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NEURAL NETWORK MODEL FOR PROGNOSTIC AS A SERVICE IN PRIVATE CLOUD COMPUTING

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ABSTRACT: *Prognostic and health management (PHM) systems are designed to predict impending faults and to determine remaining useful life of machinery. An efficient prognostic system can speed up fault diagnosis by providing an indication of what parts of the machinery are most likely to fail and will need maintenance in the near future. PHM systems for manufacturing industry have not been widely implemented despite the extensive research on PHM in academia, which is mostly due to high costs in both development and implementation of PHM solutions in industrial applications. In this paper, we are defined the predictive maintenance, prognostic and health management (PHM) architecture and present the state of the art of prognostic approaches and display the related works in this domain. After that, we are proposed a new approach that is adapting cloud computing paradigm with PHM systems that is Prognostic as a Service to provide high readiness, easy-to-configure, low cost and ondemand PHM services. We had presented our obtained results and its simulation*.

KEYWORDS: *Prognostic and Health Management (PHM), Predictive Maintenance, Remaining Useful Life (RUL), Neural Network Method, Cloud Computing, Prognostic as a Service.*

1 INTRODUCTION

It is well known that 99% of machine failures are preceded by some indicators (M. El Koujok, 2010). Therefore, condition-based predictive maintenance is probably the most economical way to maintain machinery. Its idea is to allow the determination of machinery health in a real-time, online fashion. As such, faults can be predicted before they take place. Maintenance can then be scheduled as needed. (M. Xia, et al., 2016) Reported benefits of predictive maintenance include reduced downtime, lower maintenance costs, and reduction of unexpected catastrophic failures. (C.-C. Lin and H.-Y. Tseng, 2005)
The objective of this paper is to define the predictive maintenance, prognostic and health management (PHM) architecture and present the state of the art of prognostic approaches and display the related works in this domain. After that we are proposed a new approach that is adapting cloud computing paradigm with PHM systems to provide high readiness, easy-to-configure, low cost and ondemand PHM services. We had presented our obtained results and its simulation.

2 PROGNOSTIC AND HEALTH MANAGEMENT

Prognostics and diagnostics are the key players in service planning, maintenance and minimizing the down state of equipment. Diagnostics focuses on the detection, isolation and identification of failure when they occur whilst prognosis focuses on predicting failure before it occurs. Prognosis can be referred to as the ability to predict how much time is left or remaining useful life (RUL) before a failure occurs given an observed machine condition variable and past operational profile. The figure 1 presents the PHM architecture.

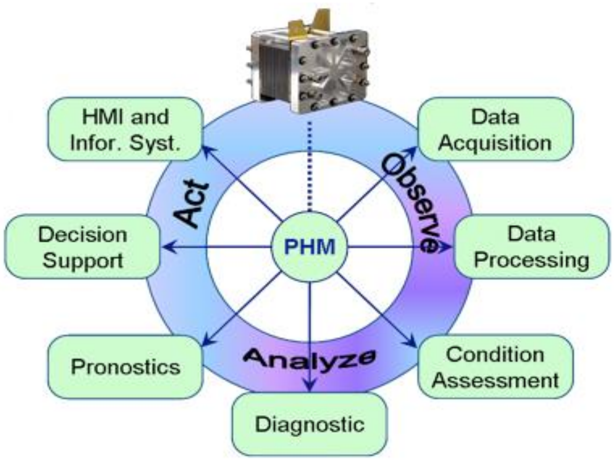

Figure1 – PHM Architecture (K. Medjaher, et al., 2011)

3 STATE-OF-THE-ART OF THE PROGNOSTIC APPROACHES

Various methods have been applied to the prognostic of degraded components. Generally, they are classified in three fundamental families:

3.1 Prognostic Based on Models

This approach is also called model-driven or physical model. As its name indicates, this approach family uses models that can be of two different types:
- Equipment's physics-based model
- Mathematical models constructed by experimentation

