A Maintenance Policy Selection Method Enhanced by Industry 4.0 Technologies

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Abstract: One of the objectives of the manufacturing system is to maximize the profit. Maintenance management is a key element to achieve this goal because it reduces the machines downtime, improving the overall equipment effectiveness of the production systems. The advances in information and communication technologies, which paved the way to "the fourth industrial revolution", provide to the experts new tools for the monitoring and analysis of the items' status of functioning. Nowadays, many companies still perform simply the corrective maintenance policies; this is due, mainly, to the difficulty to collect data and to process these data for scheduling the work orders and for assigning the best maintenance policy to each asset. The aim of this paper is to present a new maintenance framework that is able to automate the decision process leading to the choice of the more appropriate maintenance strategy among those belonging to the statistically and reliability based preventive maintenance and the newer opportunistic maintenance approach.

Keywords: Maintenance management, Industry 4.0, maintenance policy selection, opportunistic maintenance

1.Introduction

The arrival of the fourth industrial revolution, often called "industry 4.0 (I4.0)" brought great changes in the industrial world in the last 10 years. The main goal of I4.0 paradigm is to achieve a higher level of operational efficiency and productivity, as well as a higher level of automation (Yang, 2017). Rüßmann et al. (2014) estimated that the impact of I4.0 leads to important benefits in 4 industrial areas: productivity, revenue growth, employment and investment. As well known, maintenance of the assets is a vital part for enhancing the productivity of an organisation and its costs can be, in some cases, a considerable part of total production costs (Bevilacqua, Braglia, 2000); but still today, by comparing the scientific literature and the industrial knowledge, it arises that there are great differences between them. Indeed, a large part of companies today still applies corrective maintenance for several reasons; among those the main ones are:

- they are not able to collect data about components status;
- they are not able to use the data in order to decide about maintenance kind selection and scheduling.

From the other side, scientific literature on maintenance has been developing a lot in last years, especially when the Key Enabling Technologies (KET) of I4.0 became available for the industries. In addition to the classic methods, such as preventive maintenance, enhanced by some KET (Wan et al. (2017) and Zahariadis et al. (2017)), the application of more complex models such as Condition Based Maintenance (CBM) (Shin and Jun, 2015), intended as "Maintenance performed as governed by condition monitoring programmes" (ISO 13372, 2012), prognostic maintenance (Luo et al., 2003) and E-maintenance (Lee et al., 2006) became feasible thanks to the rapid evolution in collecting and analysing a large amount of data (Gullen et al., 2016). Moreover, as the Life Cycle Assessment (LCA) of products is becoming increasingly important to define the impact that production systems have on the environmental pollution, the sustainable maintenance, intended as the integration of sustainability in maintenance operations, is greatly developing, as illustrated by Franciosi et al. (2018).

The idea of this research arose to provide a system for factories that would make possible the integration among the complex maintenance models developed by scientific researches and the industrial world. The model would have to allow a maintenance management that takes into account not only one maintenance strategy (as in almost all cases in literature), but mixing various maintenance policies, evaluating which is the most suitable depending on the machines' components importance, reliability and costs.

In the framework that will be presented in the next section, three possible maintenance policies have been considered. They have been chosen in particular for "distributed" maintenance, i.e. for companies that maintain several plants far apart: corrective, preventive and opportunistic maintenance. The last one can be considered a particular kind of preventive maintenance: taking advantage of the random stops of other equipment or machines, it is performed in order to obtain an economic benefit in replacing or repairing a working component that is near or physically connected to the one for which there was the failure event (Laggoune et al., 2009 and Ba et al., 2017).

The choice of the most appropriate maintenance policy will depend on the results of a reliability analysis that will be performed by analysing data collected through sensors and then transferring these data to a central system thanks to some KET of I4.0. In particular, in our model will be used:

- Cyber Physical Systems (CPS), because of their capability to integrate sensors, actuators, controllers and other types of devices with the physical and human processes (Rajkumar et al., 2010);
- Internet of Things (IoT) to allow the communication between all devices and the sharing of information (Lee and Lee, 2015);
- Cloud Computing (CC) to enable the possibility to collect and transfer data and to have an infinite computational capability (Mell and Grance, 2009).

