A decision support system to assure high-performance maintenance service

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Abstract

Purpose – This study aims to propose a decision support system (DSS) for maintenance management of a service system, namely, a street cleaning service vehicle. Referring to the information flow management, the blockchain technology is integrated in the proposed DSS to assure data transparency and security.

Design/methodology/approach – The DSS is designed to efficiently handle the data acquired by the network of sensors installed on selected system components and to support the maintenance management. The DSS supports the decision makers to select a subset of indicators (KPIs) by means of the DEcision-MAaking Trial and Evaluation Laboratory method and to monitor the efficiency of performed preventive maintenance actions by using the mathematical model.

Findings – The proposed maintenance model allows real-time decisions on interventions on each component based on the number of alerts given by sensors and taking into account the annual cost budget constraint.

Research limitations/implications – The present paper aims to highlight the implications of the blockchain technology in the maintenance field, in particular to manage maintenance actions' data related to service systems.

Practical implications – The proposed approach represents a support in planning, executing and monitoring interventions by assuring the security of the managed data through a blockchain database. The implications regard the monitoring of the efficiency of preventive maintenance actions on the analysed components.

Originality/value – A combined approach based on a multi-criteria decision method and a novel mathematical programming model is herein proposed to provide a DSS supporting the management of predictive maintenance policy.

Keywords Decision support system, Predictive maintenance, Key performance indicator, Maintenance planning

Paper type Case study

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1. Introduction and research objectives

Blockchain distributed ledger technology is considered as one of the most promising technologies of the new economy (Savelyev, 2018). Swan (2018) defines blockchain as "a software protocol for safely transferring via Internet items of value without the intermediation of a third-party such as a bank or government". As expressed by Yang (2019), blockchain technology is particularly helpful to authenticate, record and keep information updated by guaranteeing its safe diffusion. Hebert and Di Cerbo (2019) describe the blockchain technology as a secure data framework that relies on such features as cryptographic hash, digital signature and distributed consensus mechanism, to be implemented on the basis of a peer-to-peer (P2P) network of nodes, without any trust assumption among them.

Singh and Singh (2016) suggest Bitcoin (Blockchain 1.0) as the genesis of the Blockchain application, which then developed toward smart contracts (Blockchain 2.0), and later headed to application related to the effective management of coordination and justice (Blockchain 3.0). As underlined by Vranken (2017), the main application of blockchain regards the electronic currency bitcoin, whose ecosystem is a network of users communicating with each other via the internet by means of a dedicated protocol.

Casino *et al.* (2019) provide a systematic literature review by analysing blockchain applications in various and different areas.

Morkunas *et al.* (2019) focus on general managers' and executives' perspective underlining the positive impact of blockchain on business models above all in terms of competition and operation. Chen (2018) stresses the significant support given by the blockchain technology to the world of entrepreneurship and innovation, as innovators can generate digital tokens to characterise and democratise a wide range of assets. Within this perspective, the use of the blockchain technology is particularly appropriate for innovative industrial and service systems, which must guarantee continuous operation.

Savelyev (2018) asserts that value exchanges are sequentially grouped into blocks – with each block chained to the previous one and recorded in a P2P network through mechanism based on assurance and cryptographic trust. In such a way, the author defines blockchain as a provider of a new system for storing data safely, without the need of intermediate actions from a central authority. He also stresses the most important advantages of this technology: transparency (all recorded information is shared), redundancy (each stakeholder owns a copy of the data of interest), immutability (formal consensus necessary to make any change on records has to be expressed and shared by all the involved parts) and disintermediation (thee are no costs related to the presence of intermediaries).

Blockchain plays also an important role in the internet of things (IoT) applications. As stressed by Khan *et al.* (2020), smart devices used in smart industry generate a huge amount of data. The data generated by IoT devices can be analysed and processed for performance monitoring, anomaly detection, diagnosis, predictive maintenance, asset monitoring, tracking of the complete product lifecycle from raw material to finishing goods and delivery to end consumers. However, sharing this important data with all entities involved in the process, in a secure manner, is a very challenging task. The characteristics of blockchain technology (distributed nature, traceability, survivability, trust, tamper resistance, security, inherent data provenance) make it suitable for IoT applications.

As recently highlighted by Qin *et al.* (2020), transforming the industrial internet platform through the blockchain technology can avoid data loss and tampering caused by attacks on a single data centre and improve data security of the platform. An interesting research discusses also challenges and future directions for research in privacy preservation of blockchain-based IoT systems (Hassan *et al.*, 2019) and proposes five privacy preservation strategies: anonymisation, encryption, private contract, mixing and differential privacy.

Liu *et al.* (2020) asserted that the blockchain technology provides an open but secured information storage and exchange platform for multiple stakeholders to achieve the openness, interoperability and decentralisation in era of Industry 4.0. Industry 4.0 is commonly referred to the Fourth Industrial Revolution by incorporating various emerging technologies, including cyber-physical systems, IoT, artificial intelligence and cloud computing, for developing open, secured and smart factories. The research shows as blockchain technology helps in obtaining the above-mentioned goals, illustrating a blockchain-based application between the cooperating partners in four emerging product lifecycle stages: co-design and co-creation, quick and accurate tracking and tracing, proactive maintenance and regulated recycling.

Blockchain technology is clearly functional in many fields of applications, such as data storage, supply chain management, security in missions, intelligent service systems; the latter investigated in the present research. The novelty of the present research is the exploitation of a new blockchain challenge: the integration between the blockchain technology and one of the most important organisational functions (Lopes *et al.*, 2016), namely, maintenance management for a service system. With relation to the field of maintenance, taking up this challenge allows to simultaneously optimise objectives as system reliability and availability, by assuring the safe collection of data (Ruschel *et al.*, 2017). In many cases (Madureira *et al.*, 2017; Carpitella *et al.*, 2016), according to the organisational maintenance policies, prioritising failures or anomalies is strategic for scheduling maintenance interventions and reducing risks.

Good maintenance planning is essential to increase the level of competitiveness of enterprises and to better synchronise interventions and production operations (Colledani *et al.*, 2018). Typically, a strategic maintenance plan of interventions requires an effective combination between actions implementation and performance control. Monitoring effects of maintenance actions when implementing maintenance policies is indeed fundamental and the support given by key performance indicators (KPIs) is strategic.

