A Post-Prognostics Decision framework for cell site maintenance using Cloud Computing and Internet of Things

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Abstract—Maintenance is one of the main factors of production process. The aim of maintenance strategy is not just to repair and maintain equipment in a good condition, but to implement efficient maintenance solutions to ensure the good function while minimizing the cost and time of maintenance. Maintenance strategies start by collecting information from sensors, analyze this information to predict the malfunction or failure in the system. As a result, with this information, we try to find the optimal solution for maintenance. Prognostics Health Manager (PHM) offers significant benefits for maintenance. It predicts the future behavior of a system as well as its remaining useful life. However when factory have a large number of asset with mobile and stationary equipment in different geographically sites. Making decision and collecting information become difficult to be done. In this study we interested in stationary equipment geographically distributed; and we propose a decision post-prognostics framework to help engineers to take the optimal decision for maintenance operation in order to minimize cost and time. In order to enhance the post-prognostics decision, we propose a framework based on Iot technology for real-time sensing to collect information from equipment and Cloud computing paradigm for resources management and information processing.

Keywords— Decision post-pronostics, PHM, cloud computing, Internet of Things.

I. Introduction

Manufactories face every day the challenge of keeping the machines available at the same time minimizing time and cost of maintenance. Corrective maintenance carried out after detection of a breakdown or when a machine needs to be refurbished, has gradually given way to the preventive maintenance. To reduce failure risk or performance degradation preventive maintenance plan maintenance operations in predetermined intervals [1]. With predictive maintenance, breakdown detection jumps to another level. The equipment is continuously controlled, Maintenance is carried out when certain indicators give the signaling that the equipment is deteriorating and the failure probability is increasing.

Prognostics and Health Management (PHM) represent a great opportunity to detect upcoming failures [2] by predicting the future behavior of system as well as its remaining useful life [3] . The wear of the tools when it is not detected in time may lead to damage of the processing machine (or of the tool) and sometimes to accidents. Moreover, the tool wear can impact the reliability, the availability, the security and the quality of the final products [4]. PHM promises significant benefits through reducing maintenance operation coast and time. However, this benefits are related to decision-making based on prognostics information [5].

In these days, industrial manufacturing systems are becoming more and more complex; a lot of them operate in multi-site. Managing maintenance over multiple sites has a set of challenges: Acquisition of data and the large volume of information. To avoid to this problem we propose in our work a post prognostics decision based on Cloud computing and Internet of Things.

The remainder of the paper is organized as follow: In Section 2, we describe and discuss some of the related work about PHM, decision post-prognostics and Cloud Computing, Internet of things technologies. The decision post prognostics definition and challenges are developed in section 3. In section 4 and 5 we describe Internet of things and cloud computing. Proposed framework is discussed in Section 6. Finally, the conclusion is in Section 7.

II. Related works

A. Decision post-prognostics

A few works was interested to post prognostics decision, Chretien and al. [6] propose a post-prognostics decision approach to optimize the commitment of Fuel Cell Systems. And Iyrs and al. [5] developed a decision support system using decision post-prognostics.

B. Cloud computing-based Prognostic and monitoring

Lee and al. [7] implement a PHM cloud-based platforms including developed models to real-world applications to serve the needs of industry. Yang and al. [8] propose a cloud-based prognostics system for providing a low-cost, easy-to-deploy solution for industrial big data collected in factory floors. In order to address new design requirements or resolve potential weaknesses of the original design Xia and al. [9] developed framework for the closed-loop design evolution of engineering system is proposed through the use of a machine condition monitoring system assisted by IoT and CC. Hossain and al. [10] presents a Health IoT-enabled monitoring framework, where ECG and other healthcare data are collected by mobile devices and sensors and securely sent to the cloud for seamless access by healthcare professionals.

C. Internet of Things and Cloud Computing (IoTCloud)

Cloud computing and Internet of Things (IoT) are two very different technologies that are both already part of our life. Their adoption and use is expected to be more and more pervasive, making them important components of the Future Internet.

