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Industry 4.0 for failure information management within Proactive Maintenance

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Industry 4.0 for failure information management within Proactive Maintenance

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Abstract. I4.0 revolution is permeating every technical sector, by promoting deployment of enabling technologies (ETs), also in the facility management (FM) discipline. As FM regards the integration of processes within an organization to support activities, it is clear how ETs can trigger, in the FM area, significant innovations like a better failure knowledge management and a sustainable use of resources. More specifically, the implementation in building maintenance of dynamic systems, linked to sensors networks, can allow changes into knowledge management and FM decision-making processes. Starting from these premises, the paper deals with an ongoing research, whose aim is to investigate how ETs may innovate the traditional maintenance strategies with new approaches in corrective, condition-based and predetermined maintenance. According to the above, building maintenance, which is traditionally reactive, may actually become proactive if failure management policy is set. The aim of this paper is to demonstrate how ETs adoption may promote innovation in FM processes focusing on maintenance in service equipment field. More specifically, an operative and methodological framework for reaching proactive maintenance is described through the support of a case study concerning two major healthcare infrastructures in Italy, managed by a major FM company.

1. Introduction

The importance of enabling technologies (ETs), initiated by Industry 4.0 (I4.0) advent, has been advocated in scientific discipline and applications by many practitioners. In different fields (i.e. manufacturing, logistic, inventory, and others), benefits through ETs become real if proactive strategies are put in place to achieve efficiency and effectiveness of processes.

Maintenance service, seen as a facility management (FM) application field, has recently started to be invested with ETs, in order to support service provision in an innovative way (i.e. information value, dynamic services evaluation, data elaboration and new O&M tools).

However, in current FM experiences, proactive approaches for fault detection still discloses an average maturity degree, even if some proactive strategies have already been used in industrial practices, such as fault pattern discovery and RULs (remaining useful life) estimation. What FM maintenance service has gained and used, thanks to ETs deployment, is a high-technology information management, made possible through new contents for data analytics and data storage, which enhances value from data.

FM proactive maintenance framework can be empowered by new inputs from other fields, by adopting new groundbreaking maintenance tools and methodologies, which may result in sustainability of FM maintenance processes especially if an initial proactive failure management strategy is proper set. This is further showed in the following case study.

Bringing these themes together, the aim of this paper is to develop a proactive maintenance framework which may set a promptly service equipment failure management strategy. So far, sustainability in O&M activities of complex infrastructure may be reached in terms of economic resources thanks to failure information management in maintenance service.

The contribution of this paper is double. On one hand this paper wants to switch tradition FM maintenance from cost-based to performance-based service with sustainability of processes, in the other hand to provide an overview of existing and forefront proactive maintenance practices which better used ETs. The following paper is organized as follow. Section 2 describes what proactive maintenance is intended for. Section 3 highlights the current outcomes derived from proactive approaches. Section 4 outlines a case study in which a maintenance proactive strategy is performed. Section 5 summarizes impacts of this ongoing-research and topic introduced above.

2. From traditional maintenance to I4.0 ETs support-base proactive maintenance

Proactive maintenance (ProM) is an attitude reported among different authors ([1], [6], [14], [27], [32]), who strengthen maintenance approaches with technological strategies to promptly foresee the future behaviors of their assets.

In such a way, as it has been highlighted by industrial practices, ProM framework may be currently discerned in two pervasive maintenance strategy trends: Predictive Maintenance (PM) and Prognostic Maintenance (ProgM).

PM allows to monitor asset health status through the inclusion of IoT structures within a network of stakeholder, data storage, communication architecture and data elaboration.

ProgM enhances asset life assessment through punctual fault detection and RULs estimation, by taking advantages of I4.0 analytics tools whose purpose deals with a precise virtual representation of a real object. This is made by digital twin (DT), whose realization, within ProfM models, may be reached according different strategy: reliability-based model (benchmark and parameter domain), physical-based model (physical law domain), data-driven model (data collection domain) and hybrid model (physical law and data collection domain).

In particular, ProgM includes a diagnostic maintenance (DM) part, whose aim is to explore past health status, which caused failure, in order to further plan future actions on similar events. This ProgM approach strives to promote sustainability in processes which involve RULs determination of assets to reduce equipment breakdowns.

This fully reflects Gartner's "Analytic value escalator" picture, achieved through big data analytics decision-making, which tries to answer the following questions: "*what happened*", for diagnostic, "*what will happen*", for predictive and "*what should I do (having regard with the past history data trend)*", for prescriptive (prognostic).

