FRAMEWORK FOR PHM IN THE SMART MANUFACTURING CONTEXT: INTEGRATION OF DIFFERENT APPROACHES

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Abstract: The technology has advanced at an exponentially high rate since the advent of Internet in the early 90s. The concepts like e-Maintenance, Internet of Things, Industry 4.0 are linked to this advancement in technology. All these have stimulated great potentials in industries and manufacturing. This will boost Prognostics and Health Management capabilities that will need to rely not only on consolidated algorithms and IT architectures, but also on new paradigms related with distributed computing, modularization of tools and development of new services. The paper will address such approach proposing a reference framework to highlight how predictive maintenance can be interpreted according to the new paradigm of Smart Manufacturing. The framework will be supported by an industrial case.

Key words: Condition based maintenance, Prognostics and Health Management, Smart Manufacturing, Reliability centered maintenance.

Introduction: Industrial asset management has always been a complex activity for the amount of information to be handled. Collection of data and information about maintenance events (i.e. maintenance interventions) is nowadays a key activity and it is generally carried out by Computerized Maintenance Management Systems (CMMS). Thanks to the availability of such data, other analyses can be carried out by tools for Reliability Centred Maintenance (RCM) analysis. Companies then adopt Condition Based Maintenance (CBM) programs and systems, with the purpose to monitor the industrial assets and prevent unexpected events. Such CBM systems are often used to monitor conditions as well as to generate alarms and warnings based on the conditions. Besides, a great number of techniques and methods have emerged during the last years, allowing to achieve an accurate information and knowledge about the systems' condition evolution and remaining useful life. These advances are recognized as outcomes of an innovative discipline, nowadays discussed under the term of Prognostics and Health Management (PHM); indeed, PHM is considered to lead to a "CBM enabled by PHM" [1]. Still, PHM is often not so widespread in industry; nevertheless the landscape is quite complex and requires the definition of a proper framework in order to provide new solutions for the integration of PHM in the industrial asset management practice. Some key issues are worth to be provided in order to build the proper background of the research.

The RCM approach considers maintenance engineering techniques, such as RBD (Reliability Block Diagram), ETA (Event Tree Analysis), FTA (Fault Tree Analysis), WA (Weibull Analysis), FMEA (Failure Mode and Effect Analysis), and is one of the most effective way to assess and optimise maintenance policies [2]. Besides, different works have studied the creation of a framework where RCM and CBM can be both addressed. Considering the integration with the CMMS, Gabbar [3] says that RCM is anyhow a time and effort consuming activity if not automated. It must be periodically performed, but the analysis is generally not aligned with real time data progressively stored in the CMMS. In other words, RCM results risk to be not always up-to-date. Lopez Campos et. al. [4] presented the possible interface between different systems, considering also the data model required to this end. Trapani et al. [5] also proposed how to integrate RCM and CBM considering the beneficial results of the analysis for risk assessment, while Colace et al. [6] propose how to exploit HAZOP to proper consider the risk in the analysis.

CBM is a relevant lever for maintenance transformation: in the recent decades, traditional maintenance models, considering run-to-failure or time-based maintenance, are evolving to CBM programs. In this evolution, PHM is considered one of the key factors to achieve system-level efficient maintenance and reduce life cycle costs [7]. Prognosis research field is in fact promising new capabilities to improve the system reliability, leveraging both on design and maintenance along the useful life [8][9]. Besides, PHM provides capabilities to achieve more proactivity in maintenance: in this regard, it is worth remarking that, as expectation for the future, the equipment data will be transformed by PHM solutions into valuable information to help not only maintenance managers, but also plant managers for optimising planning, saving cost and minimising equipment downtimes [10].

Thus, under the term of PHM, a body of knowledge has been nowadays created, leading to consider it as an engineering discipline [11]. This covers all methods and technologies to assess the reliability of a product in its actual life cycle conditions to determine the advent of failures, and mitigate system risks [12].

It is worth understanding the role of PHM in the modern maintenance systems. In particular, its contribution to more proactive approaches allow reaching operational excellence in manufacturing companies [1].