The data about the operating status of components will be collected and analysed by using these technologies in order to create a new maintenance management system.

2.Literature review

A complete explanation of the methods and mathematical models which govern the preventive and predictive maintenance policies is the work of Duffuaa & Raouf (2015). The selection of the best maintenance policy for a specific application is always a challenge. Bevilacqua & Bragna (2000) applied the Analytic Hierarchy Process (AHP) in order to select the most appropriate maintenance policy among preventive, predictive, CBM, corrective and opportunistic for a particular industrial case. This issue was faced also by Al-Najjar & Alsyouf (2001) who used a fuzzy multiple decision making evaluation methodology for choosing the most efficient maintenance policy. The coming of Internet gave to the companies the opportunity to build a networked environment. Lee et al. (2006) presented the pros and cons of the e-maintenance and proposed a number of case studies in order to demonstrate how this approach, in addition to intelligent prognostic technologies, could help to prevent the failures of the machines. The potentials of the newest enabling technologies of Industry 4.0 such as big data analytics and Cyber Physical systems have been investigated by Li & He (2016) with a view to understand how these technologies could be for the development of predictive maintenance policy. Before implementing a predictive maintenance which include prognostic studies on the items, we need to find out whether there are the technical possibilities to monitor and to run a diagnostic on the system. Grall et al. (2000) demonstrated how the optimisation of the replacement thresholds and the inspection schedule in a CBM policy could minimise the maintenance cost rate. Liu et al. (2013) developed a CBM policy able to minimize the expected cost per unit time and to maximize the system availability through the continuous monitoring of the degrading systems. Gullen et al. (2016) proposed a framework to represent the key components for a systematic management of CBM program; they applied their maintenance management structure for a use case. Unfortunately, CBM or predictive maintenance are not always possible; under these circumstances the only alternative to the corrective maintenance is the preventive maintenance (Liu et al. (2014) , Dui et al. (2017). Whenever the system is shut down for unplanned or planned maintenance activities there is an opportunity to repair or to replace unexpired items that have reached a certain reliability threshold (opportunistic threshold) in order to obtain an economic advantage and maximize the utility of the downtime (Laggoune et al. (2009) Zhang et al. (2017)).

3.The model

In this section, a new model for the selection of the best maintenance strategy is proposed. It is intended to support the decision maker for the planning of the maintenance activities for a distributed maintenance system in which a great amount of facilities is located on a vast geographical area. The idea is to provide a tool that can identify the sequence of activities that guarantee both an effective reduction of direct costs and an improvement of the systems' availability. The framework of the model (Figure 1) shows the information network and the possible paths of actions to be undertaken to achieve the objective mentioned.

The central system is a computer centre that shall deal the following tasks:

1. To receive data concerning the actual operating time of the components;
2. To calculate reliability distributions for each component;
3. To select the best maintenance strategy by basing the analysis both on items' cost and reliability of the assets;
4. To generate an alert when reliability gets minor of a set threshold;
5. To provide the most convenient maintenance activities scheduling that is able to minimize the cost of the overall work.

The strategies that will be taken into account are corrective maintenance (CM), Preventive Maintenance (PM) and opportunistic maintenance (OM). Preventive maintenance will be performed only for critical components, while CM or OM could be executed for non-critical components. For this reason, FMECA analysis have to be conducted to distinguish the most critical components from the others both in terms of economic effects and safety. This technique allows to estimate the quantitative index Risk Priority Number (RPN) by evaluating the degree of Detectability (D),