Common point between PM and ProgM is represented by decision-making built on big data, reached through raw data collection, data processing, data feature extraction, data evaluation and training dataset to upload model. In such a way, data elaboration techniques can be various, but ProM framework (PM and ProgM) always favors data value-chain achieved through new awareness of I4.0 technologies.

In this scenario, I4.0 enabling technologies (ETs) are proactive tools useful to achieve sustainable maintenance processes within ProM framework.

Even if many ETs have been used by practitioners and industries since Hannover Messe 2011, Piano Nazionale Industria 4.0 [38], proposed by MISE (Ministero dello sviluppo economico) in Italy, has organically listed and specified what ETs are (Collaborative robots, 3D printer, augmented reality tool, simulation process, horizontal/vertical integration, Industrial internet, Cloud computing, Cyber security and Big data Analytics).

Withstanding with this, ProM purpose seeks to improve asset performance through a ETs use, and profitability, through a better resource distribution. This result in estimating behaviors (fault/failure and performance) and condition states (RULs) over time. Here an overview of current maintenance attitudes is provided in Table 1.

Table 1. Current maintenance purposes.

Discipline	Purpose	Objectives	Weaknesses	Advantages
FM maintenance	Combination of all […] actions […] to take an item to a state in which it can perform the required function; [34]	Set of FM maintenance policy and actions to restore assets maintainability levels and to minimize maintenance costs;	Lack of analytics to actively exploit data from asset life cycle;	Data and information recovery from historic O&M supported by ICT and IoT;
Industrial maintenance	Method to identify and select failure management policies to […] achieve the safety, availability and economy of operation; [36]	Method to guarantee availability of production without a loss of production value and with a prompt failures detection;	Lack of platforms to collect and analyze data from operation stage; Early stage in IoT deployment;	Use of I4.0 analytic techniques to detect fault and predict component RUL;
Proactive maintenance	Method to control current and future asset possible behaviors, supported by I4.0 tools	/	Possible lack of company's degree of maturity in understanding initial strategies to undertake proactive approaches;	Possible integration between I4.0 analytics and storage ETs to assess components faults and RUL, supported by platforms;

3. Four proactive maintenance approach: from knowing to sharing

A proactive framework in FM maintenance is set thanks big data value-chain which allows to full balance maintenance breakdown through a better management of failure information.

Support-based I4.0 proactive approach may innovative traditional maintenance strategy through more dynamic fault diagnosis (definition from 13306) [34], according four innovative schemes (Talamo et al., (2016) [24]) which currently are practiced in many forms by different I4.0 maintenance practitioners, as has been displayed in the following literature review: sensing & responding (S&R), sensing & knowing (S&K), sensing & learning (S&L) and sensing & sharing (S&S).

Corrective maintenance, traditionally performed after fault recognition, can reduce equipment breakdown in terms of asset availability through S&R approach. S&R architecture is enabled through sensors and BMS/SCADA connection.

Betti et al., (2019) [6] presented their S&R solution for a flexible fault prediction based on gathered data from SCADA system, then implemented with a fault recognition neural network. Their model has been assessed on six photovoltaic plants, by foreseeing latent fault 7 days in advance with 95% sensitivity through historical SCADA and fault data, fault taxonomy and inverter datasheet. Leahy et al., (2017) [15] proved how prognostic capabilities may be achieved, using 10-minutes wind turbine SCADA data for fault prediction. Each turbine down-time is associated to a sub-system failure, a routine maintenance activity or a grid-related event. Automated labelling process helps here to promptly identifies faults and may be implemented for other equipment SCADA-based prediction. Bangalore and Patriksson (2017) [3] showed a S&R approach with the use of many data sources for optimal maintenance planning. A smart analysis of historical SCADA dataset, based on threshold value for

anomaly detection and mathematical cluster rules, may indicate some latent fault in critical components with many months in advance. Later inspection can be performed to determine the effectiveness of the diagnosis from the condition monitoring system, whereas maintenance reports can update SCADA monitoring to improve the probabilistic failure model.

In S&K paradigm, condition-based maintenance may benefit from I4.0 ETs to promptly detect failure patterns before critical thresholds or fault condition achievement. Actually, S&K keeps tabs on equipment thresholds thanks real-time data mining (DM) techniques and I4.0 database, where data value is widely employed in maintenance service. Here fault phenomena are controlled by service provider continuous knowledge expansion.

S&K is enacted when DM analysis techniques are used to discover interesting patterns through big data collecting-and-storing ETs.