By pursuing the integration of different systems and approaches, the need of a comprehensive maintenance platform is crucial for the industrial business, in order to have an effective tool to support the daily activity and the periodic maintenance analysis. This aspect has been analysed by scientific and industrial literature since 2000, addressing the concept of e-Maintenance as a component of e-Manufacturing. In 2006, Muller et al. [13] stated that the term "e-Maintenance" was not yet consistently defined in maintenance theory and practice. Different engineers and scientists have considered e-Maintenance in different manners and recently it has been also linked to the concept of value creation [14]. Progressively, the concept of e-Maintenance has been exploited with different keywords, while the development of Internet of Things (IoT) has also created the background for a more pervasive technology exploitation in the shop floor for all the operations and not only maintenance activity. More recently, this trend has evolved in the Industry 4.0 concept (according to the European wave) or, with a more international perspective, in the Smart Manufacturing concept. For what concern the industrial asset management scope, Smart Maintenance is then the keyword that is going to be used in the present research.

In order to develop Smart Maintenance applications, it is necessary to have a methodology to express the processes to execute and the set of data required by the processes. Indeed, projects tent to deal with an important quantity of data and information: requirements, objects, relations, restrictions, functions, etc. In order to manage such information, a proper modelling approach is needed, to enable interoperable solutions (i.e. interoperable in existent ICT systems) since its conceptualization. IDEF0 is hereafter used for this modelling activity.

Background for the proposed framework: In order to support the deployment of PHM solutions, the IMS Center proposes the 5S methodology. This approach was devised by IMS Center in order to develop and research all aspects of future maintenance infrastructures. This systematic approach consists of five key elements, that is ground on the Watchdog Agent. The Watchdog Agent is an enabling technology that shall allow for a successful implementation of intelligent maintenance. The toolbox was developed by Center for Intelligent Maintenance Systems (Center for IMS). It is a collection of algorithms that can be used to assess and predict the performances of a process or equipment based on input from sensors, historical data and operating conditions [15].

The 5 key elements of the 5S methodology are:

- Streamline: this encompasses techniques for sorting, prioritizing, and classifying data into more feature-based health clusters. This may also include reducing large data sets (from both maintenance history and on-line data DAQ) to smaller dimensions, leading to correlation of the relevant data to feature maps for better data representation.

- Smart Process: using the right Watchdog Agent tool for the right application. This requires techniques for selecting appropriate prognostics tools based on application conditions, criticality of each condition for machine health, and system requirements.

- Synchronize: converting component data to component degradation information at the local level and further predicting trends of health using a visualized radar chart for decision-ready information. Maintenance data is transformed to health information and to an automated action.

- Standardize: consisting in the creation of a standardized information structure for equipment condition data and health information so that it is compatible with higher-level business systems and enables the information to be embedded in business ERP and asset management systems. The goal here is to keep the process as a standard approach for day-to-day practices.

- Sustain: utilizing the transformed data for information-level decision making. System information is then shared among all stages of product and business life.

The present work is based on the development of a Smart Maintenance Platform that focuses on the two last steps here mentioned in order to prepare a framework to include PHM into industrial solutions.

The complete IDEF0 diagram representing the smart maintenance platform is presented in Figure 1, which represents the new framework herein proposed. In Figure 2 the diagram is

