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# An IoT-based solution for Post-Prognostics Decision in Cloud computing environment

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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:** *Maintenance, decision post-prognostics, PHM, cloud computing, Internet of Things, genetic algorithms.*

## 1 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 (Tobon-Mejia et al. 2012).
(Jouin et al. 2015a) 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 (Jouin et al. 2014) by predicting the future behavior of system as well as its remaining useful life (Jouin et al. 2015b) . 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 (Benkedjouh et al. 2013). PHM promises significant benefits through reducing maintenance operation coast and time. However, this benefits are related to decision-making based on prognostics information (Iyer, Goebel, and Bonissone 2006).
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, the decision post prognostics definition and challenges are developed. In section 3 and 4 we describe Internet of things and cloud computing. We describe the main architecture in section 5. The decision making problem and the genetic algorithm proposed are developed in sections 6 and 7. Finally the result and conclusion in section 9

## 2 DECISION POST-PROGNOSTICS

### 2.1 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 (Jouin et al. 2014).
PHM architecture integrate five layers (Fig.1) described hereafter (Jouin et al. 2014).

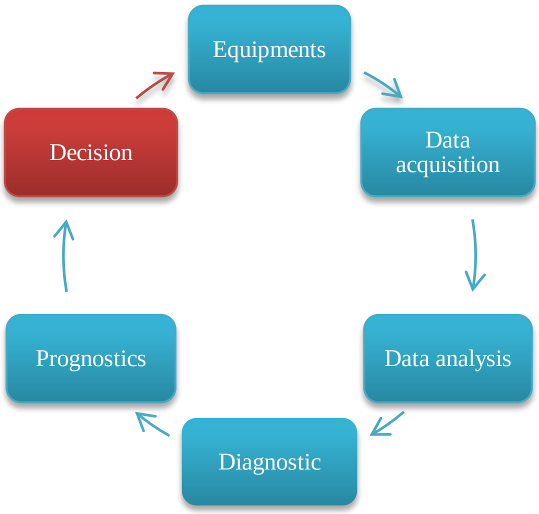


Figure 1: PHM Architecture

#### *2.1.1 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.

#### *2.1.2 Data analysis*

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

#### *2.1.3 Diagnostic*

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

#### *2.1.4 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.

#### *2.1.5 Decision*

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

### 2.2 Decision post-prognostics

A few works was interested to post prognostics decision, Chretien and al. (Chretien et al. 2015) propose a post-prognostics decision approach to optimize the commitment of Fuel Cell Systems. And Iyrs and al. (Iyer, Goebel, and Bonissone 2006) developed a decision support system using decision post-prognostics.
Decision Post-prognostics is the process use the information from prognostics to making the decision of maintenance operation(Iyer, Goebel, and Bonissone 2006) (Chretien et al. 2015).

### 2.3 Challenges

The challenge of Decision post-prognostics not just how to utilize prognostics information in making decisions(Ribot, Pencole, and Combacau 2009) or when should the maintenance action be done (Si, Hu, and Wang 2012) 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(Rasovska, Chebel-Morello, and Zerhouni 2008). For instance:

#### *2.3.1 Sensed data*

Industrial manufacturing systems are becoming more complex and distributed; this complexity introduces a large number of parameter to be monitored (Jin et al. 2015).

#### *2.3.2 Storage data*

The large number of information from different sources from different and geographically separated sites leads to a huge volume of data (Xia et al. 2016).

#### *2.3.3 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 (Church, Goscinski, and Tari 2014).

#### *2.3.4 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 (Iyer, Goebel, and Bonissone 2006).

## 3 INTERNET OF THINGS (IOT)

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 (Khan et al. 2012).
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 (Yue et al. 2015).

## 4 CLOUD COMPUTING (CC)

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(Terrissa and Ayad 2015). 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 (Xu 2012). 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 (Yang et al. 2015).
The salient characteristics of cloud computing based on the definitions provided by the National Institute of Standards and Terminology (NIST) are outlined below:

### 4.1 On-demand self-service

Users are able to provision cloud computing resources, such as server time and network storage. These resources are accessed without the need for human intervention from a client or the service provider.