Given the useful contribution of blockchain technology in recording exchanges and managing information, this paper proposes the challenge of implementing preventive maintenance policies for service systems by promoting prompt actions from maintenance crews.

The challenges in terms of data collection, data analysis and decision-making in the maintenance field are stressed by Lai *et al.* (2019). With relation to a real-world business (elevators' maintenance), the authors suggest that condition-based maintenance (CBM) can be commercialised via IoT, resulting in improvement of safety and reliability of equipment. Sarmah and Moharana (2015) developed a Web-based multi-criteria fuzzy rule model for better management of maintenance. Basri *et al.* (2017) provide a very interesting review on preventive maintenance by showing the effectiveness of approaches based on artificial intelligence, simulation, mathematical formulation and multi-criteria methods.

A combined approach based on a mathematical formulation and multi-criteria methods to support the maintenance management of a service system is proposed in this paper.

In the present paper, we investigate the topic of maintenance management, with a special focus on predictive maintenance supported by blockchain technology for maintenance records storage and exchange. We propose a case study of a system taking on a fundamental role in order to assure the required readiness during service supply, guaranteeing security and transparency of data when exchanging between the two main stakeholders involved. The main objective of the research consists of building a decision support system (DSS) supported by blockchain technology, which can be considered as a driver in implementing maintenance actions and an effective tool in evaluating maintenance performance.

In detail, this work consists of a DSS that considers interdependencies among the evaluation criteria by providing a support during the phases of scheduling and implementation of interventions. The DSS is proposed for a particular service system: an innovative street cleaning vehicle endowed with a smart remote diagnosis system. The proposed DSS involves experts and decision makers to check the efficacy of the deployed predictive maintenance policy, and it is supported by data sensors and blockchain technology. The mentioned DSS is based on a maintenance mathematical model, acquiring data through a blockchain database, leading to the calculation of performance indicators representing important drivers in maintenance intervention scheduling.

In particular, the DEcision-MAaking Trial and Evaluation Laboratory (DEMATEL) methodology (Fontela and Gabus, 1974) is used to support the selection of a representative set of indicators by taking into consideration the degrees of interdependency among them. Maintenance indicators were investigated in a previous research (Carpitella *et al.*, 2018a) where the DEMATEL method was applied to evaluate the interdependencies existing within the decision problem.

We point out that the latter is a fundamental advantage in order to use indicators that well measure the critical aspects for the analyst. These indicators represent drivers when making decisions on the maintenance actions using a mathematical model. The model uses Boolean variables to produce a consensus (or not) for the implementation of interventions. The literature offers different examples in which in a DSS, including blockchain technology, the interdependency among evaluation criteria is not modelled.

Farshidi *et al.* (2020) recently proposed an interesting study in which they investigated on the decision-making approaches that researchers have employed to address the blockchain platform selection problem. Among these approaches, methods as analytic hierarchy process (AHP) (Saaty, 1994) or Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon, 1981), in which the criteria are assumed independent, are indicated as preferable. Çolak *et al.* (2020) evaluate the appropriateness of blockchain technology in supply chain management in different areas by using a multi-criteria decision methodology based on hesitant fuzzy sets (HFSs). The weights of main and sub-criteria have been obtained through hesitant fuzzy AHP (HF-AHP), and the alternatives have been ranked according the HF-TOPSIS method that do not consider such a type of interdependency.

To demonstrate the usefulness of our approach, we propose its application to subsystems requiring predictive maintenance as the cleaning service vehicle presented in Carpitella *et al.* (2018b). Such a vehicle is endowed with an intelligent system for monitoring the information flow related to critical components. These components had been previously identified by combining the failure mode, effects and criticality analysis (FMECA) (EN 60812 Standard, 2006) with a multi-criteria approach establishing maintenance priorities (Certa *et al.*, 2017). In this context, similarly to the previously cited research of Hasan *et al.* (2019), the blockchain solution is proposed to manage interactions between the maintenance crew and the subject in charge of the cleaning service vehicle. In particular, information flow refers to components' reliability. The items of the vehicle are equipped with sensors tracking and monitoring operational conditions, e.g. degradation conditions correlated to vibration and monitored by vibration sensors. These data will be acquired in the DSS, which will be able to suggest and prioritise the maintenance actions to be implemented and then to evaluate the performance of the maintenance actions by means of a subset of indicators opportunely selected within a wider set.

The present paper is organised as follows: Section 2 discusses the advantages of blockchain technology by describing its main features and comparing it to traditional approaches, with a special focus on industrial maintenance management. Section 3 illustrates the proposed decision support system. The description of a case study is reported in Section 4, and lastly, Section 5 concludes the work.

2. The role of blockchain technology in the maintenance field: a new challenge

In this section, we investigate the use of the blockchain technology, firstly, in general industrial problems and applications and then focusing on a service system.

Chowdhury *et al.* (2018) carry out a very interesting comparison between blockchain and database technologies. They underline that the core of blockchain technology is a data framework keeping the realised transactions recorded in the network. The special feature distinguishing blockchain from other existing technologies is the immutability of the stored records. To achieve such feature, special mechanisms of consensus and cryptography are used. On the basis of the stored data in distributed nodes, blockchain technology is also known as distributed ledger technology (DLT).

Pilkington (2016) emphasises how blockchain technology aims to develop a decentralised environment without the need of transactions control from a third party. In general, blockchain can be thought as a time-stamped chain of blocks simultaneously maintained by all participating nodes. Blocks are basically containers aggregating transactions and are cryptographically chained together. In other terms, each block is digitally signed and "chained" to the previous one by including that block's hash value. New blocks can be appended just to the end of the chain; thus, the blockchain provides an immutable data storage because existing transactions cannot be updated nor deleted. For this reason, many systems built on the blockchain technology achieve secured distribution of digital assets among untrusted clients.