Botta and al. [11] focus their attention on the integration of Cloud and IoT, which is called the Cloud IoT. Liu and al. [12] study on the architecture of cloud computing technology as the starting point, research on the application of cloud computing in the field of emergency material dispatch in the Internet of things. By introducing cloud computing technology, they make a full call to the storage resource pool and computing resource pool in the cloud computing architecture, and provide high reliability for emergency scheduling cloud storage service and efficient cloud computing services to users. Song and al. [13] proposed framework realized the cloud resources independent dynamic allocation and scheduling for the massive sensor data mining using kernel methods for reducing the computation of spatial data retrieval

D. PHM for Geographically distributed systems

Jin and al [14] proposes a comprehensive Prognostics and Health Management (PHM) framework for large fleets of geographically distributed assets

III. Decision post-prognostics

A. Prognostics and Health Management (PHM)

Prognostic and health management (PHM) could provide the ability of fault detection, fault isolation and estimation of remaining useful life (RUL). It enhances the effective reliability and availability of a system in its life-cycle conditions by detecting upcoming failures. PHM has emerged as a key enabling technology to provide an early warning of failure. Early warning may be used to forecast planned-maintenance and avoid unanticipated operational problems leading to mission performance deficiencies, degradations or adverse effects on mission safety [2].

PHM architecture integrate five layers (Fig.1) described hereafter [2].

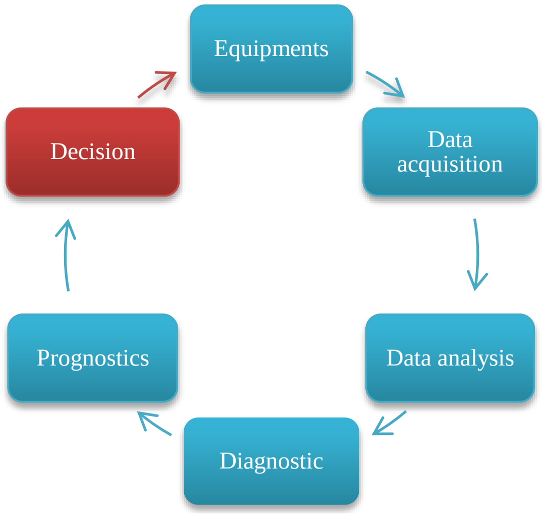

Fig. 1. PHM Architecture

a) Data acquisition: Is the process of measuring an electrical or physical phenomenon using sensor. It provides the PHM application with digitized sensor or transducer data.

b) Data analysis: It is generally necessary to analyze, filtered, interpreted, and archived the data sensor, in order to provide a useful infrastructure.

c) Diagnostic: It determines if the conditions of the system have degraded, suggests fault possibilities and identify the component that has ceased to operate.

d) Prognostic: It predicts the future reliability of a product by assessing the extent of deviation or degradation of the system from its expected normal operating conditions

e) Decision Recommend the optimal decision of maintenance action, how and when this action should be done.

B. Decision post-prognostics

Decision Post-prognostics is the process use the information from prognostics to making the decision of maintenance operation[5] [6] .

C. Challenges

The challenge of Decision post-prognostics not just how to utilize prognostics information in making decisions[15] or when should the maintenance action be done [16] to reduce global life cycle costs and increase availability. But also to have the good information where and when we need to take the strategic decisions[17]. For instance:

- Sensed data: Industrial manufacturing systems are becoming more complex and distributed; this complexity introduces a large number of parameter to be monitored [14].

- Storage data: The large number of information from different sources from different and geographically separated sites leads to a huge volume of data [9].
- Data analyze: Data is generated faster, and powerful computational resources are required to process this data. High Performance Computing is needed to satisfy such requirement [18].
- Manage and share decision: The system is monitored continuously. The information obtained by the prognosis process changes following the monitoring data, the decision must be calculated and shared through all the logistics infrastructure before the information changes [5].

IV. Internet of Things

The Internet of Things (IoT) provides information exchange and communication for device-to-device, device-to-people and device-to-environment. The IoT is a network system that connects equipped with minuscule identifying devices such as RFID, sensors and smart objects with the Internet according to the information shared by the sensing devices and the agreed protocols to realize quick, reliable and real-time information exchange and communication, achieving intelligent identification, location, tracking, monitoring and management [19].