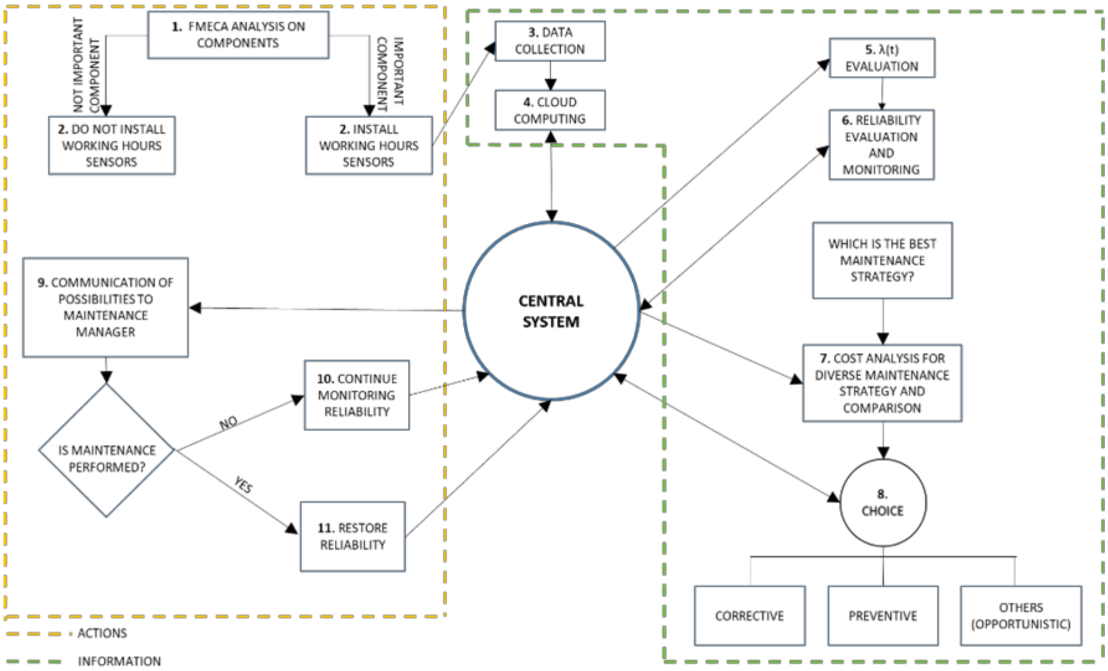

Figure 1: Framework of the model

Severity (S) and Occurrence (O). These three factors are multiplied each other to obtain RPN as in the following equation (1):

$$RPN = D \times S \times O \qquad (1)$$

According to MIL_STD approach, RPN index will be a value from 1 to 1000; the criticality increases with the number growing. In distributed maintenance, it is very likely that many components may be critical, because their failures might cause an extended down-time of the plant. An OM or PM are provided for those components that FMECA analysis has identified as medium-high critical, while for low critical components, a CM can be performed. Making reference to the framework represented above, let us explain how the proposed model works. After the FMECA analysis, sensors will be installed on components with a medium-high level of criticality in order to monitor the working hours between two consecutive failures of the components assuming that all are non-repairable. This step allows to collect data and transfer them in mass storages making use of the wireless network and of the Internet, according with CC paradigm. In this way, data becomes available for the central system that will be capable to evaluate the "failure rate" and consequently the reliability curves for components thanks to IoT that allows a continuous exchange of information between machines and the central calculation system. Since the system is not intended to be a real time system, a fast calculation is not required; it means that the central system acquires raw data which will be processed later. Otherwise the system should be equipped with smart sensors which are able to pre-process the data in order to increase the speed of calculation. Once the failure behaviour is known, the central system has the task to monitor continuously the reliability state of every component in order to compare the current reliability value R(t) at the generic time t with a pre-determined threshold, that changes according to maintenance policies. The thresholds are calculated by taking into account three important factors: criticality of components, their reliability and the cost of maintenance operations. The definition of the thresholds is the most difficult task because they greatly depend on the service levels required by the application: once the service level is fixed, the threshold for the particular item will be defined so as to ensure the service with a predetermined confidence level. If R(t) is less than preventive threshold R_P, a preventive action is scheduled; instead, if R(t) is greater than R_P and less than R_O (opportunistic threshold) at once, a cost analysis will be executed by the central system to evaluate the advantages of performing the OM. In particular, it evaluates the costs resulting from the execution the OM (Copp) at time t and compares them to the cost of CM (Ccorr) that the company should bear if the failure will occur at the time t + Δt, where Δt is the time span between the actual instant t and the next planned maintenance. These two costs are strictly dependent from the company that performs maintenance, so, they must be specialized by knowing how a company works. At this point, if the analysis gives Copp <Ccorr, the maintenance manager should assign to the maintenance worker the opportunistic activities in addition to the already planned corrective or preventive ones. When the opportunistic action is carried out, the reliability of the replaced component will be restored to the original value, assuming that it is replaced with a new item or that the maintenance operations returns the component in a state of "*as good as new*" and the central system restarts