Longo *et al.* (2019) recently designed and developed a software connector module aimed at bridging a blockchain information system with a generic enterprise information system so that companies are enabled to send data to blockchain and check their authenticity, integrity and immutability over the time. This study highlights some advantages of blockchain technology with respect to other information systems: distributed consensus on the chain state (distributed consensus is formalised on the chain state without any trusted third party), immutability and irreversibility of chain state (formal consensus is achieved among a large number of nodes by ensuring that the chain state becomes practically immutable and irreversible), data (transaction) persistence (data are stored in a distributed manner, ensuring its persistency as long as there are nodes participating in the P2P network), data provenance (each transaction is digitally signed by using public key cryptography, which validates the source of data), distributed data control (blockchain guarantees that data in the chain are stored in a distributed manner without a single point of failure), accountability and transparency (the state of the chain and each single interaction among participants can be verified by any authorised entity, promoting the high transparency of transactions).

With relation to P2P networks, Backman *et al.* (2017) report the following six-step description for the running process of a P2P network (e.g. a Bitcoin network): "(1) new transactions are broadcasted to all the other nodes; (2) each node gathers the received new transactions into a block; (3) each node elaborates a proof-of-work for the formed block; (4) when a node finds a proof-of-work, the block can be broadcasted to all the other nodes; (5) nodes accept the block only if all the transactions reported on it are valid and not already spent; (6) nodes formally accept the block by creating the next block in the chain, using the hash of the accepted block as the previous hash". Undoubtedly, using a programmable framework for the reliable interchange of information flow effectively supports exchanges between any two parties. Indeed, P2P collaborative networks of companies and individuals may strengthen their mutual interests, and this represents the objective to be optimised in complex systems management.

Sikorski *et al.* (2017) emphasise blockchain is a type of distributed electronic database (ledger) that can hold any information by setting rules about how updating them. It continually grows, as blocks (files containing data) are appended and chained to the previous block though a hash. In particular, the authors explore applications of blockchain technology to Industry 4.0 and present an example where blockchain is employed to facilitate machine-to-machine (M2M) interactions in the particular context of the chemical industry. M2M communication refers to the ability of industrial components to communicate with each other.

As asserted by Rathee *et al.* (2019), the blockchain technology can be applied to various cases and fields and, in industrial contexts, its role is particularly crucial because it allows to keep transparency among workers, by tracing each activity of all entities through IoT devices stored in the blockchain.

It is clear that blockchain-based storage system allows to store data in a fully secure and permanent way, making almost null the risk of information leaks or data tampering. Figure 1 describes the evolution of electronic data interchange (EDI) for traceability systems, from a centralised infrastructure to a cloud-based storage system to a blockchain-based infrastructure.

The recent introduction of blockchain technology represents a disruptive innovation because it allows tamper-proof data management for the first time in the history of information and communication technology (ICT) systems. As widely expressed before, the immutable nature of blockchain environment ensures indeed, on the one hand, the verification of the approved records by anyone in any moment and, on the other hand, the impossibility to make any modification once they are stored. Thanks to its immutable nature and without the need of relying on certification from third party, blockchain technology offers the great possibility of securing electronic information, enabling the reliable storage of traceability data on a global scale. With such premises, blockchain seems to be the only technology that can effectively respond to fraudulent attempts of data tampering in the industrial sector.

Yampolskiy *et al.* (2018) treat the topic of blockchain with regard to security of additive manufacturing (AM). The authors emphasise AM is increasingly growing, mainly to manufacture functional parts, including components of safety critical systems in aerospace, automotive and other industries.

Within the industrial context, as asserted by Miller (2018), a blockchain and IoT solution would support in preventing and predicting possible failures involving manufacturing plant equipment. In other terms, such a solution would support the preventive maintenance management, as in the case of the service system analysed in this paper. Equipment sensors would detect such particular conditions as excessive vibration or heat, which may lead to failures or injuries for operators. Sensors capture key threshold data captured by sensors is sent to the blockchain and can be used for the detection of trends of failures and to facilitate proactive maintenance and repair actions before failure occurrence. Third-party repair partners could monitor the blockchain for preventive maintenance and record their work on the blockchain.

As previously asserted in the introduction, the present paper focuses on preventive maintenance, and in particular, it aims to investigate the advantages gained by integration of blockchain technology. Specifically, in the proposed real case study, sensors are employed to monitor devices (that are the critical components) of a real complex system (i.e. a cleaning service vehicle). The acquired data are securely managed by means of a DSS in order to suitably perform maintenance actions.

The use of sensors refers to the predictive maintenance policy, which, according to Raza and Ulansky (2017), represents the most promising strategy for technical systems and production lines. This type of policy can be applied whenever a deteriorating physical parameter such as vibration, pressure, voltage or current can be quantitatively measured to support predictive maintenance and then to contain costs and avoid dangerous situations. Dong *et al.* (2017) develop a predictive maintenance IoT and affirm that they are indispensable for capturing various types of signals (thermal, mechanical, optical, electrical, acoustic and so on) and providing processing, transmission and analysis information, as well as feedback.

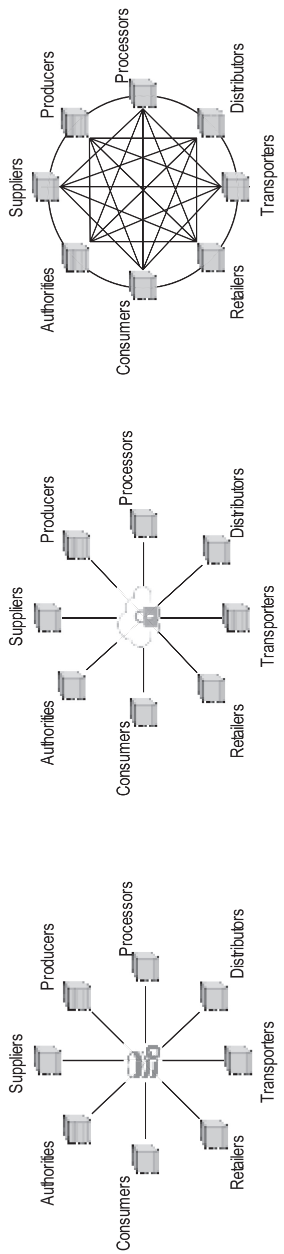

Figure 1.
Evolution of EDI systems

3. The proposed decision support system

The proposed DSS is based on the DEMATEL methodology, suggested to select the most suitable KPIs (from a list of possible KPIs) to support predictive maintenance implemented by means of a mathematical model. Thus, after a detailed description of the KPIs, this section is developed by describing the selection procedure and the mathematical model proposed to manage maintenance actions.