This "Physical model" is based on mathematical description of degradation process and on its level evolution using NDI monitoring (Non-Destructive Inspection). It is described to be more flexible and precise than the two other approaches. The degradation is then considered as a continuous variable whose evolution is characterized by a deterministic or a stochastic law. The concept of these methodologies is to make the constructed model evolve till a wanted future instant, from an initial degradation state and the future usage of the equipment (Y. XIANG and Y. LIU, 2010). The equipment is considered as faulty when the degradation variable reaches a predefined threshold in the case of an isotropic model, or a predefined surface in the case of non-isotropic model. These models can be: nonlinear equations (X. GUAN, et al., 2010), models defined by expert analysis (R. PATRICK-ALDACO, 2007), or even by physical models of chemical corrosion (A. ABOU JAOUDE, et al., 2012), of mechanical fatigue (J. LEE, 1996), etc. For some equipments and critical structures, it is necessary to estimate the initiation and the crack propagation. The models based on crack propagation are interested in the problems dealing with material properties, and they have evidently an important interest in prognostic, but they are usually adapted for a real-time treatment due to their big computational complexity (C. Y. Yin, et al., 2008). A technique, among others, capable of predicting the slope of increase and the directions of the crack, is the simulation by decomposition in finite elements. The decomposition in finite elements is used to study the behaviour of an equipment in different disciplines such as thermodynamics, fluids mechanics, structures mechanics etc...The method of finite elements is based on the idea that a complex system can be subdivided into small parts called elements. Each element is completely defined by its geometry and its physical properties. The study of each element is then simpler than the study of the complete structure that they compose. Each element can be considered as a continuous part of the structure. The decomposition in finite elements converts a continuous structure into a system of algebraic equations or into ordinary differential equations. The solution of a problem using the theory of finite elements invokes methods of research of simultaneous solutions to the reaction of each element to charges, to constraints, and to the interaction among the adjacent elements. An example of the application of this theory is the prognostic for a system of transmission of a helicopter; it is presented in (R. PATRICK-ALDACO, 2007).

3.2 Prognostic Guided by Data

This approach is also called Data-driven or evolutionary or trending or estimation based approach or artificial intelligence.
In certain cases, it happens that we dispose of a database containing the history of scenario degradation/failure represented by a set of time series. These bases are given without the use of a physical model of equipment behaviour. The evolution of the degradation indicator is then realized with the help of a statistical method. Depending on the method used, three classes of approaches can be distinguished [9,10]:
- The prognostic by trend analysis
- The prognostic by learning
- The prognostic by state estimation

The data-based approaches require that the information extracted from sensors be sufficient in quality and quantity in order to evaluate the current state or the image of the current state of the system degradation.
The concept of this approach consists of collecting information and data from the system and projecting them in order to predict the future evolution of some parameters, descriptors or features, and thus, predict the possible probable faults. Without being exhaustive, mathematical tools used in this approach are mainly those used by the artificial intelligence community, namely: temporal prediction series, trend analysis techniques, neuronal networks, neuro-fuzzy systems, hidden Markov models and dynamic Bayesian networks [4,7,9].
The advantage of this approach is that, for a well monitored system, it is possible to predict the future evolution of degradation without any need of prior mathematical model of the degradation. However, the results obtained by this approach suffer from precision, and are sometimes considered as local ones (for the case of neural networks and neuro-fuzzy methods). In addition, the monitoring system must be well designed to insure acceptable prognostic results.

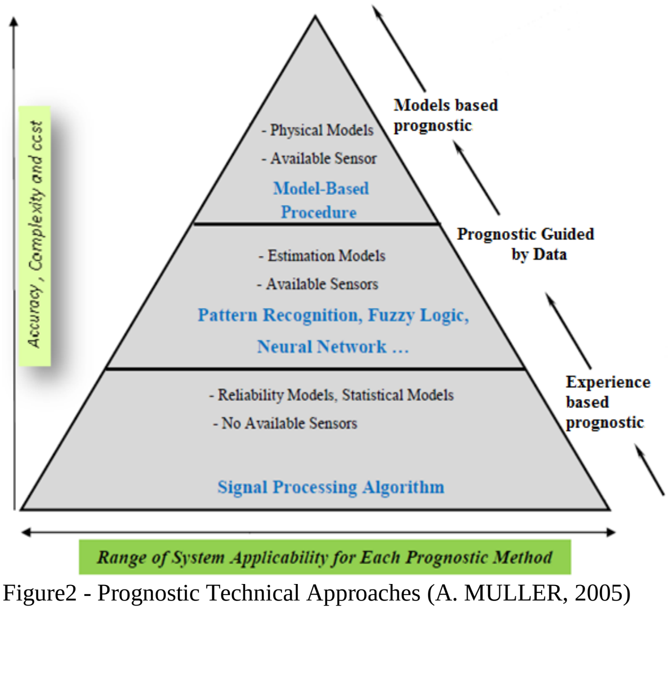

Figure2 - Prognostic Technical Approaches (A. MULLER, 2005)