to monitor the working hours and to evaluate the reliability at each time.

4.Application case

The model was applied to a real case concerning a company whose core business is the maintenance of thousands of fuel stations throughout the Italian country. The model is valid under the following conditions:

- The components shall be deemed in series. This means that the operating time of the system matches the working time of each component.
- The components are independent and their reliability is built through a Weibull distribution pattern with scale parameter α and shape parameter β.
- All maintenance activities are *as good as new.*

The model was implemented through the use of the software Matlab®. It gains as input the systems' operating time, the parameters of the components' failure probability density function (Eq. 2), the distances between plants (d_{jk}) and those between each plant and the head quarter (km_k) , all the cost and time factors.

$$f(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \qquad (2)$$

The cost related to CM (Ccorr) of the i-th component in the k-th plant is represented by the Eq. 3, where the term P_k^i is the probability of failure in the time interval between the detection instant t and the time period to the next scheduled activity (Δt) (eq. 4).

$$Ccorr_k^i = (C_{wf} \cdot km_k + C_{wf} \cdot T_{km} \cdot km_k + C_{wf} \cdot T_{mi} + C_{comp}^i \cdot Z + C_{losses}) \cdot P_k^i \qquad (3)$$

$$P_k^i = R_k^i(t) - R_k^i(t+\Delta t) = F_k^i(t+\Delta t) - F_k^i(t) \qquad (4)$$

The cost related to the OM (eq. 5) will be different depending on whether the opportunistic activity is done in the same place where a failure is detected (j=k) or in another close plant ($j \neq k$).

$$Copp_{jk}^i = \begin{cases} C_{wf} \cdot T_{mi} + C_{comp}^i \cdot R_i(t) \cdot Z + C_p & j = k \\ C_{truck} \cdot d_{jk} + C_{wf} \cdot T_{km} \cdot d_{jk} + C_{wf} \cdot T_{mi} + C_{comp}^i \cdot R_i(t) \cdot Z + C_p & j \neq k \end{cases} \qquad (5)$$

The Z term is 1 if the component is replaced, otherwise it is 0 when the item is repaired, while Cp (penalty cost) is the additional cost that incurs whenever the time of interventions exceeds the time window stated in the contract with the client; C_{losses} (Eq.3) represents the losses of income due to the fault of the system. For a fuel station, in particular, this cost is sustained because the fuel distributor is not available and, consequently, the clients can not refuel. Ccomp is the component's cost. T_m is the mean time to execute a maintenance activity for each component. The set values for this variable have been chosen on the basis of the results deriving from some interviews to the company's experts and maintenance man. The other costs are explained in Table 2. Workforce cost (Cwf), the truck cost (Ctruck) and the travel time per kilometre (Tkm) should be considered as mean values. The tool will provide a report that suggests the most cost effective policy for each item into every plant maintained by the company. After verifying the critical level of the component, the central system compares the current value of the component's reliability with the thresholds Ro and Rp and, then, it compares the costs achieved by the Eq. 4 and Eq. 5. Moreover, it gives as output a matrix that reports if an opportunistic maintenance is economically viable both for the plant in which a failure has been detected and for the plants which are *close* to it. If yes, the algorithm sets DO (i.e. the OM is cost-effective), otherwise it sets ND (NOT DO). Together with this matrix, another table is provided to show the monetary savings resulting from the execution of OM; savings are intended the difference between the opportunistic cost and the corrective cost which could emerge if the operator do not take the opportunity to perform the suggested activities in addition to that he was called for and a failure of those components occurs in the successive time interval Δt. A simulation was carried out considering 10 fuel stations in order to demonstrate the enforceability of the model. A maximum distance between each plant has been set in 15 km. A range of 100 km has been assumed, i.e. during the simulation the distance between each fuel station and the head quarter, which is the departure point of the maintenance crews, may be maximum 100 km. Table 1 and Table 2 shows the data used as input for the simulation.