The interconnected objects are inexhaustible sources of information, it create vast amount of data which need communication infrastructure, computational and processing unit to convert this data into useful information to enable real time decision making. This infrastructure is placed generally in cloud [20].

V. Cloud Computing

Despite only a few years of emergence, cloud computing (CC) as a new information technology (IT) paradigm has already started to dramatically change the IT ecosystem as well as other industries by introducing new business models, software development strategies, and research opportunities. The main thrust of Cloud computing is to provide on-demand computing services with high reliability, scalability and availability in a distributed environment. In cloud computing distributed resources are encapsulated into cloud services, SaaS (Software as a Service), PaaS (Platform as a Service) and IaaS (Infrastructure as a Service). These services define a layered system structure for cloud computing and managed in a centralized way[21]. At the Infrastructure layer, processing, storage, networks, and other fundamental computing resources are defined as standardized. Clients can use cloud services according to their requirements. Cloud users can request services ranging from product design, manufacturing, testing, management, and all other stages of a product life cycle [22]. Cloud computing can provide a powerful, secure and easy way to storage massive data and processing infrastructure to perform both online and offline analysis and mining of the heterogeneous sensor data streams [8].

The salient characteristics of cloud computing based on the definitions provided by the National Institute of Standards and Terminology (NIST) are outlined below:

A. *On-demand self-service*

Users are able to provision cloud computing resources, such as server time and network storage. These resources are