DM tools represent a process of transforming low-level data into valuable knowledge, by applying mathematical models to database. Commonly three DM practices can be distinguished in regression, , classification and clustering.

S&K-based predictions analyzes technical time series through a control interface, which acquires and stores incoming data for machine failure detection.

At this regard, Accorsi et al., (2017) [1] proposed a S&K method for maintenance decision-making which associates fault patterns to incoming failure events. In their analysis, stored dataset has been represented by equipment historical failure data provided by equipment suppliers. Data sources are parameter logs and message logs. Clustering, association rules and classification models have been analyzed and compared to assess the more accurate DM for real-time fault detection. Random forest, as classification model, represent that with higher precision on predicting stops. Rezig et al., (2018) [21] presented a list of sequential maintenance activities based on the records of maintenance data. Their sequential mining provides a method of analyzing large volume of maintenance data to suggest maintenance activities. In addition, in their S&K model, past preventive maintenance records of component are analyzed to determine the future sequential activities, with fault data and timestamp information. Phillips et al., (2015) [19] highlighted interesting classification method based on oil analysis dataset, coming from engines on mining truck, to assess equipment health status. Total accuracy of classification is evaluated through LR (logistic regression), CCNN (cascade-correlation neural network) and SVM (support vector machines). LR outperformed both the CCNN and SVM models in terms of predictive performance, by considering importance of past history on future classification of new data. LR benefit is to manage the modelling by personnel in-house. Bergmann (2012) [5] showed ProM benefits when accurate data are collected through vibration sensors. DM automated analysis techniques are crucial to add new knowledge, by reducing and analyzing data both at healthy and faulty status. By doing so, vibration time series are here used to classify possible saw-cutting-machine failures, after a cleaning and feature extraction phase with Fourier Transform and discrete Wavelet Transform. Transformer has been analyzed by Qiu et al., (2015) [20] through a nonparametric regression model in regards with the aged-based failures. They used a large equipment life cycle dataset, composed by service age and health index, in order to output health condition and risk factors analysis for planning. Nonparametric regression model can mine lifecycle data acquisition from asset management system. Djelloul et al., (2018) [9] investigated fault patterns to support diagnosis decision-making process for ProgM, through regression technique of failure data (bad warming and bad cooling). The performance of their approach is evaluated through mean square error and classification accuracy. Kovalev et al., (2018) [13] structured their S&K approach for a further IoT implementation. In their study, useful data to enact S&K are represented by time before next failure, mean time between failures, number of correctly predicted failures and number of non-predicted failures. Nagasaka et al., (2018) [17] have applied their S&K paradigm to plan prediction-based maintenance for elevators, basing on text mining. Here TM is used to recover useful data to build a statistical survival model for elevator components from KPI, maintenance records, equipment master data, troubleshooting and regular operation data. Bayes Network is used here to update survival model with collecting real time information, whereas simulations have been run to estimate maintenance costs. Wang et al., (2017) [26] have proposed a bi-

level feature extraction-based text mining method, from railway maintenance dataset collected from 2008 to 2014. They first adjusted feature weights of few fault classes based on statistical distributions. Then they reselected the common features according their relevance and Hellinger distance, at the syntax level. Lastly, they extracted semantic features to assess fault diagnosis. Bin et al., (2017) [7] have used onboard system fault recording files to recover fault information described in maintainers short-text, by using TM through the construction of fault text dictionary for word segmentation and fault text chain for processing data. Text-chain tool, based on closest matching method, allowed to turn human handwriting into structural data and to further build a faults distribution. Yuan et al., (2018) [31] have proposed a TM approach for S&K in fault text records of a certain aircraft as experimental data. Their method consists in measuring of similarity of fault text data and classified similar faults into one class for further proposing a new text similarity measurement model based on the word embedding distance. Then, on the basis of classification, a text mining algorithm with an event window is proposed. New knowledge is later available to build predictive model. Gunay et al., (2019) [10] presented their method to achieve knowledge from HVAC work order. Their approach allows to convert work orders descriptions into a mathematical form. Association rule-mining identifies here the coexistence fault patterns among the terms of clusters. Their outcomes displayed insights on equipment breakdown history.

Predetermined maintenance, established by intervals of time, may take advantages of forecasting ability on asset behavior and its RUL, reached through S&L, which regard large big data collection technologies (cloud, edge, dew, fog storage), and machine learning (ML). Value here is built on virtual learning model with failure and energy data.

