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An efficient cloud prognostic approach for aircraft engines fleet trending

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ABSTRACT
The implementation of prognostics and health management solutions is becoming increasingly important. Many industrials are interested in this maintenance process, especially Predix by General Electric and EngineWise by Pratt & Whitney. Predix allows to create innovative industrial internet applications that transform operational data in real-time into actionable information in several domains (aviation, healthcare, . . .). EngineWise is a world leader in the design, manufacture and service of aircraft engines and auxiliary power units. The prognostic process is a main step to predict failures before they occur by determining remaining useful life (RUL) of equipment. However, it also poses challenges such as reliability, availability, infrastructure and physics servers. To address these challenges, this paper investigates a cloud-based prognostic system that defines an approach 'Prognostic as a Service.' This approach will provide an efficient prognostic solution in the cloud computing. In this paper, three data-driven algorithms, Artificial Neural Network, Neuro-Fuzzy System and Bayesian Network, are discussed and implemented to estimate the RUL. They are tested for aircraft engines fleet. Furthermore, and in order to test the efficiency of our solution, we have studied the performance of the prognostic system according to the accuracy, precision and mean squared error.

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Prognostics and health management; remaining useful life; prognostic as a service; cloud computing; measure performance

1. Introduction

Prognostics and health management (PHM) of machines enable to ensure product quality, perform just-in-time maintenance, minimize equipment downtime, and avoid catastrophic failure [1].

With these benefits, PHM has become increasingly important for universities and industry. Several researches have been done to develop solutions for the diagnostic and prognostic systems [2,3].

The prognostic of industrial systems become currently an important aim for industrialists knowing that the failure, which can occur suddenly, is generally very expensive in terms of repairing and production interruption, and is bad for reputation [4].

One of the main approaches of the prognostic is data-driven approach who offer an advantage of being able to learn models based on empirical data and uses artificial intelligence methods [5].

The remaining useful life (RUL) of the monitored asset is the outcome of prognostics and is used in prognostic assessment by applying appropriate metrics and additional criteria. There is a wide range of methods dealing with RUL computation and calculation [6].

The cloud computing is being developed quickly and it offers new opportunities for evolutionary design in such tasks as data acquisition, storage and processing [7].

In this paper, we present a cloud-based prognostic solution. It is an approach that offers the prognostic as a service in the cloud computing.

We have implemented three data-driven methods: Artificial Neural Network (ANN), Neuro Fuzzy system (NFS) and Bayesian Network (BN) to estimate the RUL. To test these methods, we have applied it on aircraft engines fleet. To extract the performance of the prognostic system, a comparative study between methods is evaluated.

The paper is constructed as follows. In 'Prognostics and health management' section, we give an overview of industrial maintenance and PHM, and the role of prognostics. Following that, a thorough survey on the classification of prognostics approaches is presented. Next, an overview about the cloud computing in 'Cloud Computing technology' section is explained. In 'Related work' section, the important works in the Cloud PHM domain are summarized and compared. Then, the proposed approach is detailed in 'Prognostics as a Service' section.

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In 'Experimental study' section, we have implemented three methods to estimate the RUL of aircraft engines fleet. In 'Performance measures of prognostic system of methods' section, we have compared the previous methods by calculating accuracy, precision and mean squared error (MSE) to extract the performance of the prognostic system. The presented cloud-based prognostics is hosted on a cloud environment of Synchromedia laboratory Datacenter of the Department of Automation Engineering at the École de téchnologie supérieure of University of Québec.

2. Industrial maintenance and PHM

The current industrial context makes it possible to explain the evolution of the maintenance function.

The search for optimal equipment maintenance conditions, based on the knowledge of reliability, made it possible to go well beyond the gains that the existing types of maintenance [8].

The different maintenance concepts can be classified into three big categories, which are corrective maintenance, preventive maintenance, and predictive maintenance [9].

The corrective maintenance is the maintenance that intervenes after the occurrence of failure in the system, whereas the preventive maintenance is realized when the system is currently functioning [9]. Predictive Maintenance is to predict when maintenance should be performed. The purpose of predictive maintenance is to repair systems before they fail [9].

We are interested in our work by the predictive maintenance.