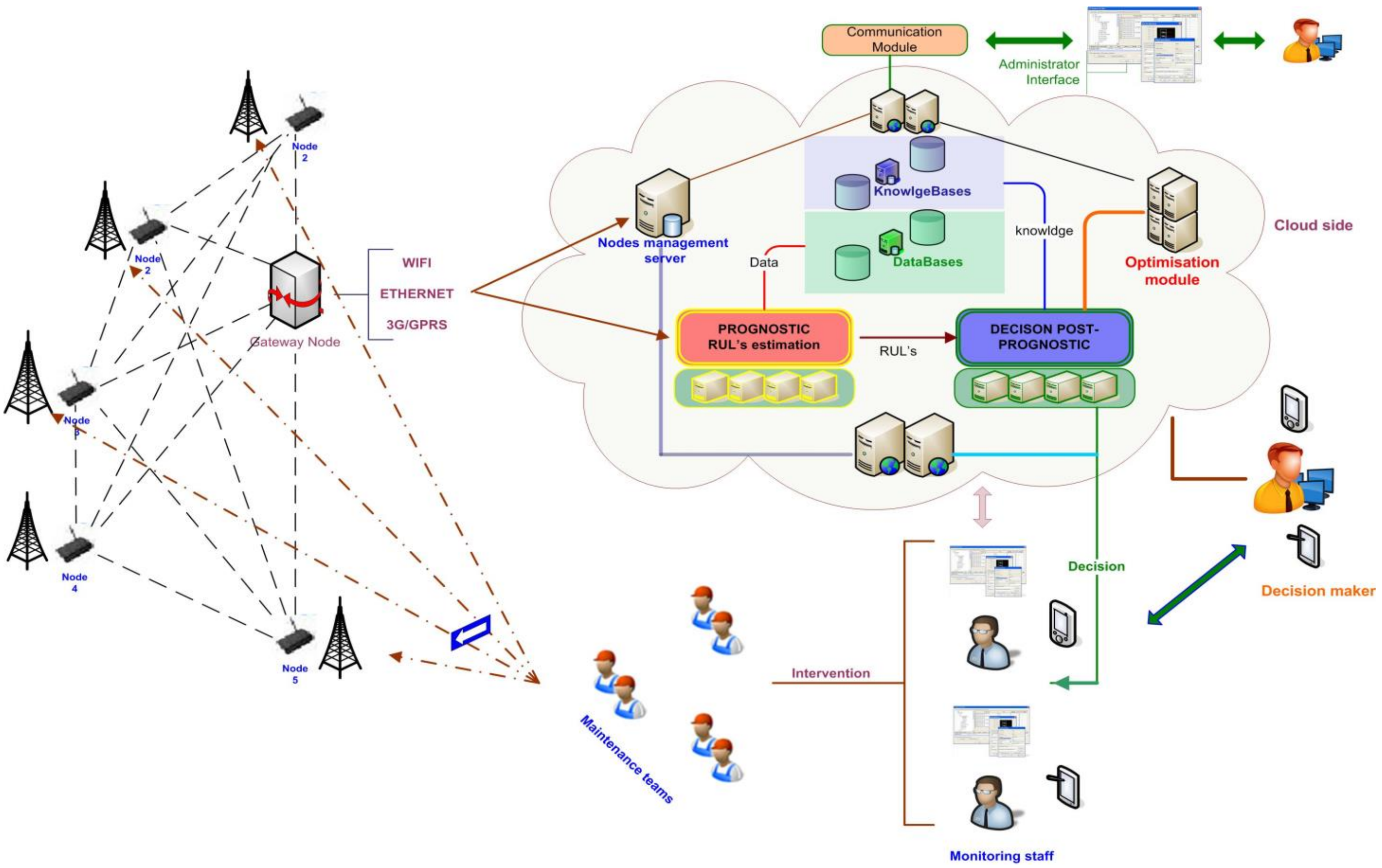

Fig. 2. Main architecture

accessed without the need for human intervention from a client or the service provider.

B. *Broad network access*

Cloud computing resources are accessible over the network, supporting heterogeneous client platforms such as mobile phones, tablets, laptops, and workstations.

C. *Resource pooling*

Computer resources of provider offer a pool of computing resources that can be dynamically assigned to a large number of simultaneous users. The system dynamically allocates these resources (storage, processing, memory, and network bandwidth) according to customer requirements. The users themselves have no control over the physical parameters.

D. *Rapid elasticity*

Capabilities can be elastically provisioned and released on-demand and/or automatically. This will make consumer application have exactly the capacity it needs at any point of time.

E. *Measured service*

Cloud systems automatically control and optimize necessary resources depending on the needs of users and required types of services (e.g., storage, processing, bandwidth, and active user accounts). All these services are measurable and their usage is transparent, both for the provider and clients

VI. Decision post-prognostics using CC and IoT

A. *Architechture*

The increasing number of cell phone users and the usage of cell phones have demanded the network service providers to increase the number cell tower and extend it to all places. A cell tower, also referred as a cell site, is a tower or long vertical pole includes radios, antennas for receiving and transmitting RF (radio frequency) signals, computerized switching control equipment, GPS receivers, power sources and protective cover.

Cell site maintenance activities help network service providers to leverage their key infrastructural assets and promise high quality uninterrupted services to their consumers.

These cell sites are geographically distributed and a lot of them in remote areas. The maintenance teams are also in different sites. To maintaining these cell sites in work will minimize the cost of maintenance, a predictive maintenance using PHM is applied. The first step is to collect and analysis data from cells sites, then the prognostics process predict the remaining useful life (RUL) of each cell site, based on these RULs a decision of maintenance operation is made.

The IoT collect, sort, synchronize and organize the data in real time from the different equipment in the different sites, the application of IoT brings a huge number of data from whole components. In order to process the continuously changing sensor data streams, the IoT application system terminal equipment must implement the massive sensor data storage and the powerful computing ability for real-time collection, dissemination and extracting of sensor data to users and administrators anytime and from anywhere.

By introducing cloud computing technology and it characteristics (on-demand self-service, broad network access, resource pooling and rapid elasticity), we can make a call to the storage and computing resource in the cloud computing architecture (Fig. 2).

B. *Problem statement*

The system is composed of a set of machines $\{\mathrm{M}_1, \mathrm{M}_2, \dots, \mathrm{M}_m\}$, these machines are geographically distributed (Fig.3). Each machine M_i is described by her position (x_i, y_i), Rul_i the remaining useful life and D_i the duration of maintenance of this machine. We suppose that these machines are stationaries equipment, her position don't change. And it can be used simultaneously and independently from each other.

The Team of maintenance experts $\{E_1, E_2, \dots, E_e\}$ have the same expertise. They are in different sites.