Langone et al., (2015) [14] presented support vector machine (SVM) technique for real-time condition monitoring of a packing equipment. Their approach takes advantages of data collected by accelerometers positioned on some jaws, in which degradation process of the equipment has been deduced. Data from a thermal camera provided the input for time-series analysis with a nonlinear auto-regression, which assesses dirt accumulation on component.

Janssens et al., (2016) [11] proposed a convolutional neural network model (CNN), fed by raw amplitudes of the vibration data frequency spectrum data. CNN allows to learn transformations on data that result in useful representation for fault classification (i.e. different levels of lubricant degradation). In particular, CNN advantages consist in a less required domain expertise for feature learning. Yang et al., (2019) [29] highlighted a ML reconstruction approach for fault detection framework in a wind turbine system, by creating several fault indicators and components health index (HI). Useful data here are those regarding temperature failure data acquired with SCADA system under 200 different signals forms. Model reconstruction is achieved through SVR (Support vector regression). Bangalore and Tjernberg (2015) [4] proposed condition maintenance approach based on an artificial neural network (ANN) for gearbox bearings of wind turbine. Fault events are derived from SCADA. Their ANN approach is able to indicate damage in component almost a week before the reached fault threshold. Here fault decision-making based on faults may be crucial for optimal maintenance policy with a possible reduction of the overall replacement cost. Wu et al., (2016) [27] presented Random Forest algorithm for fault classification aided by a Cloud storage solution, taking advantages from two different data sets extracted by cutting forces, vibrations, acoustic emissions electrical current, acoustic emissions and spindle. They showed how collecting large volumes of streaming data from equipment can empower learning capabilities of ML in cloud system.

Smart maintenance, triggered by IoT vertical structure to digitalize maintenance (warehouse, spare parts, assets performance and assets RULs) needs, may further obtain additional value through S&S ETs. This can be achieved through platform, which includes analytics for maintenance needs and enables future buying and selling data in an integrated cluster-platform ecosystem.

S&S paradigm in ProM arises from "collaboration" principle, described as partnerships of actors who work together to create value (Yu et al. 2016) [30].

Mazak corporation, a machine tool builder company teaming up with MEMEX Inc., a manufacturing communications platform provider, and Cisco systems to deliver "Overall Equipment Effectiveness"

(OEE) solutions. Trenitalia, SAP and AlmavivA join together to deliver Dynamic Maintenance Management System solution. Due to the complex nature of maintenance challenges, proactive IoT solutions require a set different specialized firms to partner and specify a unique solution for a given customer [37].

In this light, in ProM approaches platform support can add value for all stakeholder, even if this actually is not a widespread reality in most maintenance practices.

Taie et al., (2019) [23] presented remote diagnosis and maintenance approach aimed to RULs and failure prediction for critical sensored-components, supported by database and analysis servers through different MLs. Use training data set is built from actual records reported remotely by RDMP (Prognosis Analysis and Self-Learning System). However, initial dataset can be created from laboratory tests, simulation and theoretical analytical methods. Wan et al., (2017) [25] stated the need to shift to more collaborative forms between different maintenance stakeholders, focusing on knowledge management, communication and the decision-making processes. They proposed a collaborative maintenance planning system, by indicating improvement which may be achieved with product lifecycle data and platform integrations. Balogh et al., (2018) [2] theorized a reference IoT cloud-based collaborative maintenance services platform for the collection of available equipment data to be analyzed and assembled for forecasting system health status. The scheduling of predictive maintenance needs may be supported by the existing company maintenance planning tools. Actually shared data come from numerous machinery suppliers and IoT platform may act as an open market where specialized maintenance services and data value can be evaluated by companies. Their architecture is composed by three levels represented by physical resources layer, equipment data layer, and services or processes layer, interconnected with APIs. Katipamula et al., (2017) [12] proposed a ProM framework supported by an open-source platform which exploits distributed sensing and supports energy and maintenance needs, with BMS and CMMS integration. Platform allows to link devices and external signals to the Cloud. Zargar et al., (2011) proposed collaborative platform with regards to collaborative and data-driven intrusion detection system. Their framework is composed by three levels: infrastructural level, comprised of network, host and global layers, platform level, made of logically-separated layers for one cloud provider, and software level. Collaboration is at the center of their framework and database, used for detection and prevention by all contributing cloud providers.