Table 1: Data used in the simulation for each selected components

Component	Ro	Rp	RPN	Ccomp [€]	Tm [h]
Pump	0.6	0.3	400	930	1
Filter	0.6	0	250	6.35	0.25
Flow meter	0.7	0.3	320	334	0.83
Junction connection	0.7	0	290	29.64	0.5
Belt	0.6	0.3	390	1.2	0.25

Table 2: Values of cost and time factors

Cwf [€/h]	Ctruck [€/Km]	Tkm [h/Km]	Cp [€]	Closses [€]	Z
20	0.5	0.025	0	200÷300	1

It should be noted that R_O and R_P thresholds are considered first attempt values. Furthermore, the penalty cost is set to 0, while the cost related to the economic losses is a variable value between 200 € and 300 €. Z is set to 1, i.e. each activity shall be considered as a replacement. Data concerning the effective working time between two consecutive faults of an item were not available. From the database provided by the company, the only information were about how many elements of a defined population are failed in a specific time span. In this case, since it is impossible to evaluate the realistic failure rate, the Reliability curves have been obtained through the application of a Renewal Process (Erto et al., 1995). The fundamental renewal equation is shown below (Eq. 6):

$$F(t_i) = M(t_i) - \Delta t \cdot \sum_{j=1}^{i} \frac{F(t_{i-j+1}) + F(t_{i-j})}{2} \cdot m_j \qquad (6)$$

$$m(t_i) = \frac{N_{gi}}{N} \frac{1}{\Delta t} \qquad (7)$$

Where $M(t_i)$ is the expected number of faults in the interval t_i and it is also known as “renewal function”; $m(t_i)$ is the approximate failure rate function that is obtained through the ratio between the number of failures in the i-th interval (N_{gi}) and the number of the entire population of components (N) , as shown in the Eq.7. F(t) is the probability density function, which identifies fault distribution, n is the number of intervals in which the time is divided.

In Reliability theory this process is used to estimate the time to failure both for repairable and non-repairable components under the hypothesis that the broken unit is good as new after the maintenance activity. The values $F(t_i)$ for each chosen component have been represented in a Weibull chart (log-log graph) through the following equation (Eq. 8) **:**

$$\ln\left[ln\left(\frac{1}{1-F(t_i)}\right)\right] = \beta \ln(t_i) - \beta \, ln\, \alpha \qquad (8)$$

The parameters α (scale parameter) and β (shape parameter) have been achieved by applying the linear regression method. Their values together with the correlation coefficient R^2 have been noted in the table below (Table 3). A Matlab function has been used to generate random values of the systems’ operating time in

Table 3: Parameters of the Weibull failure rate

Component	α [h]	β	R^2
Pump (C1)	89028	1.044	0.9937
Filter (C2)	20100	1.049	0.9984
Flow meter (C3)	88916	1.122	0.9962
Junction connection (C4)	45194	0.964	0.998
Belt (C5)	61390	1.044	0.9945

order to perform the simulation and, furthermore, to generate the time period Δt related to the planned operation. The function generates pseudorandom integer ranging from two limits. A simulation has been run with these data. The resulting matrices related to the filter are shown in the following figures. There are as many matrices (such as those shown in Figure 2 and Figure 3) as there are number of system’s selected components (pump, filter, flow meter, Junction connection, belt).