divided in the modules that implement the proposed architecture. The focus of the present paper is on the Decision Support Tool (DST).
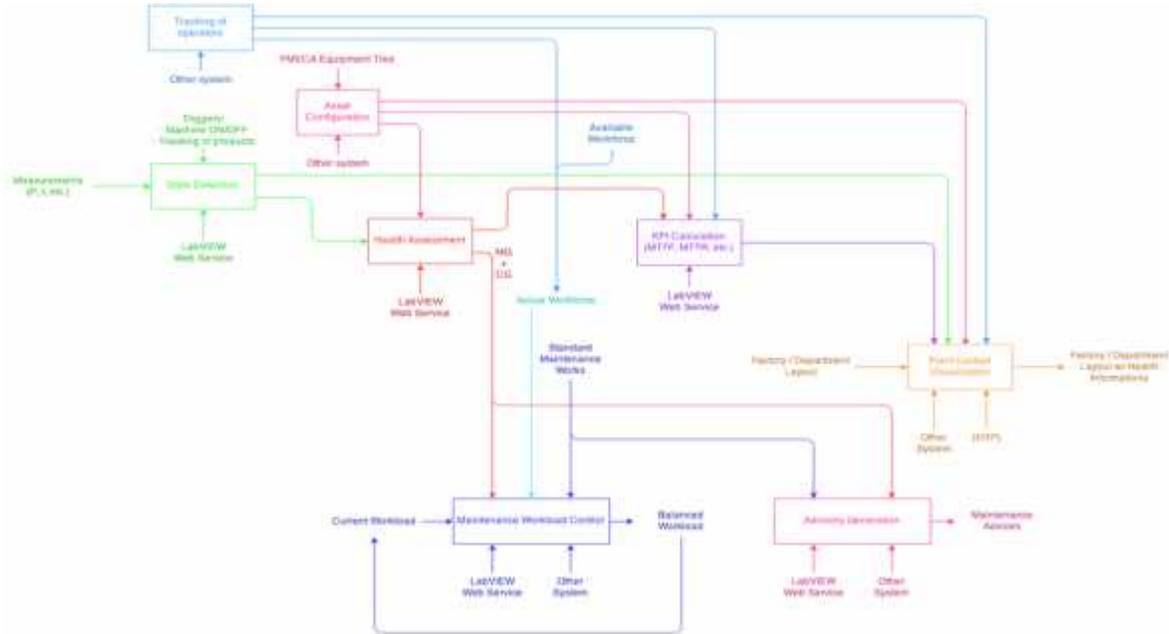

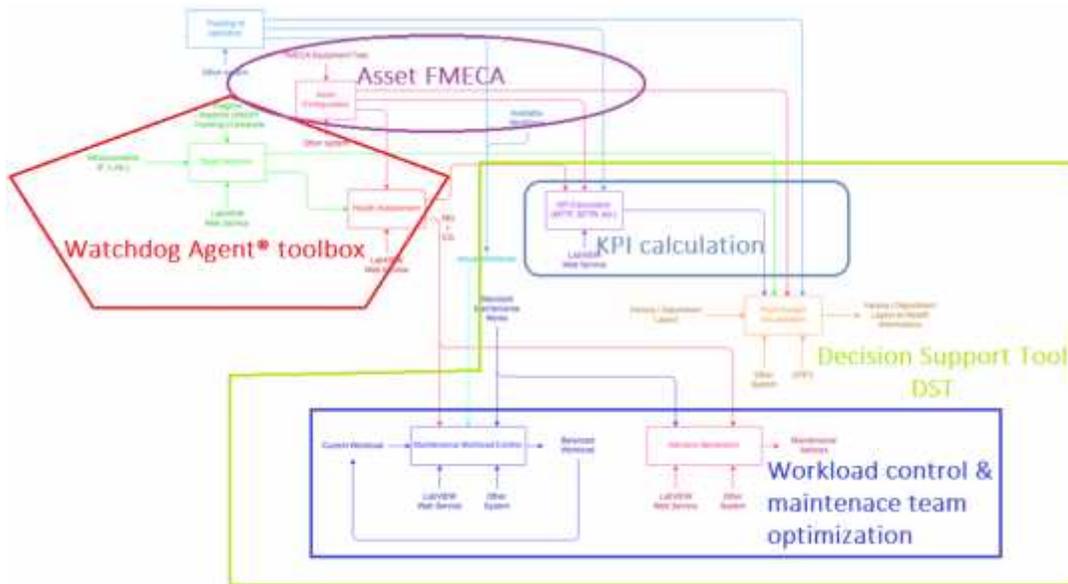Figure 1: Proposed framework (designed with IDEF0 standard).