A new ProM service among S&S paradigm may enabled by a multi-tenant distributed simulation cloud environment suggested by Peng et al., (2018) [18]. Here a neural network is used to transform simulation tasks in specific resource requirements in terms of their quantities and qualities. Complex resource allocation in a multi-tenant computing environment may be supported by multi-objective analytical model. This may be based on K-means approaches which considers tenants satisfaction, total computational costs and multi-level load balance. Mourtzis et al., (2016) [16] provided a ProM method to support enterprise sustainability by reducing costs through collaborative information on mean time between failures, achieved with equipment sensors output and the maintenance division expertise and knowledge. Das et al., (2015) [8] hypothesized benefits from local and global Clouds collaboration model, exploiting ML techniques to foresee resource requirements for different users. Salza et al., (2017) [22] presented a collaborative Cloud platform architecture which takes advantages of a ML classification algorithm to monitor system performance.

Yamato and Kumuzaki (2017) [28] presented a maintenance lambda platform where edge nodes analyze sensors data and extract promptly a new detection rule for Cloud maintenance orders. Their analysis reported the detected fan failures through sound sensors and sequentially stream data, which are elaborated in a ML. Edges of system, where local database have been placed, are represented by different factories which may benefit from prediction of failures on collected data. In Table 2 is provided an overview of the current practiced maintenance categories.

Table 2. I4.0 practised maintenance paradigm categories.

Authors	S&R	S&K	S&L	S&S	Data	Techniques	Monitor
Betti et al., (2019) [6]	✔				Failure data, Electrical parameter	SCADA +Algorithm	Inverter
Leahy et al., (2017) [15]	✔				Alarm data, Maintenance logs	SCADA + Algorithm	Turbine
Bangalore and Patriksson [3] **(2017)**	✔				Operation data, Inspection reports	SCADA + Algorithm	Gearbox
Accorsi et al., (2017) [1]		✔			Expertise knowledge, Sensor data	Random forest	Systems
Rezig et al., (2018) [21]		✔			Maintenance logs, Sensor data	Classification	Belt conveyor
Phillips et al., (2015) [19]		✔			Oil analysis dataset, Sensor data	LR, SVM, CCNN	Mining truck engine
Bergmann (2012) [5]		✔			Vibration sensor data	Classification	Saw-cutting-machine
Qiu et al., (2015) [20]		✔			Service age, Health index, Sensor data	Nonparametric regression	Electrical component
Djelloul et al., (2018) [9]		✔			Operation status data	Regression + Neural network	Industrial machine
Kovalev et al., (2018) [13]		✔			Failure rates, Sensor data	Multicriteria	Systems
Nagasaka et al., (2018) [17]		✔			Maintenance logs, KPI, Sensor data, Troubleshooting data	Text mining + Bayes model	Elevator
Wang et al., (2017) [26]		✔			Maintenance logs, Sensor data	Bi-level feature extraction-based text mining	Railway
Bin et al., (2017) [7]		✔			Maintenance logs, Sensor data	Text-mining	High-speed train
Yuan et al., (2018) [31]		✔			Test-bed data, Sensor data	Sequential Pattern Mining	Aircraft
Gunay et al., (2019) [10]		✔			Maintenance logs,	Association rule-mining	HVAC
Langone et al., (2015) [14]			✔		Accelorometr sensor data, Thermal camera sensor data	LS-SVM	Jaws component
Janssens et al., (2016) [11]			✔		Vibration sensor data	CNN	Rotating machinery
Yang et al., (2019) [29]			✔		Tmperature sensor data	SCADA + Fault indicator + ML reconstruction	Turbine
Bangalore and Tjernberg (2015) [34]			✔		Sensor data	ANN	Gearbox bearings
Wu et al., (2016) [27]			✔		Multi-Sensor data	Random forest + Cloud	Milling machine

Authors	S&R	S&K	S&L	S&S	Data	Techniques	Monitor
Taie et al., (2019) [23]				✔	Sensor data	KNN, SVM, ANN	System
Balogh et al., (2018) [2]				✔	Sensor data	Collaborative Predictive Platform	Manufacturing system
Katipamula et al., (2017) [12]				✔	Sensor data	Open-source automated platform	Building system
Zargar et al., (2011) [32]				✔	Sensor data	Collaborative Predictive Platform	System
Peng et al., (2018) [18]				✔	Sensor data	Collaborative Predictive Platform + NN	System
Mourtzis et al., (2016) [16]				✔	Expertise knowledge, Sensor data	Collaborative Predictive Platform	System
Yamato and Kumuzaki (2017) [28]				✔	Sensor data	Maintenance lambda platform	Manufacturing system