3.3 Prognostic Based on Experience

This approach is called experience based, probability based, or statistical based prognostic approach. It is necessary where we cannot use the two previous approaches. It is based on a reliability function or on a Bayesian process where the parameters are taken from feedback experience or expert opinion. This prognostic approach consists of using probabilistic or stochastic models of the degradation phenomenon, or of the life cycle of the components, by taking into account the data and knowledge accumulated by experience during the whole exploitation period of the industrial system. (O.E. VASILE, 2008)

4 REMAINING USEFUL LIFE (RUL)

Predicting the remaining useful lifetime of industrial systems becomes currently an important aim for industrialists knowing that the failure, which can occur suddenly, is generally very expensive at the level of reparation, of production interruption, and is bad for reputation. RUL and its attributes are the outcome of prognostics and are used in prognostic assessment by applying appropriate metrics and additional criteria. There is a wide range of methods dealing with RUL computation and calculation. (C. Y. Yin, et al., 2008)

5 CLOUD COMPUTING

The definition of NIST (National Institut of Standards and Technology) is:
"Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction."
"The interesting thing about cloud computing is that we've redefined cloud computing to include everything that we already do." [Larry Illison, Oracle's founder]
This cloud model is composed of five essential characteristics, three service models, and four deployment models.

5.1 Characteristics of Cloud Computing

There is five essential characteristics of cloud computing: (L. Sadek. Terrissa, 2015)

- On demand self-service: a consumer can request and receive access to a service without an administrator or
- Broad Network Access: cloud services should be easily accessed. Users should only be required to have a basic network connection to connect to services or applications.
- Resource pooling: it is accomplished using virtualization. Providers can host multiple virtual sessions on a single system.
- Rapid elacticity: it describes the ability of a cloud environment to easily grow to satisfy user demand.

Measured services: cloud services must have the ability to measure usage. Services are measured according to the duration and the quantity of used resources.

5.2 Service models of Cloud Computing

- SaaS (Software as a Service): is a model of software deployment where an application is hosted as a service provided to customers across the internet. Gmail, Hotmail, SalesForce.com and Microsoft Office Online are some of the well-known SaaS products and providers. (Z. Mahmood and R. Hill, 2011)
- PaaS (Platform as a Service): This refers to software and product development tools (e.g. application servers, database servers, portal servers, middleware, etc.) which clients lease so they can build and deploy their own applications for their specific use. Google App Engine and Windows Azure are examples of PaaS products and providers. (Z. Mahmood and R. Hill, 2011)
- IaaS (Infrastructure as a Service): is essentially hardware devices, e.g. visualized servers, storage, network devices, etc. It generally refers to a virtualization environment where services enable the Cloud platforms and applications to connect and operate. Amazon Elastic Cloud Compute (EC2), VMWare are some of the IaaS products and providers. (Z. Mahmood and R. Hill, 2011)

There is another type of service that is defined recently

- XaaS (Everything as a Service): EaaS or *aaS is a subset of cloud computing, according to Wikipedia, which calls EaaS "a concept of being able to call up re-usable, fine-grained software components across a network. (R. Jennings, 2009)

5.3 Deployment models of Cloud Computing

- Private Cloud: The Cloud infrastructure is owned or leased by a single enterprise and is operated solely for that organization. (Z. Mahmood and R. Hill, 2011)
- Public Cloud: The Cloud infrastructure is owned by an organization selling Cloud services to the general public or to a large industry group. (Z. Mahmood and R. Hill, 2011)
- Community Cloud: The Cloud infrastructure is shared by several organizations and supports a specific community. (Z. Mahmood and R. Hill, 2011)
- Hybrid Cloud: The Cloud infrastructure is composition of two or more Clouds such as private, community, or public that remains unique entities. (Z. Mahmood and R. Hill, 2011)

6 RELATED WORKS

In (A. Mosallam, et al., 2014), authors have presented a data-driven method for remaining useful life (RUL) prediction. The method learns the relation between acquired sensor data and end of lifetime (EOL) to predict the RUL. The proposed method extracts monotonic trends from offline sensor signals, which are used to build reference models. From online signals, the method represents the uncertainty about the status, using discrete Bayesian filter. The method predicts RUL of the monitored component using integrated method based on K-nearest neighbour (k-NN) and Gaussian process regression (GPR). The performance of the algorithm is demonstrated using two real data sets from NASA Ames prognostics data repository. The results show that the algorithm obtain good results for both application.