Figure 2: Key elements of the proposed framework.

Watchdog Agent tools have been considered for the proposed framework. They take care of State detection and Health assessment blocks. Decision Support Tool (DST), instead, must implement KPI calculation, Maintenance Workload Control and Advisory

Generation, considering also the appropriate Plant Cockpit Visualization activity in order to properly communicate with the operators and maintenance engineers.

Table 1: Summary of the literature analysis

Decision parameters & model	When it is applicable	Procedure	Source
Use of RPN of different failure modes	Simple model with detailed FMECA. It can be used also for those assets that are not involved in a PM policy	According to the values of RPN, one can decide if the intervention is needed (RPN high) or not (RPN low)	FMECA decomposition [5]
Cost model	All cost data are available: maintenance intervention cost, down- time cost (production losses, etc.), etc.	A cost analysis is done for each failure. By means of cost functions it is calculated if it is convenient to wait for the intervention or to implement the maintenance action	"An Options Approach for Decision Support of Systems with Prognostic Capabilities" [12]
RPN + ANP/AHP techniques	FMECA is detailed and interdependencies among failure modes must be considered. Moreover, an expertise knowledge is needed in order to assign weights. This model takes into account the domino effects of first and higher level	RPN is calculated in a detailed way by considering interdependencies among failure modes. A complex Multi-Criteria approach is used in order to have a more robust decision process	"ANP/RPN: A Multi Criteria Evaluation of the Risk Priority Number" [16]"
Model for production machines with buffers	Buffer levels are monitored and machines are prioritized	Machines are prioritized according to their production importance. Buffer levels are taken into account in order to implement Preventive and Opportunistic maintenance policies	"Simulation platform for anticipative plant- level maintenance decision support sys- tem" [17]
Model for production lines considering production rate and costs	Cost data are available both for production and maintenance activities	A Genetic algorithm is used in order to optimize maintenance scheduling. A cost function is set to highlight the most critical failure modes	"Maintenance scheduling in manufacturing systems based on predicted machine degradation" [18]
Prioritization by CRI index	Detailed information about the asset are available. Asset condition can be monitored	Two Fuzzy Inference Systems (FIS) are used. The former is able to calculate the Basic Condition index, the latter al- lows to compound the Basic Condition (BC) and Operating Condition (OC) values to calculate the CRI (Composite Risk Index). CRI is used to prioritize maintenance actions.	"Substations SF6 circuit breakers: Reliability evaluation based on equipment condition" [19]

The remainder focuses on the Maintenance Workload Control. Literature background has been considered looking for effective procedures for maintenance prioritization. This

assessment has allowed to identify the best suitable model for the specific problem under concern.

The decision-making process is not a simple activity to face: it must be chosen whether a maintenance intervention must be launched and what kind of actions needs to be implemented. Besides, it may happen that more than one intervention is needed, therefore prioritization is considered.

The research is focused also on whether to launch or not the work order according to specific conditions. Models have been investigated, in order to take into account as much cases as possible and have a wide-ranging application of the algorithms.

The Table 1 presents the summary of the literature analysis done to identify the model to support the decision-making process by exploiting different types of information data and parameters. The examined models are synthetized in order to identify in a faster way the most suitable one according to the different case characteristics.

The idea is to try to optimize the actions of maintenance team: the interventions can be performed contemporarily each other, if possible, according to the failure mode and/or the maintenance team competences and skills needed.

The vision can be thought more global and complete, taking into account the whole plant or even the company. Ideally, one can think to schedule the interventions of the maintenance team (also "external" and third party teams) according to the failure modes occurred or that are going to happen (monitored parameters). The objective is to try to associate more than one intervention to failure modes that need the competences and skills of the same team. This could be done in order to optimise the resources and reduce time for the following interventions.

Industrial case study: The equipment available for the industrial case study development is a vacuum and refrigerant charging machine used in the production line of a refrigerator manufacturer. The main function of this equipment is to fill with refrigerant fluid the circuit of refrigerators or freezers. It automatically performs discharge, leak tests and charging, together with all the diagnostic and self-diagnostic tests.