The decision post-prognostics process must provide the maintenance plan specifying who will do what and when. In condition that the maintenances of each machine must be done in the instance t before broken down time: $t < RUL$.

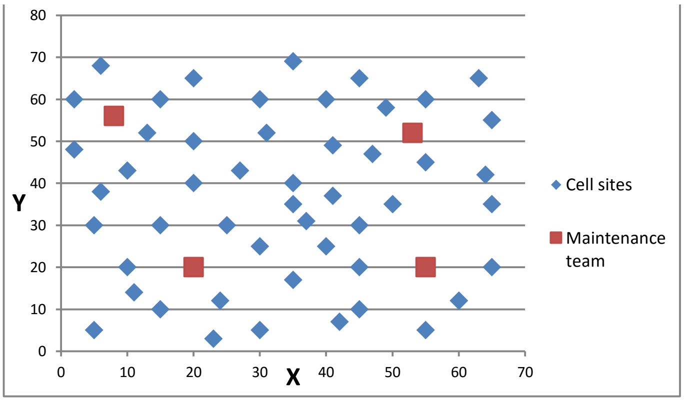

Fig. 3. Machines and maintenance experts positions

C. *Implementation*

The first step is to assign a set of machine for each expert; each machine is assigned to the closer expert using the Euclidian distance. A machine M_i is assigned to the expert E_j if:

$$dis\left(M_i, E_j\right) = \min[dis(M_i, E_k)] \qquad (1)$$

$$\forall\, k, 1 < k < e \text{ and } k \neq j$$

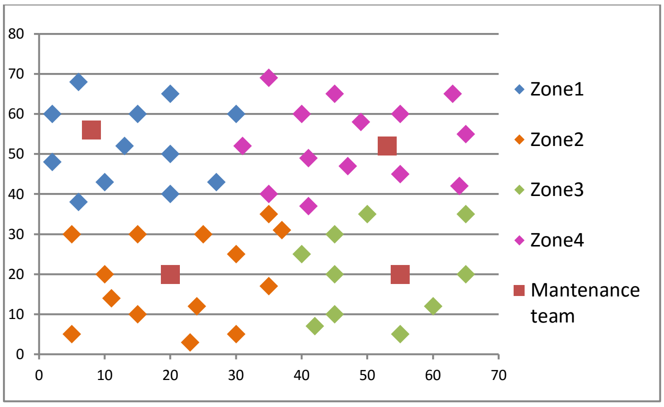

Fig. 4 Assigned machines to experts

The next step is to set up the schedule of the maintenance tasks for each expert. We use the genetic algorithm to minimize the distance crossed by every maintenance expert.

1. *Generate an initial random population of chromosomes*
2. *Test fitness of population*
3. *Select parents*
4. *Reproduce from selected parents to produce a new population (crossover and mutation operators)*
5. *Correct and validate the new solutions*
6. *Evaluation*
7. *Repeat 3 to 6 until termination criterion is met.*

A chromosome or solution represents the order of machines; the first step generates *N* random solution. A solution is accepted if the start time of the maintenance of each machine doesn't exceed her RUL. New population is generated by the crossover and mutation of selected best parents. The new solutions are corrected, the duplicate machine in the same solution are replaced by missed ones. If the solution satisfies the condition of RUL then this solution is accepted. In the last step the best solutions from old and new population represent the population used in the next iteration.

Fig.5 represents the order of maintenance operation of machines in the zone 2. The maintenance operation of the first machine starts in the instance $t_0 = 0$ the next ones in the instance:

$$t_i = t_0 + \sum_{j=0}^{i-1} D_j \qquad (2)$$

To compare the proposed method, we use the intuitive affectation of maintenance operation to expert, we start by the machine which has the smallest RUL and assigned the available closer expert (Fig.6).