4. Proactive maintenance methodology: A case study for hospital building service equipment

The following methodology has been applied to an on-going research, whose aim is to fully enact ProM framework for further IoT implementation. However, before proceeding with an ETs based-ProM framework, an initial failure management policy should be set up. This starting strategy allows to reach a systematic process for moving-company to digitalization and efficient sensored-maintenance. This research's promoter is an Italian specialized FM maintenance service provider, which strives to exploit its valuable data storage, collected over 4-year assets monitoring process within healthcare infrastructures. Assets taken into account are represented by hospital buildings SE (service equipment), such as HVAC, electrical, waterworks, fire system and ICT and civil works (Enclosures and furniture). As described in the following section, methodology to prepare real ProM strategy is displayed through: Inventory process, Registry structure, Database creation, Sensor registry, FMECA/FTA, New FM maintenance model and IoT implementation.

At its early stage of this research, in order to support information and data collection to better represent assets behaviors, an inventory process has been initiated (figure 1).

Inventory information, through gradual information acquisition principle and continuous process of retrieval, selection, validation, acquisition and updating of information, has involved following documents: *As built*, technical drawings, SE technical sheets, maintenance manuals, surveys, contracts between maintenance provider and infrastructure owner. Registry, as hierarchical structure in which information is collected and connected, is the core framework for SE breakdown structure, useful in classification and coding of apparatus. In its practical representation classification have been analyzed among different systems, such as: UNI 8290, UNIFORMAT II and OMNICLASS schemes.

Due to the complexity of entire SE systems and to future further SE integrated-BIM implementation for maintenance simulation, OMNICLASS 22 Work Results [35] has been employed. Here, through a representation in hierarchical tables, relevant elements involved in maintenance process are classified. However, OMINCLASS 22 is an open system which may include additional components to further expand the classification.

After the registry setting phase, which is continuously sustained by information coming from inventory process, the purpose of registry system is achieved through the creation of a database, which synthesizes key functions of information system in relation to maintenance requirements.
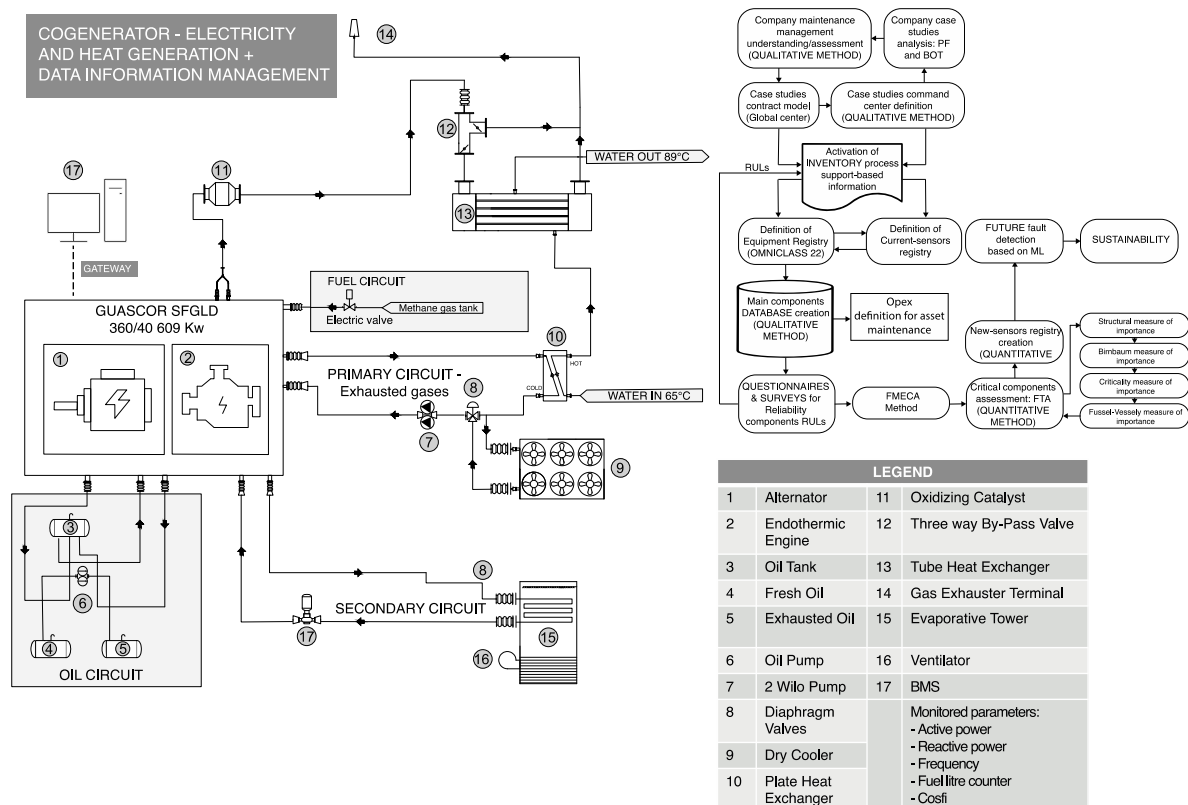
Figure 1. Cogenerator functioning scheme and process to enable failure assessment.