The identified model to apply for the case study implementation is described by Vianna et al. [19], and it is based on the use of two Fuzzy Inference Systems. Actually, the model defines three critical indexes (Basic Index, Operating Index and Composite Risk Index) to prioritize maintenance actions. On the other hand, the developed tool for this particular case study, exploits the benefits of Fuzzy Logic Systems by considering the already available information about criticality (RPN – Risk Priority Number) and maintenance plan.

The use of Fuzzy Logic, by the method proposed in the study of Vianna et al. [19], allows the application of knowledge of experts in drawing up rules. Instead, traditional Boolean logic is two-valued in the sense that a member either belongs to a set or does not. Values of one and zero represent the membership of a member to the set with one representing absolute membership and zero representing no membership.

Fuzzy logic allows for partial membership, or a degree of membership, which might be any value along the continuum of zero to one.

The system designed for the case study considers as Input Variables the RPN value of the failure and a quantity defined as TtP (Time to Preventive). This last index takes into account the left days between the failure date and the preventive maintenance intervention

date for that specific failure. In this way, the RPN and TtP indexes are the Input Variables of the Fuzzy System.

In particular, the RPN index can assume three linguistic terms (Low, Medium, High) according to the failure criticality and the ranges defined in Fuzzy Logic. On the other hand, the index TtP can adopt three linguistic terms (Close, Halfway, Faraway), that identify the temporal "distance" from the preventive maintenance action for that failure.

The Output Variable is called "Work order" and can assume three linguistic terms:
- ʃ Repair the failure (RF): it accounts for the case in which the failure needs to be repaired immediately;
- ʃ Repair the failure and implement preventive action now (BN): in this case, both the failure fixing and preventive intervention are implemented immediately;
- ʃ Wait preventive intervention (WP): this option considers that the identified failure will be fixed only when the preventive intervention will be executed.

The Input and Output Variables are represented in a matrix that is shown in Figure 3.

		RPN		
		Low	Medium	High
TtP	Close	WP	WP	BN
	Halfway	BN	WP	BN
	Faraway	WP	RF	RF

Figure 3: Matrix of Fuzzy System Rules.

The Rules are designed by considering the combination of RPN and TtP indexes. In particular, the AND (Minimum) antecedent connective is taken into account, that specifies to use the minimum degree of membership of the antecedents.

Figure 4 depicts a Test of the designed Fuzzy System, done through the Fuzzy System Designer available in LabVIEW. The platform user interface developed in LabVIEW environment, consists of several tabs, through which it can be possible to surf among the available information. Previous works developed the "Asset" tab, that allows to choose the asset and depicts the functional scheme of the equipment; "Threshold Values" tab that can be useful to change the threshold value of a specific failure and update its Risk Priority Number (RPN); and the "FMECA" tab that shows the Failure Modes, Components and related RPN of the selected asset. Previous researches with the use of such tools are reported in [20] and [21].

The tabs "Maintenance Work Orders" (Figure 5) and "Workload" are generated by referring to the optimization algorithms and Fuzzy Logic System developed. The idea is to embed all the available information about failure modes (indicated in the Figure 5 as Failure Code), failure criticality, and maintenance team skills in one screen.

LabVIEW environment is used in order to guarantee integration with Watchdog Agent tools.