In particular, the model is a predictive maintenance mathematical model that suggests the scheduling of maintenance actions by taking into account the data acquired by sensors.

An exhaustive description of the concept of predictive maintenance is given by Forsthoffer (2017), which defines this kind of policy as based on monitoring components in order to acquire data on important parameters (e.g. temperature or vibration). The collection of these data is aimed at predicting the root cause of change in operational conditions before failures occur, and so, avoiding unnecessary interventions of preventive maintenance.

Nguyen *et al.* (2015) demonstrate the efficacy, also in terms of cost savings, of predictive maintenance in managing interdependencies and in reacting to changes related to the deterioration state (especially for critical components).

De Benedetti *et al.* (2018) underline the usefulness of techniques aimed at detecting anomalies in a timely manner and affirm that the availability of daily predictive maintenance alerts would perfectly meet the need for promptly reacting and planning maintenance interventions. Lindberg *et al.* (2015) consider the number of alarms over a period of time as a KPI for the maintenance area. The authors also enumerate a list of KPIs that could be used to monitor operative conditions of systems and predict when maintenance will be required (heat transfer rate in heat exchangers, pump efficiency, equipment wear and vibration amplitude as measured for predicted performance.) These factors are considered in the proposed case study of Section 4, which deals with an innovative street cleaning vehicle fitted with an intelligent telediagnosis system. This system was designed within a project carried out by the University of Palermo in collaboration with other organisations and developed in a previous research (Carpitella *et al.*, 2018b).

When accomplishing the process of maintenance monitoring, the advantages deriving from the use of KPIs are potentiated through the presence of a network of sensors monitoring the state of wear of critical components. As underlined in Carpitella *et al.* (2018a), a KPI-based assessment enables critical, synthetic, significant and key information to be obtained by measuring the main results of the maintenance actions on the overall system. Given the wide variety of indicators, a structured methodology is suggested to select the most representative indicators in Fangucci *et al.* (2017).

Measurements of indicators can be summarised into three main categories: cost, time and quality measurements. In Carpitella *et al.* (2018a), we proposed to evaluate the relationships among some of the main KPIs related to the topic of maintenance, as reported in a study led by Gonzalez *et al.* (2017). The result was the selection of five KPIs whose variations can correspond to variations of all the monitored aspects. They are in order: total downtime, percentages of schedule compliance, total annual maintenance cost, number of interventions and equipment reliability. These indicators refer to the general aspects of maintenance monitoring. Our aim consists in enlarging the previously set of five KPIs, specifically including those related to predictive maintenance (mentioned by Lindberg *et al.*, 2015) and select the most suitable KPIs. Table 1 summarises the considered KPIs. Specifically, the DEMATEL method is herein proposed to select those KPIs to be used to monitor the efficiency of preventive maintenance actions for the analysed components.

The state of critical components can be monitored by means of a suitable network of sensors. The check of the service state of the vehicle is based on the measurements provided by the selected indicators. The use of blockchain technology to store and share the value of indicators simultaneously assures data transparency and reliability.

Table 1. List of maintenance KPIs

N	ID	KPI	Description
1	SC	Schedule compliance (%)	Ratio between scheduled maintenance tasks completed in time and total number of tasks
2	CEF	Component efficiency	Measured by efficiency of specific components (*i.e.* heat transfer rate of heat exchangers and so on)
3	NA	Number of alarms	Number of predictive maintenance alerts in a time period
4	ER	Equipment reliability	Ability of equipment to perform given conditions for a given time interval
5	TD	Total downtime	Time the system is down over total monitoring time
6	NI	Number of interventions	Scheduled and unplanned interventions to lead in management strategies
7	SW	System wear	System functioning conditions and mainly based on operating hours, speed, load, vibration amplitude of equipment and so on
8	AMC	Total annual maintenance cost vs annual maintenance budget (%)	Used to assess if expenditure is as anticipated or higher on specific asset maintenance

Indeed, organisations rely on internal/external maintenance teams to make repairs or substitutions in complex systems, being the incorporation of blockchain technology helpful to manage the related information flow among maintenance stakeholders. A DSS integrating the DEMATEL methodology and a mathematical programming model is proposed in the next section, and the related results are formalised for a complex real-world service system in the case study section.

The DEMATEL method is used to support the selection of a representative set (from all the indicators presented in the previous section) by taking into consideration the degrees of interdependency among them. These indicators represent drivers when making decisions on maintenance actions by using a mathematical model. The model uses Boolean variables to produce a consensus (or not) for the implementation of interventions.

The implementation of the DEMATEL methodology can be broadly summarised through four steps (Tafreshi *et al.*, 2016) described next, summarised in Figure 2 and then described in detail. The goal of the problem and the main considered elements must be identified with the help of experts.

Step 1 – building the direct relation matrix, A

The first step must be implemented after producing as input data the non-negative matrices $X^{(k)}, 1 \leq k \leq H$, where H is the number of involved experts issuing judgments concerning the mutual influence between pairs of elements. The elements $x_{ij}^{(k)},\ i, j = 1, .., n$, where n is the number of compared elements of matrices $X^{(k)}$ are the numerical values encoding the judgments. The numerical value meanings for a typical element $x_{ij}^{(k)}$ are defined as: 0 (no influence), 1 (very low influence), 2 (low influence), 3 (high influence), 4 (very high influence). The main diagonal of each matrix is filled with zeroes.