(PHM is a systematic approach that is used to evaluate the reliability of a system in its actual life cycle conditions, predict failure progression, and mitigate operating risks via management actions [10].

The Open System Architecture for Condition-Based Maintenance (OSA/CBM) specification is a standard architecture for moving information in a condition-based maintenance system [10,11].

OSA/CBM is seen as an architecture integrating many layers as shown in Figure 1 [10,11].

- 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 [10].

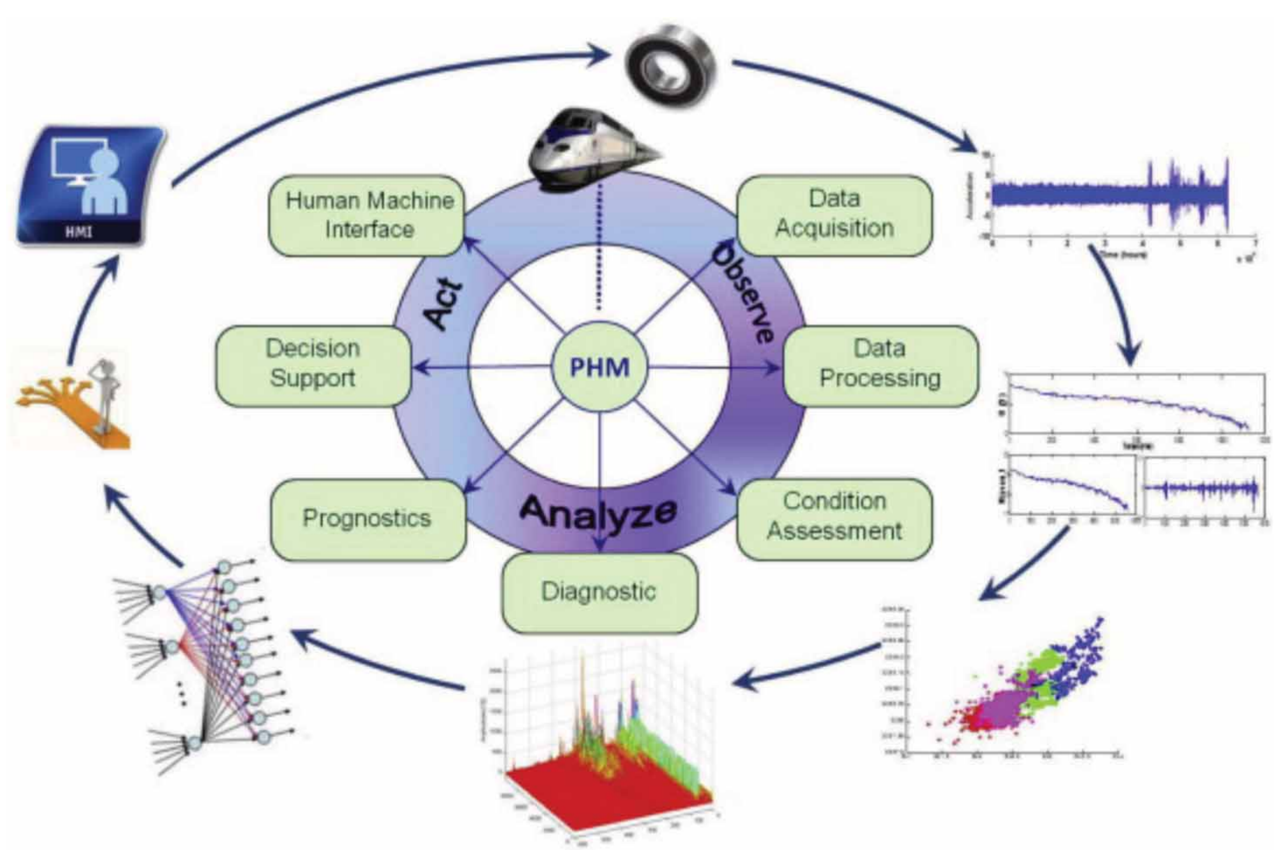

Figure 1. Distributed OSA/CBM architecture [12].

- Data processing

It receives data from the sensors (or transducers or signal processors), and performs signal transformations and features extraction, reduction and selection [10].