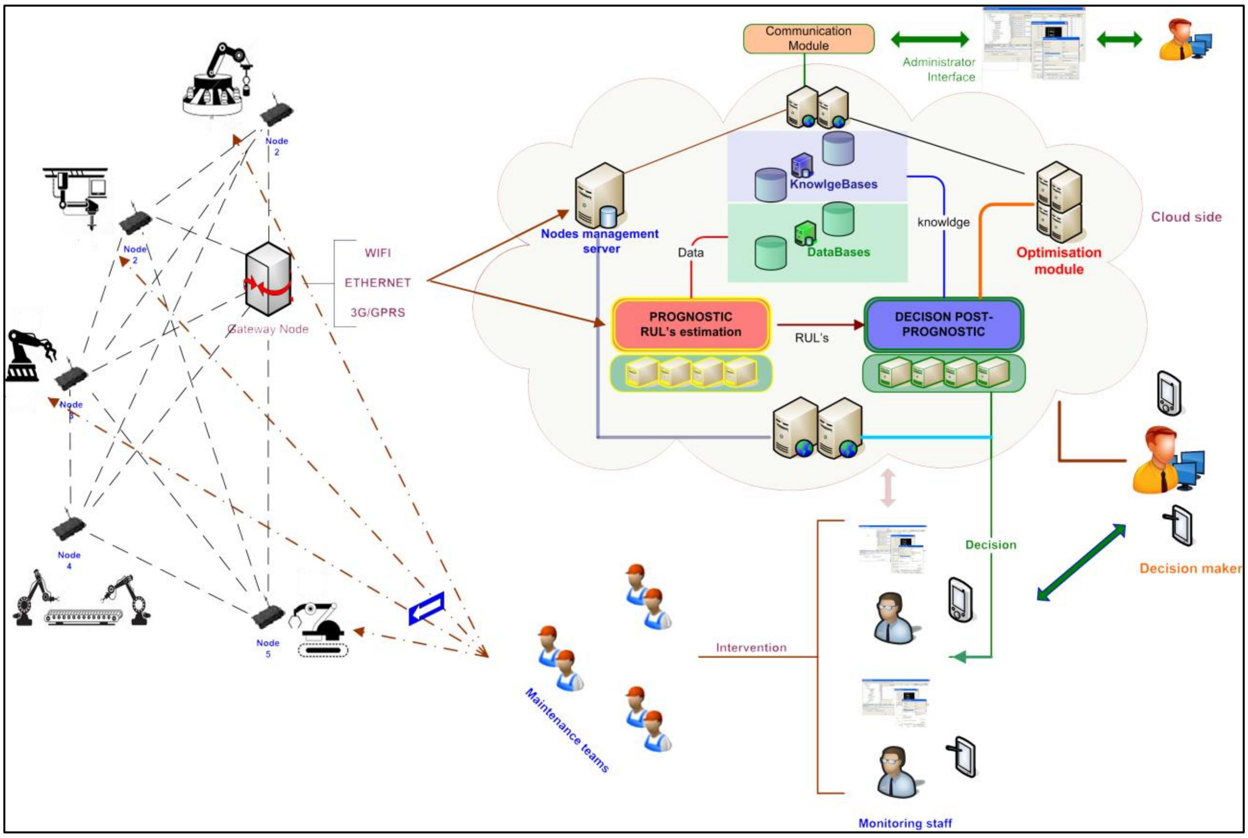


Figure 2: Main architecture

### 4.2 Broad network access

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

### 4.3 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.

### 4.4 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.

### 4.5 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.

In our approach the core value of introducing cloud computing lies in the concept of storage, cloud computing and sharing

## 5 ARCHITECTURE

The proposed architecture integrates equipment that communicates using IoT technology. The IoT collect, sort, synchronize and organize the data in real time from the different equipment. These data are analyzed by the PHM technology integrated in a cloud platform. Using the cloud computing provide storage and computing resources to analyze and storage the huge number of data brings by IoT and sharing the decision and information provided by the PHM. The prognostics process provide the RUL of the machine according to real time data, these RUL and other information (the maintenance team, product system, sport part,…) are used in post-prognostics decision in order to elaborate a maintenance scheduling.