In (M. El-Koujok, et al., 2010), authors have treated the problem how to build a prognostics system with no human intervention, neither a priori knowledge. The proposition is based on the use of a neuro-fuzzy predictor whose architecture is partially determined thanks to a statistical approach based on the Akaike information criterion. The last one has been introduced in order to provide a mathematical formulation of the principle of parsimony in the field of model construction (A. Saxena and K. Goebel, 2008). This criterion enables to judge from the quality of fit of an estimator and can be used with prediction models. It consists in using a cost function in the learning phase in order to automatically generate an accurate prediction system that reaches a compromise between complexity and generalization capability.

In (J. Lee, et al., 2013), a cloud-based prognostics and health management system for manufacturing industry has been developed based on Watchdog Agent tools and the ideology of PHM as a Service. In addition to traditional data acquisition and management functions in a machine condition monitoring system, the cloud based PHM platform is able to further provide on-demand, customizable and low-cost data analysis service. Machinery data accumulated within the cloud system further enables more advanced services such as machine-to-machine comparison, data mining and knowledge discovery.

In (M. El-Koujok, et al., 2008), authors deal with fault diagnosis and prognosis in dynamic systems by using static and dynamic bayesian networks. In the first case, static bayesian networks are used to compute the a posteriori probabilities of the most probable causes of an observed abnormal situation on the system (called evidence or observation). In the second case, dynamic Bayesian networks are used in order to take into account the systems dynamic and to predict its future behaviour according to its actual state and other exogenous variables or constraints.

7 PROPOSED ARCHITECTURE

The prognostic process in industrial maintenance is a main step to predict failure in machinery. In order to estimate the remaining useful life for a machine before a failure, many works in PHM domain have shown that to realize a reliable estimation, the necessity of:

- Facilitate the maintenance access and the availability.
- Secure maintenance's data
- Ensure the production continuity
- Maximize power of data processing
- Increase memory space of storage data
- Decentralize the sites involving in the PHM domain
- Share the experiences of PHM providers
- Personalize the PHM solutions
- Minimize the maintenance cost
- Improve the QoS

These requirements can be satisfied by the introduction of the cloud computing paradigm. This brings us to design and implement an architecture that defines a new approach that is Prognostic as a Service (prognostic-aaS). This approach will provide a suitable and efficient PHM solution as a service via internet, at the request of a client, in accordance with a SLA contract drawn up in advance to ensure a better quality of service and pay this service per use (pay as you go).
This architecture is composed of three parts:

- PHM-Client Side,
- PHM-Cloud Side,
- Communication module.

a. PHM-Client Side

This side represents the consumer services offering by cloud providers (Prognostic as a Service), in general is the factory. In our approach we suppose to have many factories that are situated in many sites (zones) and which can communicate both between each others and the PHM-cloud side using several protocols (Http, Https, Ssh,…). According to this architecture the PHM-client benefits of a software application (in the case of Prognostic as a Service) that allows the management and supervising of the prognostic process. Also he benefits of characteristics of PHM-Cloud Side by sending the necessary data recovered from machines (or local Databases) to cloud databases and enjoy the PHM technical assistance.

b. PHM-Cloud Side

The Cloud PHM side is provider whose holds the infrastructure and tools to provide PHM services. It is a classical cloud architecture within several layers. It provides the necessary resources (software, platform and infrastructure) to accomplish complicated prognostic tasks. The virtual layer, and basing on the elasticity principle, allows a strong and real-time PHM computing level. In this side, we have two actors:

- Cloud Administrator: Represents the traditional cloud administrator (L. Sadek Terrissa and S. Ayad, 2015), he has the complicated task of cloud management and monitoring. He deploys the available services (Prognostic SaaS, Prognostic PaaS, and Prognostic IaaS) to a Client (factory).
- General PHM Supervisor: He is responsible of the processing, supervision data, and prognostic phase. His task of monitoring guarantees the good prognostic process

c. Communication module

The set of protocols and technics used to ensure the connection and the communication between the Client and the Cloud.