As this database arises from the purpose to enact ProM, useful information headings are those which regard: Estimated RULs [years], Maintenance Operators Expected RULs, Adopted maintenance strategy, Critical parameter(s), Benchmarks, Modalities & Measurement instruments, Controlling driver (Algorithm), Fault modalities, Fault rate [fault rate/year], Sensor detection [Yes/Not], Proposed adding-sensors, Component economical value (Cost per unit [Euro], Labour cost [Euro/h] and Decomissioning costs [Euro] and Component quantities [pieces]).

Moreover, in order to provide an insight of timing indication and maintenance expected cost, a maintenance schedule of 20 years has been added to the database, in order to allocate future replacement cost for SE.

Critical part of this database creation regards RULs definition. As part of this ProM strategy for hospital building SE focuses on the prevision of further dynamic RULs estimation, at this early research stage RUL value have been defined on a statistical basis, by considering components which would have similar operating and exposure conditions. Sources of this RULs estimation have included: Service Life and Maintenance Cost ASHRAEE Database [39], supplier's survey and other scientific databases.

Then, in order to refine RULs estimations to approximable-real values, surveys and questionnaires for on-site maintenance personnel have been performed for two hospital buildings which, for their geographical location, environmental exposure class and entry-to-service time, provide different RULs values with regard to the same component. RULs definition allows to allocate maintenance costs in 20-years maintenance schedule so that expected Operating Expense may be planned for the whole concession period. As real RULs estimation for component in ProM practice is desired, understanding of current sensors solution is required to know which signals are registered and which adding-sensors need to be implemented. A dedicated database of registered signals is required to realize if existing monitored-values may be used to potentially build a particular system data-driven model, which allows to investigate latent fault and RULs.

Consequently, a sensor registry is built by including all the sensors which have been used on components, thanks BMS recording of analogical (on-off) and digital (precise value) Input-Output.

With regards of previous database creation, sensor registry headings take into account: Component, Sensor, Recorded variable, Actual component working-range (benchmark), Implementing-Component variable, Proposed adding-sensors, Commercial proposed adding-sensors.

This assessment allows to start the proposal part of this on-going research.

Continuous activated-inventory allows to gather value from information to find out which is the critical component determining the most frequent consequent-system failure and the most relevant operative maintenance costs. This analysis is performed through FMEA and FTA process activation.

FMECA process (BS EN IEC 60812:2018) [33], feeding by maintenance manual troubleshooting and maintenance operator information, provide the structure for bottom-up approach data slotting, so that Fault/Failure registry may be set up, by breaking down into elements and, for each element in turn, failure modes and effects are identified and analyzed. This is to identify any required improvements by reducing adverse effects. The purpose of based-FMEA analysis is to enable prioritization of the failure modes. Qualitative criticality analysis method evaluates risk and prioritize corrective actions, by rating the severity of the potential effects of failure and rating the likelihood of occurrence for each potential failure mode. Failure modes have been compared via a Criticality Matrix, which identifies severity on the horizontal axis and occurrence on the vertical axis.

Consequence-of-failure (CoF) and Probability-of-failure (PoF) are the outcomes of this process.

