated as a general rule, since it would reduce the probability to underestimate the potential occurrence of some failures, by considering them as less important. Indeed, even when this may likely seem so, hidden factors may always concur to globally increase the risk evaluation at a system level. We may conclude that maintenance interventions aimed at managing risks related to the identified failures have to be carried out with high and medium-high priority and no intervention can be excessively postponed in time.

A sensitivity analysis has been led by varying the cutting level λ as well as weights of risk factors (i.e. criteria of the decision-making problem), showing no changes in final results, then confirming their robustness.

Again, differently from traditional FMECA, the possibility to consider different degrees of importance for severity, occurrence and detection is a strength of our approach, and other criteria may be added to the analysis. Once failures have been sorted, the DEMATEL procedure has been applied to depict the causal dependencies [87] and identify the most significant alternatives within each class. These failures directly impact on the occurrence of other failures belonging to the class of reference and their management implies global risk minimisation.

Regarding class A (high risk), the method indicates that such failures as PI_I (fault distribution system in Pump I), RSS_5 (mechanical fault of start-up engine of right-side brush), LSS_5 (mechanical fault of start-up engine of left-side brush), RSS_1 (sweeping elements not lubricated through right-side distributor) and LSS_1 (sweeping elements not lubricated through left-side distributor) require immediate priority. It is also possible to note that, among the failures indicated, RSS_1 and LSS_1 can be considered as causes, the remaining ones as effects.

Their prompt management would be aimed at reducing the probability of occurrence of such related failures as, for instance, RSS_12 (mechanical fault of start-up engine of right-side roller), LSS_12 (mechanical fault of start-up engine of left-side roller), RSS_9 (worn journal boxes of right-side brush) and LSS_9 (worn journal boxes of left-side brush). Moreover, this could have a positive influence on pump I subjected to PrdM, upgrading its functioning state and optimising the related maintenance cost.

Similarly, the method indicates that such failures as PI_2 (mechanical fault in pump I), RSS_3 (mechanical fault of right-side hydraulic cylinders), LSS_3 (mechanical fault of left-side hydraulic cylinders), RSS_11 (stopped start-up engine of right-side roller) and LSS_11 (stopped start-up engine of left-side roller) require priority when leading interventions for managing failures belonging to class B (medium risk). The method indicates that these failures can be considered as causes, according to the positive values of prominence $(r_i - c_i)$.

Summing up, it is clearly demonstrated as interventions aimed at optimising pump I, critical component subjected to PrdM, but also the engines ruling the sweeping elements as well as their lubrication are crucial for keeping the complex system object of study in effective functioning state, maximising its level of performance over its lifecycle. According to the MCDM application, focusing on these specific failures would also imply the reduction of the probability of occurrence of the other failures belonging to the same category. The failures highlighted as most critical are indeed the ones whose occurrence may likely impact the occurrence of all the other failures.

5. Conclusions and future developments

The present research focuses on the topic of complex systems subjected to PrdM and, in particular, proposes a MCDM methodological combination aimed at improving such traditional methods of risk analysis as approaches based on FMECA technique. The last one can be very useful to deeply characterise complex systems, by getting awareness of meaningful reliability issues and critical aspects related to components with a great level of detail. However, the phase of risk evaluation by RPN can be further improved.

In such a direction, our procedure proposes to first apply FMECA by characterising specific boundaries of analysis, i.e. by focusing on those subsystems directly related to the critical component(s) subjected to PrdM. Once identified failure modes along with related causes and effects, a hybrid MCDM procedure making use of ELECTRE TRI and DEMATEL is integrated with FMECA results to 1) sort failures into risk classes and 2) identifying the most influencing failure mode(s) within each class. Risk parameters used for the calculation of traditional RPN are herein considered as evaluation criteria of the decision-making problem, and different scenarios considering diverse degrees of importance are taken into account. The method has been extensively applied to a real service system, offering managerial insights and testing the validity of the approach. In particular, we analysed a core subsystem belonging to a vehicle deputed to provide street cleaning service, whose core components are subjected to PrdM. After having identified and assessed thirty-six failure modes, they have been sorted to classes representing high and medium risk conditions. Two separated stages of DEMATEL have been led to eventually highlight the most interdependent failures within each class. Findings show as interventions aimed at optimising one of the hydraulic pump as well as the engines ruling the sweeping elements along with proper lubrication activities are crucial for optimising the whole system. Focusing on the most influencing failures would also prevent the potential occurrence of other related failures.

Future lines of development may regard the integration of the fuzzy set theory to manage input data and reduce uncertainty of subjective evaluations. In addition, the use of Bayesian Networks can be integrated to model and represent conditional dependence, and therefore causation, by edges in a directed graph. This model may integrate human factors as main elements of analysis, by considering the experience of human resources when leading their tasks as well as the expected probability of human error.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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