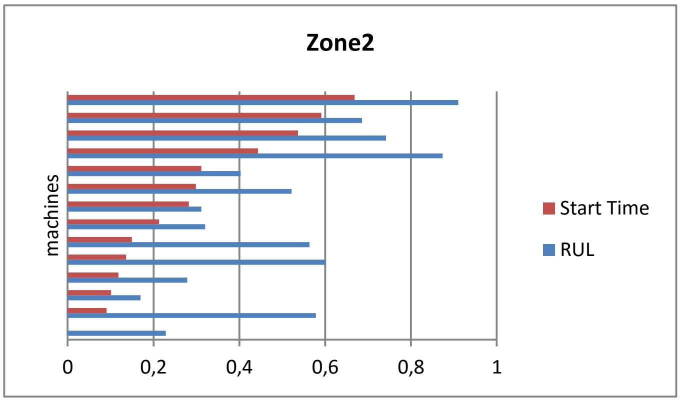

Fig. 5. Start time of maintenance and Ruls of machines in zone2

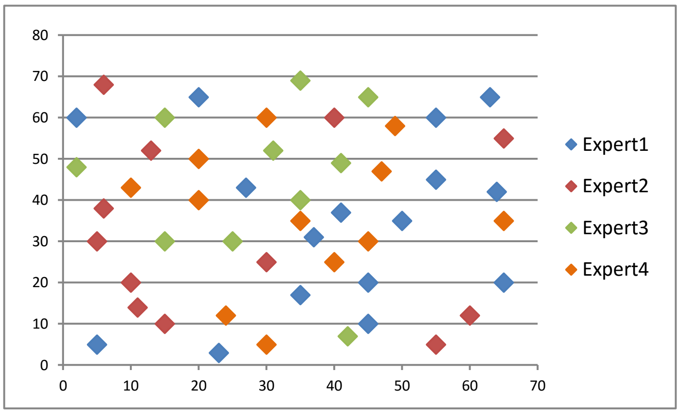

Fig. 6 assigned machine to experts

The distance crossed by each expert is shown below (Fig. 7)

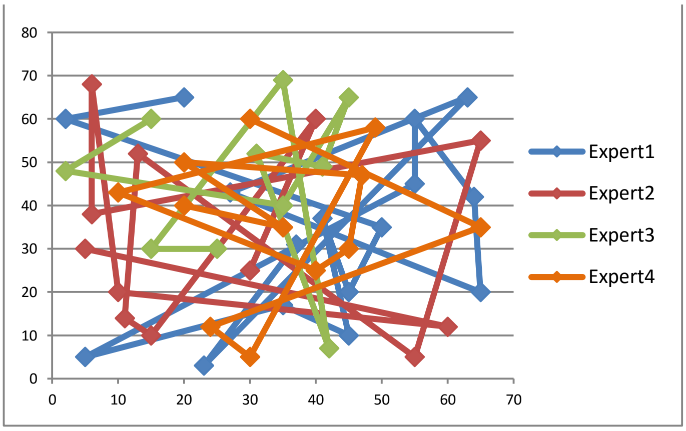

Fig. 6. Crossed distance by each expert

The results of the both methods are compared in the table below; the distance crossed by each expert is widely optimized. The total distance crossed by the maintenance team is decreased from *1577.62* to *687.12*.

TABLE I. DISTANCE CROSSED BY EACH EXPERT

	Min RUL		Proposed method	
	Machines number	Distance	Machines number	Distance
Expert 1	16	490,76	12	178,11
Expert 2	12	498,11	14	212,44
Expert 3	10	268,05	10	115,96
Expert 4	12	320,70	14	180,61
Total	50	1577,62	50	687,12

VII. CONCLUSION

PHM can be defined as a technology to enhance the effective reliability and availability of a system in its life-cycle conditions by detecting upcoming failures. It aims at predicting and protecting the integrity of equipment and complex systems. The prognostics predicted the useful life reaming; according to this RUL a decision of maintenance must be planned a decision post-prognostics process must be integrated. The industry system in our days are more complex and distributed in different sites, this need more resources to storage data and availability in a distributed environment.

Collaboration, Internet of things and cloud have been used in this paper to collect information from machine, analyze and storage this data to provide a decision post prognostics solution as a cloud service, we proposed a method for the planning of maintenance using genetic algorithm to minimize the distance crossed by maintenance team to ensure that the maintenance operations are done before broken down time of machines.

As future work, we wish to take into consideration the expertise of maintenance team, cost and availability of replacement part. We also wish to integrate the production schedule to choose the best time of maintenance operations.

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