The client sends the necessary data recovered from machines to databases in the PHM-Cloud Side, the general PHM supervisor treats recovered data using knowdge data calculate the RUL on the virtual machine with the selected method, and display the results to the client.
The Figure 3 presents the proposed system's architecture.

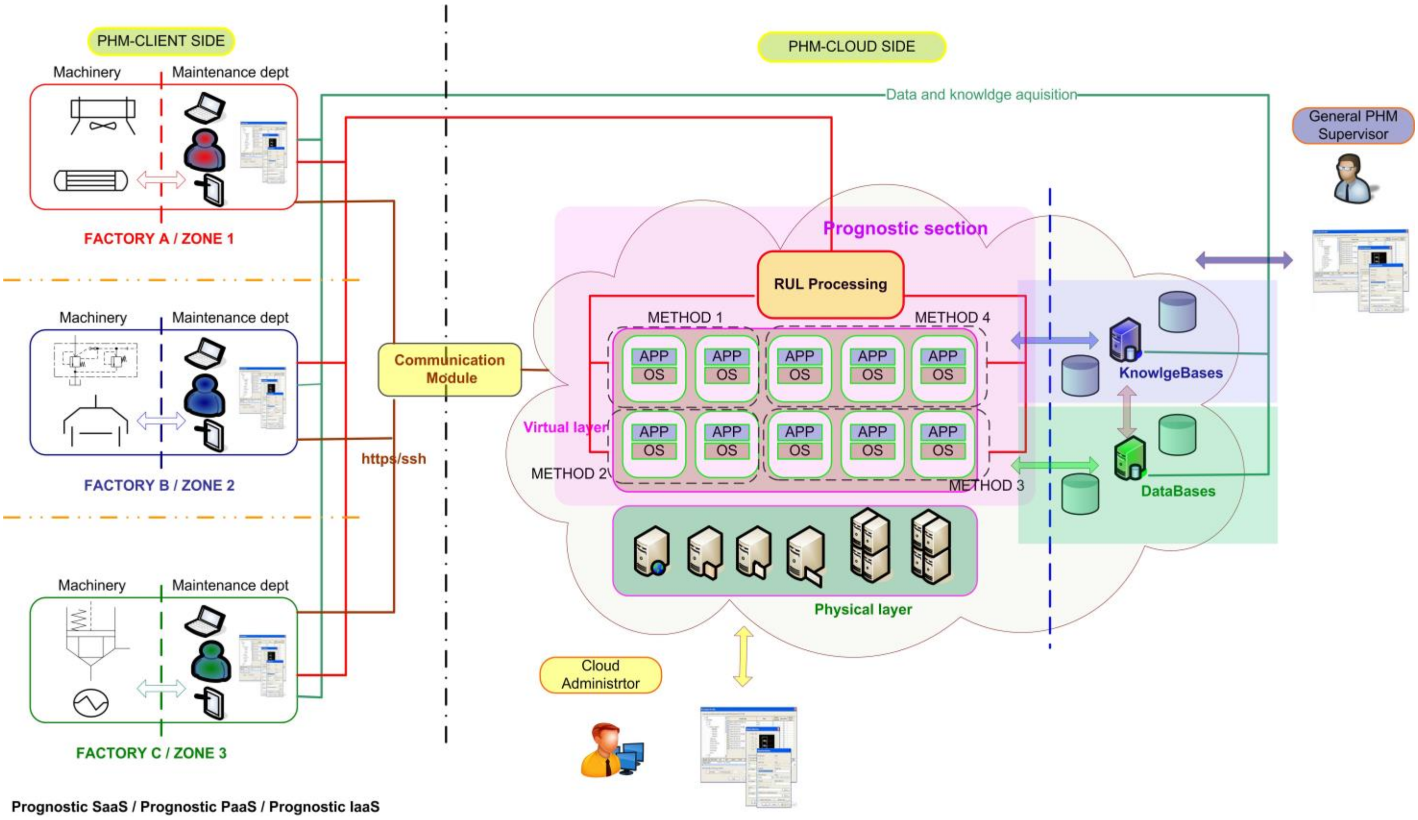

Figure3. Main architecture of Prognostic as a Service

8 IMPLEMENTATION AND SIMULATION

To test our approach, we used the following elements:

1) *Database:* We used PHM08 Challenge Data Set of Aircraft Engine from NASA's Prognostics Data Repository. Data sets consist of multiple multivariate time series. Each time series is from a different engine – i.e., the data can be considered to be from a fleet of engines of the same type. Each engine starts with different degrees of initial wear and manufacturing variation, which is unknown to the user. The data are provided as a zip-compressed text file with 26 columns of numbers, separated by spaces. Each row is a snapshot of data taken during a single operational cycle; each column is a different variable (A. Saxena and K. Goebel, 2008) (Link: ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/)

2) *Used method:* To implement our approach, we used the nonlinear autoregressive neural network method with external input (NARX) with the Levenberg–Marquardt algorithm (LMA). NARX can learn to predict one time series given past values of the same time series, the feedback input, and another time series, called the external or exogenous time series. LMA is used to solve non-linear least squares problems. These minimization problems arise especially in least squares curve fitting. It is a data-driven approach that learns from historical data. *[MATLAB Help]*

3) *Cloud Infrastructure:* The cloud infrastructure used during our experiment is the IaaS LINFI's infrastructure (de-

velopped by the LINFI Laboratory at Biskra University). It is composed of many work stations (HP model Z820 with double processor, Intel Xeon E5-2640 6C 2,5GHz, 24GO RAM and a graphical card NVIDIA Quadro 4000 2GB), this infrastructure use DevStack software and kvm as supervisor.

In this work, we developed a software prognostic a as Service which is composed of a client interface and several software to estimate the Remaining Useful Life. The Figure 4 presents the principle client interface and the role of each bottom.

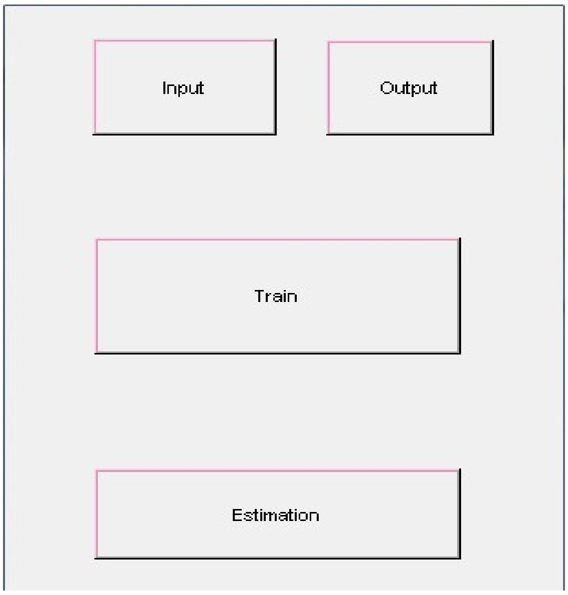

Figure4. Principle client Interface

- **Input**: select the input data file of neual network (25 data number).
- **Output**: select output data file (1 data number).
- **Train:** permit to do the neural network training and validation and test the data.
- **Estimation**: estimate the RUL and display the real and the estimated output.

In our experiment, there are 25 inputs, which are:

- the first one is current age (t_i),
- three are operational conditions
- 21 are sensor measurements.

The output of the network is the percentage residual life (R_l) of engine calculated using the equation 1:

$$R_l = \frac{TimetoFailure - CurrentAge}{TimetoFailure} \qquad \textit{Equation 1}$$

In this experiment, we have used 10 neurones for the hidden layer. We have used a set of data 150 series for the training step, 34 series for the validation and 34 series for the test. Each time series is from a different engine – i.e., the data can be considered to be from a fleet of engines of the same type. The figure 5 presents 4 graphs of 4 engines. Each graph represented the both simulations real (blue line) and estimated (red line) RUL values versus Age of engine.