## 6 PROBLEM STATEMENT

Maintain the product system of a factory in work while minimizing the cost of the maintenance operation is the aims of maintenance strategy. A decision maker must elaborate a maintenance scheduling according to the health of the product system machines

The PHM is one of the most used technologies in the predictive Maintenance. The remaining useful life of each machine is calculated by the prognostics processes. The decision maker can know which machine needs a maintenance operation and assure that the maintenance operation of each machine will be done before broken down time. Although, the number of machine has complicate the decision making, this is why a decision post prognostics tools must be integrate to provide the optimal maintenance scheduling witch minimize the cost.
The maintenance cost depends on various parameters, like spare parts, material, and maintenance labors (manpower). In this paper we interest on optimizing the maintenance labor cost.

Maintenance labor represents all labor skills that directly work on maintenance, usually comprises a team of several skills to ensure the quality and cost effectiveness of the maintenance. Each person in the maintenance team has one or more skills and his wage depends on these skills. Each person has a maintenance scheduling of a set of machine which required one or more of his skills. A maintenance operation which needs several skills can be assigned to one person who has these skills or many people who have each one, one or more of these skills. For each machine the maintenance cost (4) could be divided on two parts, the cost of the labor wage *(LM)* (1) and the cost of the component which must be changed (2).

$$LW = \sum_{i=1}^{m}\left[\sum_{j=1}^{p}(w_j \times D_i)\right] \qquad (1)$$

$m$ is the machine number .
$p$ is the number of person who must do the maintenance operation of the machine i.
$w_j$ Is the wage of the person j who have to do the maintenance operation of the machine i.
$D_i$ is the maintenance duration operation of the machine i.

To optimize the cost of component we suppose that the maintenance operations must be done as late as possible to not change a component that is in good condition. the cost of component *(CCo)* is given by:

$$CCo = \sum_{i=1}^{m}[(RUL_i - t_i) \times C_i] \qquad (2)$$

$t_i$ : The start time of maintenance operation
$RUL_i$ : Remaining useful life of the machine i

The $C_i$ is the allocation of the cost of purchase to the estimated life time of the component which must be changed

$$C_i = \frac{CP_i}{ELT_i} \qquad (3)$$

$CP_i$ cost of purchase of the component.
$ELT_i$ the estimated life time of the component.

The cost of the maintenance operation is given by:

$$Cost = LW + CCo \qquad (4)$$

In this work, genetic algorithms (GA) were adopted as an optimization tool to elaborate a maintenance scheduling that optimizes the total cost of maintenance.

## 7 GENETIC ALGORITHM

Genetic algorithms (GA) are stochastic-based search techniques that comprise a population of individuals, where each individual encodes a candidate solution in a chromosome. GA was applied to resolve maintenance problem. (Samhouri 2009) a genetic algorithms are used, as an optimization tool to compare the cost of premature replacement with the cost of downtime if grounded for the sole purpose of replacement. (Hinow and Mevissen 2011) shows the application of GA to optimize the substation LCC by finding the best maintenance strategy. A GA that optimizes system availability, and cost with system-maintenance constraints is presented in (Camci 2009) .
An implementation of a genetic algorithm begins with a population of (usually random) chromosomes. One then evaluates these structures and allocates reproductive opportunities in such a way that those chromosomes which represent a better solution to the target problem are given more chances to reproduce than those chromosomes which are poorer solutions. The goodness of a solution is typically defined with respect to the current population.
The main steps of proposed genetic algorithm could be summarized as follow:

1) Generate an initial, random population of chromosomes
2) Validate the chromosomes
3) Select parents as the most fit members of the population according of each criterion
4) Reproduce from selected parents to produce a new population
5) Mutate according to some probability
6) Repair the new population
7) Validate the new population
8) Test the fitness of each chromosome in the new population
9) Evaluation
10) Iterate steps 3 to 7 until termination criterion is met

### 7.1 Chromosome representation

The algorithm uses chromosomes which codify the scheduling of maintenance operation in a vector of length *P*, where *P* is the number of person in the maintenance team. Thus, each gene represents the scheduling of maintenance operation of one person; it contains a set of machines which need maintenance operation.

| $P_1$ | $P_2$ | … | $P_p$ |
|---|---|---|---|
| $M_6$ | $M_1$, $M_2$, | … | $M_2$, $M_9$, $M_{10}$ |

Figure 3: Chromosome representation

### 7.2 Initial Generation

A machine is randomly chosen. A set of persons who have the required skills for the maintenance operation of this machine are randomly selected. A candidate person could have one or several skills of the required skills for the maintenance. The maintenance operation of the machine chosen is added to the scheduling of the selected persons. This process is repeated until all machines are associated to a maintenance team.