- Condition assessment

It helps in determining the system current state-of-health by detecting and localizing a system fault. It compares online data with expected values of systems parameters. It should also be able to generate alerts based on present operational limits [10].

- Prognostic

It predicts the RUL of the monitored system, subsystem or component. The module should be able to acquire data from all previous modules (propagation from causes to effects) [10].

The RUL is the useful life left on an asset at a particular time of operation [13].

Predicting the RUL 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 [11].

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 [11]. We are interested in our work by the prognostic.

- Decision support

Its primary function is to provide recommended maintenance actions or alternatives on how to run the system until the mission is completed. It should be done automatically [14].

- Human –machine interface (HMI)

This module receives data from all previous modules. This module could be built into a regular HMI [10].

2.1. State-of-the-art of the prognostic approaches

The field of prognostic approaches is very broad, based on [11,15–18] we distinguish the following approaches.

2.1.1. Physics-based prognostics

This approach is also called model-driven or physical model. The implementation of this type of approach is generally based on a mathematical representation of the degradation mechanism [11]. The implementation of this type of approach is generally based on a mathematical representation of the degradation mechanism.

Physics-based approaches combine a physical damage model with measured data to predict future behavior of degradation or damage and to predict the RUL [11]. The behavior of a physical model depends on the model parameters that are obtained from data test, or estimated in real time based on measured data up to the current time. Finally, the RUL is predicted by progressing the damage state until it reaches a threshold [11,15].

The main advantage of this approach is its ability to incorporate physical understanding of the monitored system. Moreover, if the understanding of the system degradation improves, the model can be adapted to increase its accuracy and to address subtle performance problems. Consequently, it can significantly outperform data-driven approaches (next section). However, this closed relation with a mathematical model may also be a strong weakness: it can be difficult, even impossible to catch the system's behavior. Further, some authors think that the monitoring and prognostic tools must evolve as the system does [15].

2.1.2. 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 the users dispose of a database containing the history of scenario degradation/failure represented by a set of time series [11]. These bases are given without the use of a physical model of equipment behavior. 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 [15]:

- The prognostic by trend analysis.

This type of approach is based on the derivation of the indicator of the degradation state from its normal functioning state. The tools used in order to put in work these approaches are the tools of prediction of time series and the models of multi-variables classification [15]. The choice of a tool depends on the number of degradation indicators as well as on the number of modes of functioning identified. The tool may be very simple like for example a linear regression [15].

- The prognostic by learning.

This type of prognostic uses principally techniques issued from machine learning and artificial intelligence. Currently, the principle techniques used are ANNs [15]. An ANN is a tool, generally used for nonlinear models, that allows establishing a functional relation between an inputs vector and a desired outputs vector. The parameters of these models are adjusted in order to have optimal performances. Different techniques can be used to adjust these parameters such as the optimization technique [15].

The network is, firstly, trained by using data representing the evolution of degradation during the whole equipment lifetime, until a failure occurs. Afterward, the network is used to detect or predict an evolution of the degradation indicator using other data, always remaining in the same modes of functioning during the period of learning [15].

- The prognostic by state estimation.

The approach by state estimation is usually used when a monitoring system by images and pattern recognition is already put at work on the equipment. The form is, in this case, considered like an image of the equipment degradation. The goal of prognostic is then to predict the form evolution [15].

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 [17]. 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 [17]. 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, NFSs, hidden Markov models and dynamic BNs [17].

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 [18]. 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 [18].

2.1.3. Hybrid approach

A hybrid (Hyb) approach is an integration of physics-based and data-driven prognostics approaches, that attempts to leverage the strengths from both categories. The main idea is to benefit from both approaches to achieve finely tuned prognostics models that have better capability to manage uncertainty, and can result in more accurate RUL estimates. According to literature, hybrid modeling can be performed in two ways parallel approach [16].

3. Cloud Computing technology

Cloud Computing as the new delivery model for IT services is aiming at envisioning the abstraction of IT infrastructure and addressing the complexities of servers, applications, data and heterogeneous platforms [19]. Nowadays the Cloud Computing Paradigm is being utilized by many small and medium enterprises that will get most of their computing resources from external providers [20]. The definition of NIST (National Institute 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 [20].