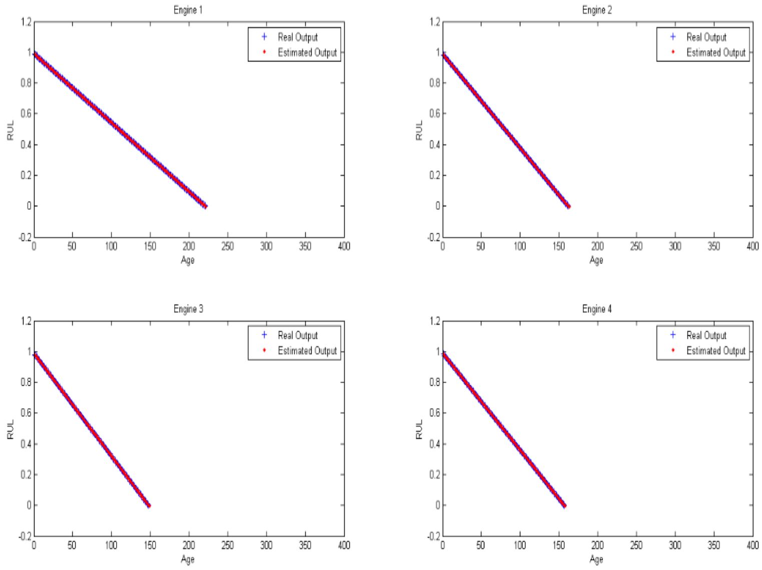

Figure5. Estimation of the RUL (RUL/Life Cycle) for 4 engines

The RUL is normalized between 0 and 1, which gives same order of magnitude variables to avoid numerical instability. The value 1 indicates that 100% life is remaining (compenent is new) and the unit is failed when the residual life percentage reaches the value 0. We can observe clearly the decreasement of the RUL that means the degradation of the engine. We can also observe that the estimated RUL values are close to the real ones. The Mean Squared Error is evaluated according to the equation 2.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad \textit{Equation2}$$

Where, t_i= Predicted value, a_i= Actual value, N= Number of data points.

The figure 6 shows a graph of many engines (40) that is represented the simulation of the RUL values versus Age.

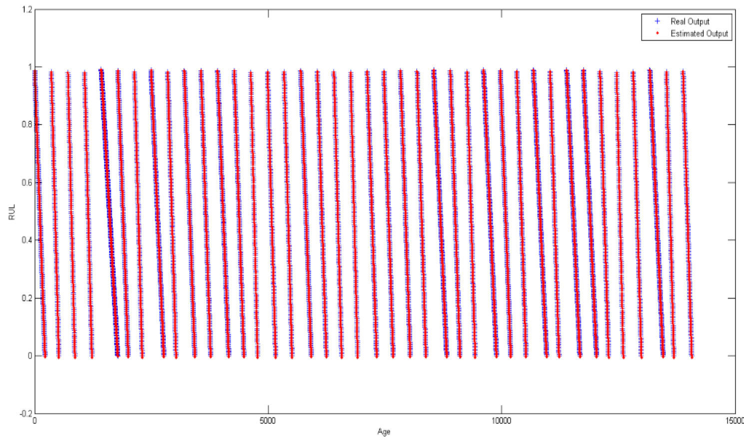

Figure6. Estimation of the RUL (RUL/Data) for 40 engines

The figure7 presents the calculated MSE. We can observe clearly that the error of training phase and test phase are closes.

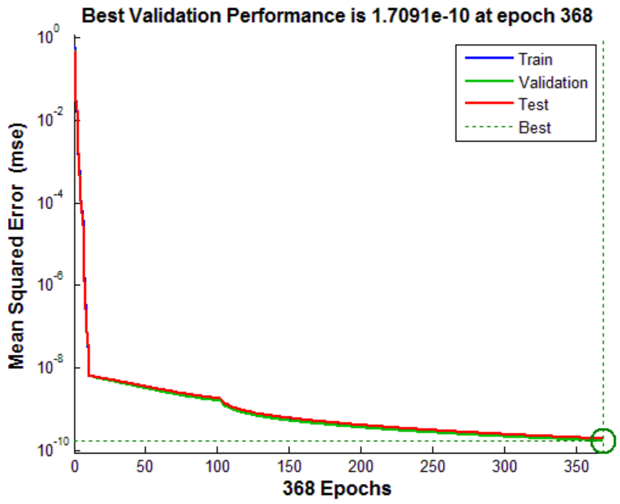

Figure7. The Mean Squared Error

9 CONCLUSION

In this paper, we have presented our design of Prognostic as a Service. It is an architecture that it introduces the cloud paradigm in the PHM domain. We have tested our approach using Neural Network method for a first validation. The next step of this topic will be the test of our architecture within several RUL estimation methods on real Cloud infrastructure like Amazon EC2.

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