Having registered components failures and classified critical item, FTA process has been undertaken to assess components criticalities of the same apparatus (i.e. Cogenerator) in order to weight which component determines the Top Event, based on its reliability (figure 2) . Construction of SE fault trees may be useful to recognize which are critical parameters to be monitored with new sensors.
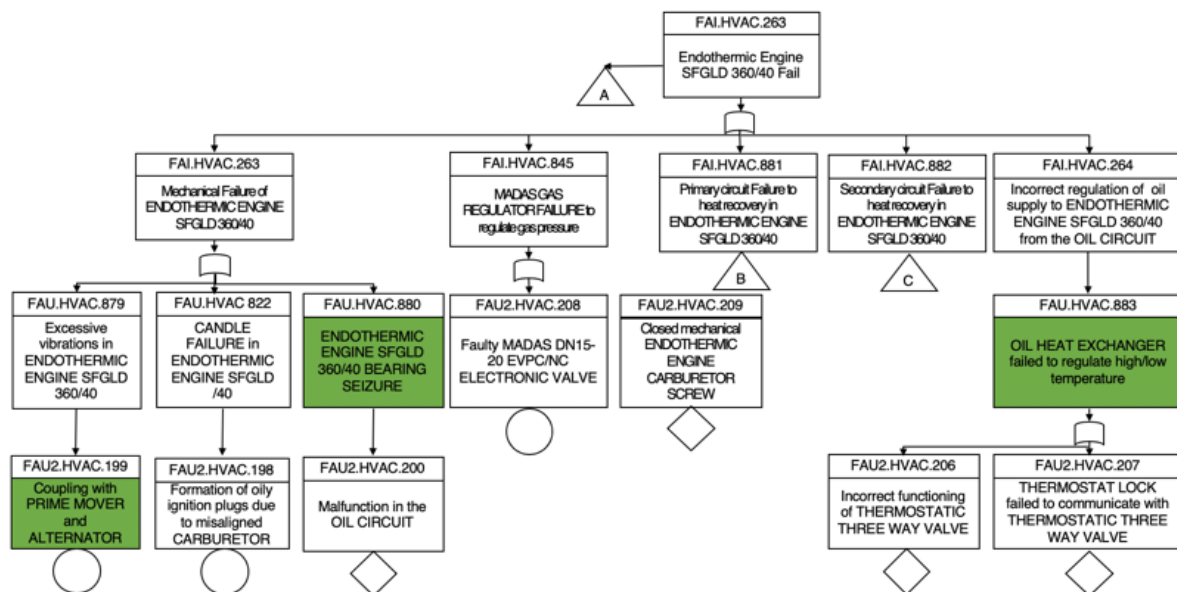

Figure 2. Example of fault tree for cogenerator and transfer gate. Critical elements are in green.

Estimation of critical components here goes through four consequential moments: *Structural measure of importance*, for assessing leaves elements which determine probable failures given the Boolean gates set, *Birnbaum measure of importance*, for deepening component importance analysis by using provided fault rate in a stochastic process, *Criticality measure of importance*, for detecting minimum cut sets for the entire apparatus, and *Fussel-Vessely measure of importance*.

New FM maintenance model, at this stage, represents the future step. New FM model for ProM, indeed, may take advantage of formal and informal knowledge, respectively from sensors and maintenance personnel/expertise, to build an useful asset data-driven model for monitoring latent faults and RULs. This approach may implement the one assumed in previous surveys and statistical approach for RULs estimation. Having traced failure modes of SE through FTA, new sensors may be deployed on critical components. This, however, should be part of an IoT-supported maintenance strategy which identifies an integrated architecture of sensing layer, network layer and service layer. The use of a platform may be useful to connect service provider hospital buildings which require a ProM strategy, in order to further export this model to new contracts of hospital buildings for the same service provider adopting this technique. Collected real-time data can be exploited jointly with BMS to extrapolate trends for RULs assessment and failure prevision of SE, resulting in dynamic maintenance plans which reduces corrective maintenance. Sustainability here may be estimated by measuring benefits of ProM maintenance in terms of failure decreasing which corresponds to less energy demand for SE turn on and off. An aware data collection may be useful to create value and to further sell this value in a future digitalized worldwide service market.

5. Conclusion

Proactive maintenance approaches in building sector may benefit from roll out of maintenance practices in industrialized sectors which is using I4.0 ETs. Facility management may now change its traditional reactive/preventive paradigms toward more proactive maintenance forms which exploit value of data. Moreover, through the deployment of a platform whose aim is reaching sustainability in failure management policy, transformation process of data in information and, then, to knowledge may be possible. This can easily result in a new dynamic and real-time SLA and KPI definition also in maintenance contracts, in new analysis for faults management, and in more appropriate SCADA/BMS system configurations to manage equipment services. IoT, in this sense, can support proactive FM maintenance practice thanks its heterogeneity, by exploiting big data features (5V). Under this premise, a specialized maintenance company, which moves its first steps toward digitalization of services, may innovate sustainability of processes with proactive strategies and new failure management policy when internal knowledge are successful used jointly with big data.

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