'The interesting thing about cloud computing is that we've redefined cloud computing to include everything that we already do.' [Larry Illison, Oracles founder]

3.1. Characteristics of Cloud Computing

There is five essential characteristics of cloud computing [21]:

- On demand self-service: a consumer can request and receive access to a service without an administrator or some sort of support staff having to fulfill the request manually [21].
- 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 [21].
- Resource pooling: it is accomplished using virtualization. Providers can host multiple virtual sessions on a single system [21].
- Elasticity: it is possible with Cloud to acquire new resources according to the evolution of the business needs, and the customer can either increase or decrease for example the number of machines and/or their powers. Generally, this task is automated and it is the service operator who adjusts the resources as needed [21].
- Measured services: cloud services must have the ability to measure usage. Services are measured

according to the duration and the quantity of used resources [21].

3.2. 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 [20].
- Public Cloud: The Cloud infrastructure is owned by an organization selling Cloud services to the public or to a large industry group [20].
- Community Cloud: The Cloud infrastructure is shared by several organizations and supports a specific community [20].
- Hybrid Cloud: The Cloud infrastructure is composition of two or more Clouds such as private, community, or public that remains unique entities [20].

3.3. 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 [19,20].
- 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 [19,20].
- 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 [19,20].

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 [21].'

3.4. Mathematical formulations of cloud computing

There are various mathematical approaches that have been used to model cloud systems. Most of them are formulations of cloud processes as optimization problems that aim to analytically identify a cloud's configuration settings that would optimize its quality of service (QoS), performance or energy efficiency under given constraints.

A detailed description of mathematical approaches that have been used to model cloud systems can be found in [22].

3.4.1. Performance modeling based on queuing theory

Queuing theory is a mathematical theory in the domain of probabilities, which studies the optimal solutions for queue management, or tails. A queue is necessary and will be created of itself if it is not anticipated, in all cases where the supply is lower than the demand, even temporarily.

An M/G/m queue is a queue model where arrivals are Markovian (modulated by a Poisson process), M stands for Markov and is commonly used for the exponential distribution, service times have a General distribution and there are m servers [23].

The authors in [24] model each PM in the cloud center as an $M[x]/G/m/m + r$ queuing system. Each PM may run up to m VMs and has a queue size of r tasks.

The cloud center consists of many physical machines, each of which can host a number of virtual machines, as shown in Figure 2. Incoming requests are routed through a load-balancing server to one of the Physical Machines. Users can request one or more VMs at a time [24].

When a prognostic-task arrives, the load balancing server attempts to provision it – i.e. allocate it to a single Physical Machine (PM) with the necessary capacity. The incoming prognostic-tasks are processed as the following pseudo code:

```
Pseudo Code: Prognostic task
Input: Prognostic Task
Output: RUL
Begin
If (PM with sufficient space capacity = true) then
        The prognostic-task is provisioned immediately;
        Calculate RUL;
Else
    If (PM with sufficient space in the input queue = true) then
        The prognostic-task is queued for execution;
        Execute the prognostic-task;
        Calculate RUL;
    Else
          The super-task is rejected.
    Endif
Endif
End.
```

3.4.2. Execution time and energy consumption

In paper [25], the authors have defined the execution time of a given workload on a cloud as the time required to