The available information is presented in a readable fashion way and identifies for a specific failure mode the date and criticality data such as RPN and Time to Preventive.
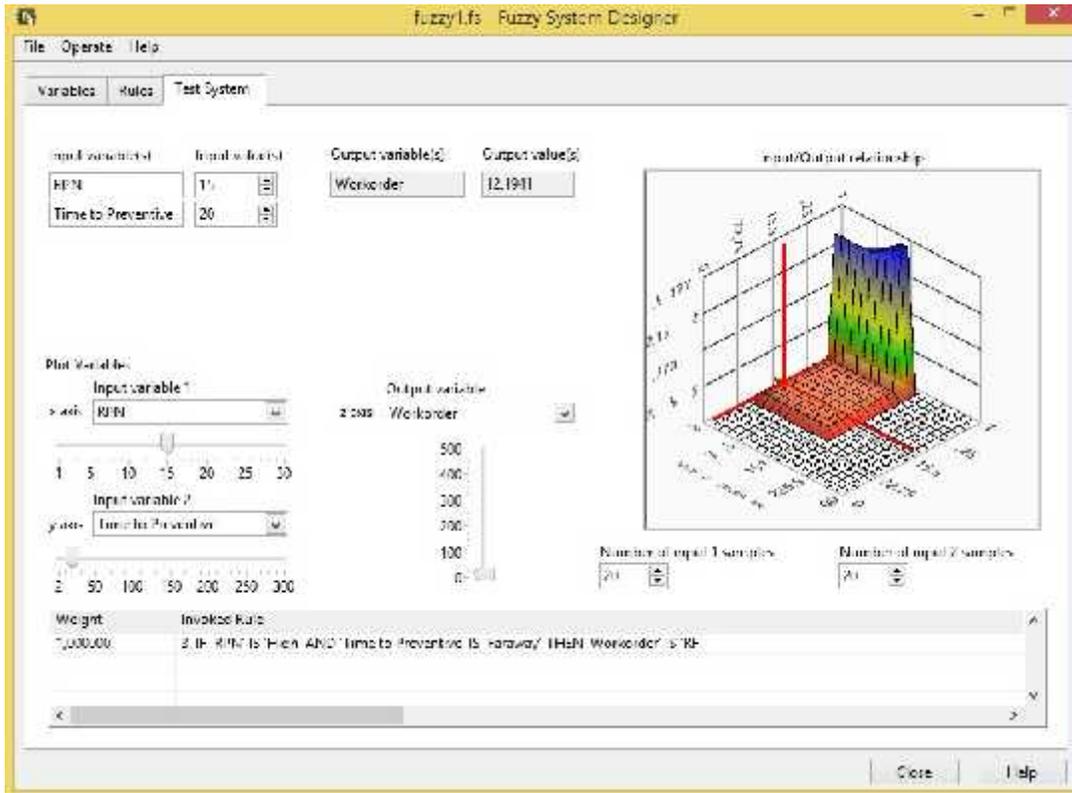

Figure 4: Fuzzy System Test through System Designer in LabVIEW.

Figure 5: Maintenance Work Orders tab.

Moreover, the downtime for the failure is highlighted, together with the associated maintenance team and the advice resulting from the application of Fuzzy System. Finally, a brief legend reminds the meaning of advices' acronyms.

The last tab named "Workload" shows the maintenance plan for the equipment. In particular, it can be possible to surf among all the months and verify the already planned preventive interventions and the updating plan according to the output results of the decision support system. The availability of these information and the easiness of reading and understanding them are very useful, enabling to have a wide and clear picture of team workload and, eventually, of detection of problems or not standard behavior of the system.

Conclusions: This work presented the proposal of a Smart Maintenance framework to allow the integration of PHM, combining the features of different functions, into operational management activities. The analysis of Watchdog Agent Toolbox results a strategical step in order to understand the potentiality of right management of information and data captured by monitoring systems. The use of the described tools in order to assess equipment health state or implementing prognostic investigation, means having the availability of almost infinite solutions for any possible case. The development of a Decision Support Tool becomes essential to apply the knowledge about the system previously gained. Moreover, use of the solution by the operators could be further improved Human-Computer interaction is enhanced by mixed interface [22].

Then, the necessity of optimization algorithms for workload and maintenance team scheduling appears evident. It has been underlined how the algorithms become necessary in order to increase the efficiency of workload planning. The advices given by the system that takes into account both failure criticality and distance from preventive intervention allow the company to react in a proactive way managing failure events. The maintenance plan and maintenance team scheduling become "dynamic", by considering not only historical events and past analysis, but also updated data. To this end, future development can consider the proper integration of the proposed solution with smart sensors [23] [24], in order to complete the integration of the platform.

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