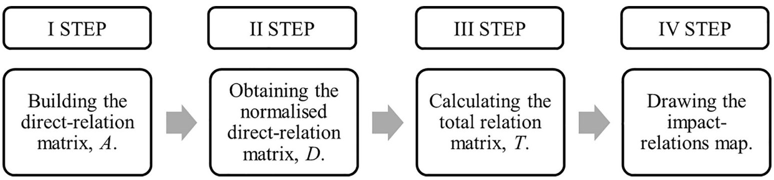

Figure 2. Steps for implementing the DEMATEL methodology

Lastly, the output of this step is the calculation of the direct relation matrix A, aimed at incorporating the matrices filled in by the experts. A is a $n \times n$ square matrix whose entries a_{ij} are obtained by:

$$A = \frac{1}{H} \sum_{k=1}^{H} X^{(k)}. \tag{1}$$

Step 2 – obtaining the normalised direct relation matrix, D

The second step consists in building the normalised direct relation matrix from the direct relation matrix obtained as output in the previous step. The normalised matrix is calculated as $D = s\ A$, s being given by:

$$s = \min \left[\frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} a_{ij}}, \frac{1}{\max\limits_{1 \le j \le n} \sum_{i=1}^{n} a_{ij}} \right]. \tag{2}$$

Step 3 – calculating the total relation matrix, T

The third step of the procedure is aimed at incorporating direct and indirect effects, through the calculation of the total relation matrix T, obtained as the sum of the series of powers of D, given by:

$$T = D(I - D)^{-1}; \tag{3}$$

I being the identity matrix of the suitable order. Equation (3) follows from equation (2) and the definition of D. One has to consider that $\lim\limits_{n \to \infty} D^n = 0$, because the spectral radius of matrix D is smaller than 1. Then, as observed by Meyer (2000), the power series of the normalised direct relation matrix converges to $(I\text{–}D)^{-1}$. To note, the main diagonal of matrix D is filled with zeroes (expression of no direct effect of each element on itself), whereas the diagonal entries of the total relation matrix T collect all the non-direct effects related to their corresponding factors.

Step 4 – drawing the impact-relations map

The fourth step aims to obtain a causal diagram by previously defining r_i and c_i as $n \times 1$ and $1 \times n$ vectors, respectively, representing the sum of rows and sum of columns of the total relation matrix T. In particular, r_i represents both direct and indirect effects of element i on the others, whereas c_i summarises both direct and indirect effects of the other elements on element i. In this way, the sum $r_i + c_i$ gives the overall effect of element i, and the subtraction $r_i - c_i$ helps in dividing the elements into cause and effect groups. As generally assumed, the elements are grouped into the cause group if the subtraction is positive and into the effect group otherwise.

The output consists in drawing an impact-relation map indicating noticeable given and received influences among elements. The chart is obtained by mapping the dataset of $(r_i + c_i,\ r_i - c_i)$ after establishing a proper threshold to avoid also considering negligible effects. The threshold value is determined as the average value of the elements belonging to T, as a method suggested by Sara *et al.* (2015) among other possible ways proposed in literature (see, for instance, Azadeh *et al.* (2015) or Lee *et al.* (2013)). We stress the importance of the process of threshold determination because, on the one hand, values too high may cause the exclusion of important factors from analysis, and on the other hand, values too low may lead to the inclusion of irrelevant factors, which may unnecessarily complicate the problem.

With relation to the maintenance KPIs of Table 1, their ranking has been achieved by using the DEMATEL, and a case study involving three experts ($H = 3$) was developed. These experts are managers in the technical area, which were asked to fill in the three non-negative matrices (Tables 2–4). Such an approach is useful to translate technical skills acquired by the experts to maintenance management. The direct relation matrix A aggregating expert judgments and total relation matrix T are, respectively, reported in Tables 5 and 6, whereas the final chart of interdependencies among the three selected KPIs (considering a threshold fair to 0.802) is shown in Figure 3. Relations with and among the other KPIs, despite existing, have been omitted for the sake of graphical clarity.

By observing the final ranking of KPIs, it is possible to note that the indicators TD, AMC and NA present a higher value associated with relation to the sum $r_i + c_i$. This means that their variations can correspond to variations of all the other aspects. Moreover, by considering the values of the subtraction $r_i - c_i$, the indicators TD and NA belong to the cause group, whereas the indicator AMC belongs to the effect group.

H_1	SC	CEF	NA	ER	TD	NI	SW	AMC
SC	0	4	3	3	3	4	4	4
CEF	2	0	2	3	4	3	3	3
NA	4	3	0	4	4	4	4	4
ER	3	3	3	0	3	2	4	4
TD	4	4	3	3	0	4	4	4
NI	3	3	2	3	4	0	2	4
SW	1	3	3	3	3	2	0	3
AMC	4	3	3	3	3	2	2	0

Table 2. Non-negative matrix filled in by expert H_1

H_2	SC	CEF	NA	ER	TD	NI	SW	AMC
SC	0	3	3	3	3	3	3	3
CEF	3	0	3	2	4	4	4	3
NA	3	4	0	4	4	4	3	4
ER	2	3	2	0	3	3	3	3
TD	4	3	3	3	0	4	3	4
NI	3	4	3	2	4	0	2	4
SW	4	4	4	3	4	4	0	3
AMC	4	4	4	3	4	4	3	0

Table 3. Non-negative matrix filled in by expert H_2

H_3	SC	CEF	NA	ER	TD	NI	SW	AMC
SC	0	3	3	3	4	3	4	4
CEF	3	0	2	3	3	4	3	3
NA	4	4	0	4	4	4	3	4
ER	4	3	2	0	3	3	3	3
TD	4	3	4	3	0	4	4	4
NI	2	4	4	4	3	0	2	4
SW	3	3	3	4	4	3	0	3
AMC	4	3	3	4	4	3	2	0

Table 4. Non-negative matrix filled in by expert H_3

The following preventive maintenance mathematical model has been formulated on the basis of the selected KPIs (all referred to an annual basis), with the purpose of providing a support during the phases of scheduling and implementation of interventions.

Let us consider a set of critical elements identified by means of a preliminary reliability analysis. Considering that these elements are monitored by sensors measuring parameters directly correlated to their wear state y, we indicate with m_k the value of this parameter acquired at time $t_k = k \cdot \Delta t$. By hypothesising a linear bound between m and y (Curcurù *et al.*, 2010), we have that:

$$m_k = a + by_k + \delta_k; \tag{4}$$

in which a and b are the coefficients of linear transformation, and δ_k represents the error due to imprecision of the sensor measuring the trend of the wear state y.