### 7.3 Selection

In each generation, the individuals, which provide the facilities to their succession substations, have to be chosen by a selection procedure. The first step is to calculate the fitness of the population relative to each criterion; the best individuals according to each criterion are selected.

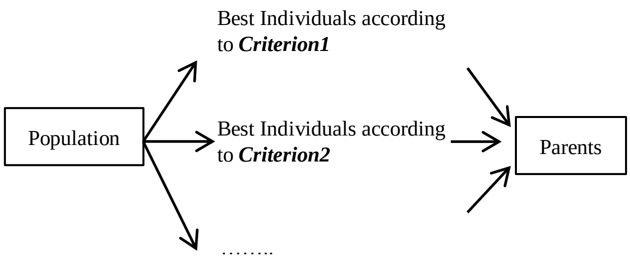


Figure 4: Multi-criterion selection

### 7.4 Crossover

The interesting behavior happens from genetic algorithms because of the ability of the solutions to learn from each other. The crossover is based on the principle that pairs of individuals of the selected population generate successors whose abilities are a mixture of their parent's abilities.
Many crossover techniques exist. In this work we use single point crossover; a position is randomly selected at which the parents are divided into two parts. The parts of the two parents are then swapped to generate two new offspring.

### 7.5 Mutation

One machine randomly changes it position from a person to another. The two persons must have the same skill required by this machine. The purpose of mutation is to diversify the search direction and prevent convergence to the local optimum.

### 7.6 Evaluation

After producing offspring they must be inserted into the population. The best individuals of the original population and offspring form the new population.

### 7.7 Validate:

A solution is accepted if the start time of the maintenance operation of each machine is before its broken time. After the generation of new individual, the start time of maintenance is calculated for all machines. If the start time for one or many machine exceeds the RUL of the machine, the new individual is not accepted.

### 7.8 Repair

The genetic operators may produce infeasible schedules that contain duplicate or missing maintenance operation or precedence relationships. Infeasible chromosomes are rectified in three steps:

1. Delete duplicate operation
2. Add missing operation
3. Adjust Operation precedence

## 8 EXPERIMENT RESULTS

This section includes the implementation of the presented method. The proposed GA was tested with a set of 50 machines and 10 persons in maintenance team. This GA was applied to optimize the cost of maintenance operations.
For each iteration the maintenance cost (4), labor wage (1) and component cost (2) of the best solution were calculated. Figure 5 present the evaluation of these costs.

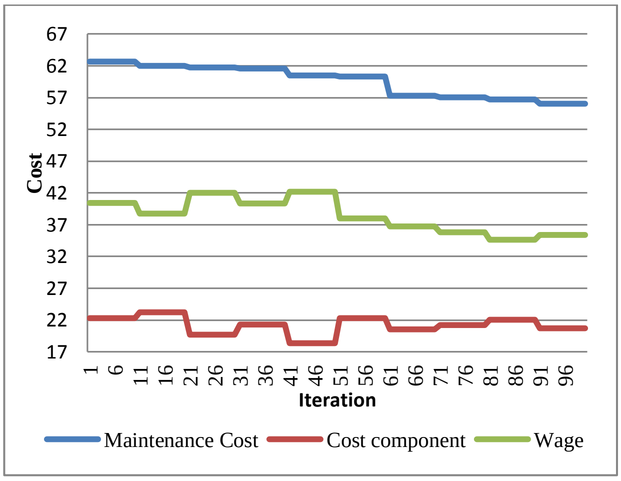


Figure 5: Best solution in each iteration

## 9 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 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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