	TO									
FROM	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
S2	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
S3	ND	ND	DO	ND	ND	ND	ND	ND	ND	ND
S4	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
S5	ND	ND	DO	ND	ND	ND	ND	ND	ND	ND
S6	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
S7	ND	ND	ND	ND	ND	ND	ND	ND	DO	ND
S8	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND
S9	ND	ND	ND	ND	ND	ND	ND	ND	DO	ND
S10	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND

Figure 2: Matrix DO/ND for the filter

	TO									
FROM	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	0	0	0	0	0	0	0	0	0	0
S2	0	0	0	0	0	0	0	0	0	0
S3	0	0	2.2	0	0	0	0	0	0	0
S4	0	0	0	0	0	0	0	0	0	0
S5	0	0	0.2	0	0	0	0	0	0	0
S6	0	0	0	0	0	0	0	0	0	0
S7	0	0	0	0	0	0	0	0	0.1	0
S8	0	0	0	0	0	0	0	0	0.3	0
S9	0	0	0	0	0	0	0	0	0	0
S10	0	0	0	0	0	0	0	0	0	0

Figure 3: Savings matrix to be associated to the DO/ND matrix

On the rows there are the fuel stations (S) that represent the source nodes , while on the columns there are the destination nodes. In Figure 2, DO appears, for example, in the cell C5,3. It means if an operator goes from the head quarter to the station 5 (S5) due a request for assistance, the algorithm suggests to replace the filter in the station three, and, moreover, it informs this action will lead to a savings of 0.20€ (Figure 3). By aggregating the matrices related to the other components, it was possible to get the matrices showed in Figure 4 and in Figure 5. The values in the Component-Fuel station matrix are the savings related to the replacement of each component for the fuel stations in which OM is cost effective, e.g., focusing on column three, if the technician is at station S_3, he should perform the recommended interventions on the filter (C2) and on the belts (C5), as shown in Figure 4, in order to obtain a total saving of 16.40 € (Figure 5). The total saving array could be used as a priority table for the scheduling of the maintenance activities, i.e. the manager might think to prioritise the interventions related to the plant that is characterised by the highest total saving value.

It appears from the results of the simulation that the algorithm never suggests the replacements of a pump or of a fuel meter. This is probably due to the high cost of these two items and to how their failures has been modelled (the pump's scale factor is four times higher than that of filter) .

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
C1	0	0	0	0	0	0	0	0	0	0
C2	0	0	2.2	0	0.2	0	0.1	0	0.3	0
C3	0	0	0	0	0	0	0	0	0	0
C4	0	0	0	0	0	0	0	0	0	0
C5	13.5	0	14.2	14.0	3.0	11.7	10.2	5.9	10.2	20.0

Figure 4: Component-Fuel station matrix

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
13.5	0	16.4	14.0	3.2	11.7	10.3	5.9	10.5	20.0

Figure 5: Total saving array resulting from the simulation

5.Conclusions

The aim of the paper was to present a new tool for maintenance policy selection enhanced by the use of CPS, IoT and CC. A framework of the model is proposed and its application is carried out through the use of a Matlab code.

Results of the simulation show the applicability of this model for the definition of the most cost effective maintenance policy for a company that is involved in a distributed maintenance. In particular, results provide a report that supports decision making manager to schedule the maintenance activities because it allows to know the costs deriving from a kind of policy rather than another.

The main limitation of the proposed application is the absence of the real operating time between two consecutive faults. This data is fundamental for the evaluation of the realistic values of the reliability parameters. In fact, since β is approximately equal to 1 for all the components, it is impossible to perform a reliability based preventive maintenance because the components seem not to be in the wear out period. This limitation can be eliminated by installing sensors that monitor the components and sent the real working hours to a storage. In this way, the central system is able to evaluate the failure rate and to choose the best reliability model to apply for the specific cases, allowing also the evaluation of the most cost effective policy of maintenance interventions.

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