Let us fix a programmed and constant interval of time T_{pj} for executing preventive maintenance interventions on generic critical component belonging to the set $i = 1 \ldots I$. As the state of critical components is monitored by sensors, on the basis of the acquired information, it is necessary, at each temporal instant t_k, to decide whether to execute maintenance intervention at $t_k + \Delta t_k$ or not. If the decision about executing the intervention is not made at time t_k, the decision will be postponed to the next observation, without excluding the possibility of executing the intervention at the end of the programmed interval of time T_{pj}. In particular, a scheduled intervention of preventive maintenance (whose duration will be fair to T_{pS_i}) will be executed as programmed if, during the various observations, the number of alerts (S_i) given by sensors related to a specific component i is lower than a fixed threshold S_i^*. Instead, if S_i is higher or equal to S_i^*, an intervention of predictive maintenance will be executed before the programmed time, and the related duration will be fair to T_{pD_i}.

This condition is verified if the value of monitored parameter m_k given by equation (4) belongs to the range $(m^*, \ m^{**})$, where m^* is the value of parameter corresponding to an

A	SC	CEF	NA	ER	TD	NI	SW	AMC
SC	0.00	3.33	3.00	3.00	3.33	3.33	3.67	3.67
CEF	2.67	0.00	2.33	2.67	3.67	3.67	3.33	3.00
NA	3.67	3.67	0.00	4.00	4.00	4.00	3.33	4.00
ER	3.00	3.00	2.33	0.00	3.00	2.67	3.33	3.33
TD	4.00	3.33	3.33	3.00	0.00	4.00	3.67	4.00
NI	2.67	3.67	3.00	3.00	3.67	0.00	2.00	4.00
SW	2.67	3.33	3.33	3.33	3.67	3.00	0.00	3.00
AMC	4.00	3.33	3.33	3.33	3.67	3.00	2.33	0.00

Table 5. Direct relation matrix A

T	SC	CEF	NA	ER	TD	NI	SW	AMC	$r_i + c_i$	$r_i - c_i$	Ranking
SC	0.70	0.84	0.75	0.79	0.88	0.84	0.79	0.89	12.809	0.142	TD
CEF	0.74	0.67	0.68	0.73	0.83	0.79	0.73	0.81	12.532	−0.588	AMC
NA	0.91	0.94	0.73	0.91	0.99	0.95	0.87	0.99	13.114	1.470	NA
ER	0.73	0.75	0.66	0.62	0.79	0.74	0.71	0.80	12.006	5.795	SC
TD	0.89	0.90	0.81	0.84	0.82	0.92	0.84	0.96	13.860	0.089	NI
NI	0.76	0.81	0.72	0.76	0.85	0.69	0.71	0.86	12.720	−0.409	CEF
SW	0.77	0.81	0.73	0.78	0.86	0.80	0.65	0.84	12.290	0.191	SW
AMC	0.83	0.83	0.75	0.79	0.88	0.82	0.75	0.76	13.308	−0.480	ER

Table 6. Total direct relation matrix T and final ranking

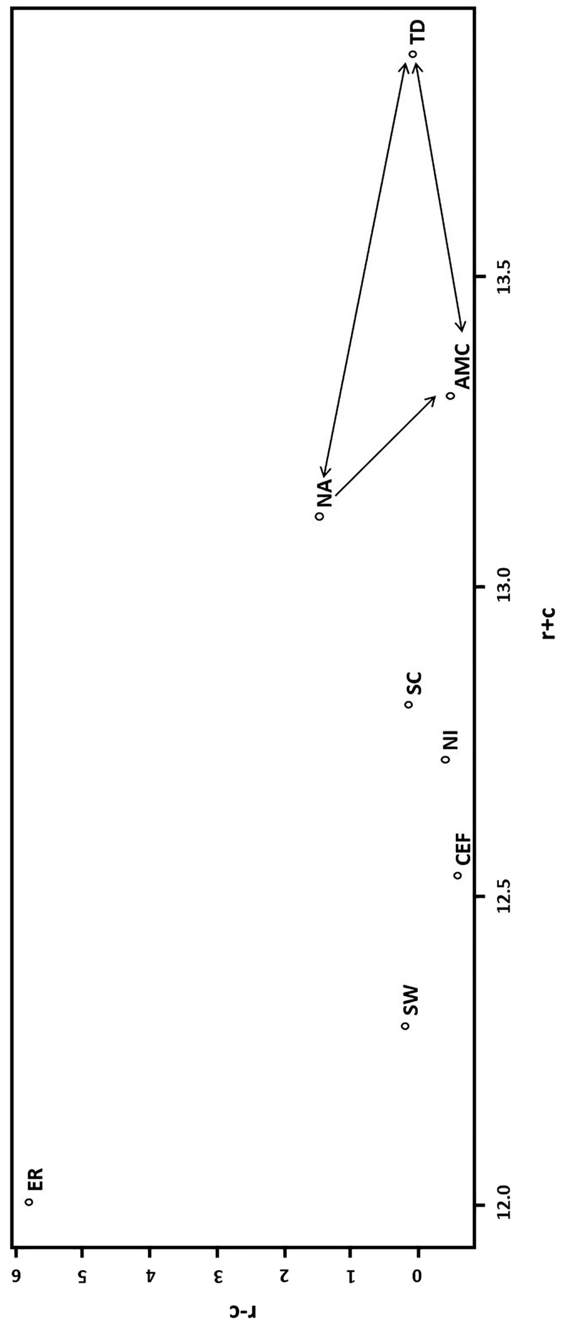

Figure 3.
Impact-relations map

accepted value of failure probability $F(t_{k,i})$, called $Risk^*$, at the time k for the component i, whereas at m^{**} the component fails.

The objective function of the proposed model is expressed as a minimisation of the unavailability U of the analysed system. The formulation of the just cited objective function has been guided by the KPI occupying the first position in the ranking obtained by the DEMATEL method – that is the total downtime (TD):

$$U = TD = 1 - \left[\frac{\sum_{j=1}^{N}\left(T_{p_j} - \sum_{i\in I}\left(T_{pD_i}\cdot X_{pD_i}\right) + \sum_{i\in I}\left(T_{pS_i}\cdot X_{pS_i} + \sum_{i\in I}\left(T_{M_i}\cdot X_{S_i}\right)\right)\right)}{\text{number of working hours per year}}\right]; \quad (5)$$

where:

$j = 1\ldots N$ is the index defining the interval in which the programmed intervention of preventive maintenance is executed;

$i = 1\ldots I$ is the index representing the generic critical element belonging to the system to be monitored;

X_{pD_i} is the Boolean variable assuming value fair to 1 if the intervention of predictive maintenance is executed in advance with respect to the programmed time, 0 otherwise;

X_{pS_i} is the Boolean variable assuming value fair to 1 if the intervention of preventive maintenance is executed at the programmed time, 0 otherwise;

X_{S_i} is the Boolean variable assuming value fair to 1 if the condition $S_i \geq S_i^*$ is verified within the reference interval, 0 otherwise.

T_{M_i} is the time needed to organise the activities for monitoring and controlling the wear state of components belonging to the set I. These activities will be implemented only when the number of alerts is higher than or equal to the fixed threshold, and it implies that the time T_{M_i} will be $\neq 0$. This condition is assured by means of the constraint (7) and, in such a case, the cost C_{S_i} (considered in the calculation of the total cost CT in equation (9)) will be computed.

The following relation exists among the various components of time considered within the model:

$$T_{M_i} > T_{pS_i} > T_{pD_i}.$$

Moreover, the optimisation problem is subjected to the following constraints.

$$X_{pD_i} + X_{pS_i} = 1 \quad \forall i \in I. \quad (6)$$

The constraint (6) expresses that the intervention can be executed in advance with respect to the programmed time or at the programmed time.

$$\begin{cases} X_{S_i} \geq \dfrac{S_i - S_i^*}{S_i^*} \\ X_{S_i} < \dfrac{S_i}{S_i^*} \end{cases} \quad \forall i \in I. \quad (7)$$

The constraint (7) ensures that the Boolean variable X_{S_i} is equal to 1 if the number of alerts S_i given by sensors is higher than or equal to a fixed threshold S_i^*, 0 otherwise. Moreover, the number of S_i alerts over the programmed interval of time T_{pj}, corresponds to the KPI occupying the third position in the ranking obtained by the DEMATEL method.

$$\begin{cases} X_{pD_i} \geq F(t_{k,i}) - Risk^* \\ X_{pD_i} < \dfrac{F(t_{k,i})}{Risk^*} \end{cases} \qquad \forall k, \forall i \in I. \tag{8}$$

Constraint (8) guarantees that the predictive maintenance intervention is executed if the accepted level of failure probability is overcome.

$$AMC = \frac{CT}{\text{Annual budget}} = \frac{\sum_{i \in I} \left(C_{pD_i} + C_{pS_i} + C_{S_i} \right)}{\text{Annual budget}} \leq 1. \tag{9}$$

The last constraint (9) ensures that the annual cost budget constraint, related to the execution of the maintenance actions, is respected. The AMC is the indicator in the second position of the DEMATEL ranking.

4. Description of the case study

The present section shows the application of the proposed DSS to the real complex system previously analysed in Carpitella *et al.* (2018b). Summing up, the DSS consists in a combined methodology based on a multi-criteria method and a mathematical model. In particular, the first one is the DEMATEL method, proposed and applied by involving different experts to select a representative set of maintenance indicators. The method permits indeed to take into account the degree of interdependency existing among indicators. Furthermore, the proposed mathematical model aims to make decisions on the implementation of maintenance actions formulated through the indicators previously selected by the DEMATEL.

The analysed system is an innovative street cleaning vehicle endowed with a smart remote diagnosis system. The cleaning service activities were grouped into three main phases, namely, vehicle handling, waste collection and tank emptying. The vehicle begins its service by moving from the starting point to the destination point at high speed. Then, it reduces speed to about 7 km/h during waste collection.

The hierarchical structure of the system, from which the reliability block diagram represented in Carpitella *et al.* (2018b) was derived, is shown in Figure 4.

In the mentioned research, a combined multi-criteria decision-making approach was applied to rank failure modes resulting from the related FMECA. The obtained ranking of failure modes highlights the major criticalities. A sensitivity analysis was made to test the influence of criteria weights on the ranking results. The final rankings vary by varying criteria weights, but five failure modes appear as the most critical in all the different scenarios considered by the sensitivity analysis. These failure modes are presented in Table 7 along with their failure causes, effects and related involved component.

By observing the components of Table 7, which are those mainly involved in failure modes and related failure causes, it is clear that functioning of the various sweeping subsystems directly depends on the state of the hydraulic system. This system is influenced by the state of the related hydraulic pumps, whose moving parts and supports are subjected to progressive wear, which causes increased vibrations.

The pump degradation state can be then correlated to a parameter associated with vibration and monitored by suitable and widely available vibration sensors installed on the three main hydraulic pumps.

With relation to the herein proposed DSS, the KPIs selected using the DEMATEL method (namely, TD, number of alarms (NA) and total annual maintenance cost vs annual maintenance budget (AMC)) are used to decide and monitor efficiency of preventive maintenance on analysed components carried out by means the mathematical model in which the KPIs represent drivers.

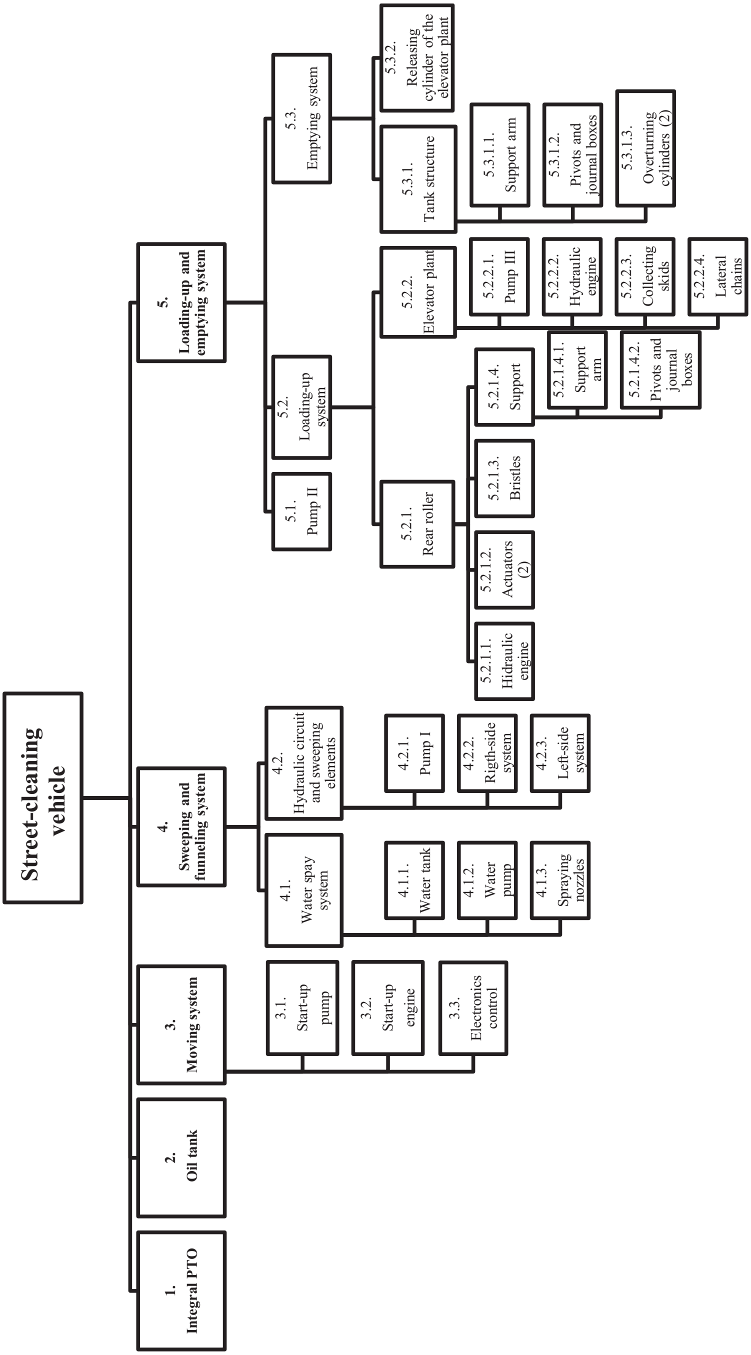

Figure 4.
Hierarchical structure of the complex system "street cleaning vehicle"

ID	Failure modes	Failure causes	Failure effects	Component
2A	Overheated oil	(1) Exchanger clogging (2) Lack of water	(1) Hydraulic system blocked	Oil tank
5.2.2D	Broken chain	(1) Hydraulic system fault (2) Impacts or wear	(1) Blocked motion (2) Loading not carried out	Lateral chains (elevator plant)
5.2.2C	Broken skid	(1) Detachment of one or more skids from the waste action support	(1) Difficulty in conveying waste (2) Clogging near the rear roller	Collecting skids (elevator plant)
5.3.1B	Slackened pivots or worn journal boxes	(1) Incorrect assembly/ stress due to load	(1) Excessive vibration (2) Overturning defects	Tank structure (emptying system)
1B	Worn power take-off (PTO) bearings	(1) High usage time; lack of lubrication	(1) Compromised functionality of hydraulic circuits	Integral power take-off (PTO)

Table 7.
List of most critical failure modes

By solving the model, the maintenance decisions on the generic element i will be made on the base of the assumed values of the decisional variables defined in Section 3:

$$X_{pD_i}, X_{pS_i}, X_{S_i}$$

In particular, the set I of elements i to be monitored consists of pump I (component ID: 4.2.1.), pump II (component ID: 5.1.) and pump III (component ID: 5.2.2.1.). Acceleration is the parameter correlated to the wear state y of pumps to be measured by sensors. The execution of maintenance activities related to pump faults are characterised by an operational time between 2 and 4 h. The modality of the maintenance action execution also implies a medium-complex level of difficulty for pumps because the related intervention needs a specialised maintenance team. Indeed, it is not possible to carry out the intervention in the same place where the failure occurs, and this must take place in the repair shop. This means that vehicle transport time must be necessarily taken into account, with a consequent impact on the performance of the provided service. The role of blockchain technology is then fundamental in exchanging data in a secure way with the available maintenance crew. For this reason, the proposed DSS represents a tool capable to support the maintenance management with the fundamental aim to assure a high level of operational readiness, a high level of service performance in respecting transparency and security of the data.

5. Conclusions

The present paper highlights the useful role of the blockchain technology for predictive maintenance. Blockchain plays an important part in exchanging information flow with maintenance crews so that interventions can be quickly and effectively implemented by assuring security of the exchanged data.

The novelty of the present research consists of a DSS based on the integration between the DEMATEL methodology and a mathematical programming model. On the one hand, the DEMATEL-based approach enables to take into account interdependencies among the main elements of a complex problem. The method is applied within the process of preventive maintenance control, with the purpose of selecting a subset of KPIs (among those belonging to a wider set) by providing opinions given by a team of experts. On the other hand, the mathematical programming model provides useful support in planning and executing interventions by focussing on the selected KPIs, namely, the TD, the NA and the total annual maintenance cost vs annual maintenance budget (AMC).

A real-world service system is presented, in which a cleaning street vehicle is analysed. The combined approach is proposed to monitor the state of the pumps of the hydraulic system of the vehicle by means of a network of sensors. Pumps represent critical components for the whole system. The blockchain technology is integrated with the network of sensors monitoring pumps for preventive maintenance, in terms of exchange and management of reliability data and pumps' wear state.

The main result of this paper is the proposal of an end-to-end methodology to support the maintenance management by respecting transparency and security of data through a blockchain database. The adoption of the DEMATEL methodology to select KPIs and the proposed mathematical model to support the planning of interventions has been proposed on a real case scenario.

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