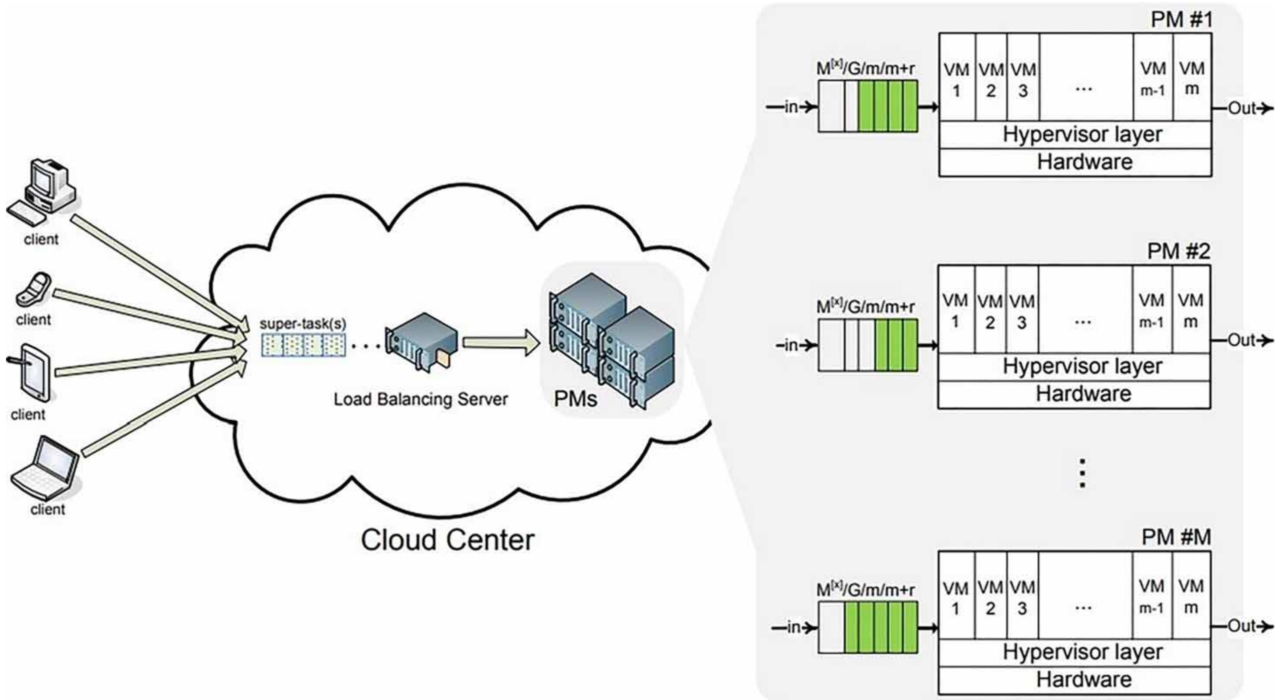

Figure 2. The architecture of the cloud center [24].

finish a workload consisting of m job units. When some job units are assigned to more than one virtual machine, the execution time is bounded by the virtual machine that finishes last.

To calculate the execution time E_t of p virtual machines, the authors assume that the response time for executing a job unit in such a cloud is uniformly distributed from a seconds (the fastest node) to b seconds (the slowest node), they have used the following equation:

$$E_t = \frac{ma}{2np}\left\{2n + \left(\frac{b}{a} - 1\right)p\right\},$$

where $n = 3p/2$.

Energy consumption E_c is the total energy needed to complete a given workload. In particular, when some physical nodes finish their assigned job units before the others, these nodes will not consume energy while waiting for the others to finish [25].

$$E_c = W \times \frac{m}{p}\left\{a + \frac{(b-a)p}{2n}\right\}p,$$

where W represents a physical node's power.

A detailed description of execution time and energy consumption can be found in [25].

4. Related work

This section reviews relevant literature related to the Cloud Prognostics with emphasis on the data-driven prognostics approaches and algorithms. In the literature, a considerable amount of studies has been focused on the Cloud prognostics due to the significances of their applications on several domains.

According to [1], authors have proposed a methodology for adapting PHM systems to a cloud environment, where PHM solutions are more reconfigurable, reproducible and easy to implement in manufacturing industry. A new approach that is 'Prognostic as a service' was introduced, we have integrated the cloud into existing Toolbox Watchdog Agent developed by IMS Center which provides a set of intelligent algorithms such as neural network, principal component analysis, among others, to convert data or information from many sensors to valuable health assessment and prediction results.

The reasons for using cloud according to the authors in this article are:

- Virtualization of IT infrastructures and Networking techniques are integrated together.
- An easy access.
- Cloud Computing scalability makes algorithms in the cloud easy to develop.
- 'Whole system snapshot exchange': A preconfigured operating system with the necessary software installed for a certain purpose can be easily duplicated in a new server instance so that the computation can be more reproductive.
- The cloud-based PHM system also offers easy ways to share PHM solutions between users.

- Virtual machines (instances) are provided as PHM servers at the request of the user.

The architecture of the proposed approach represents two modules: PHM module where the system uses IMS modular algorithms from IMS Watchdog Agent Toolbox as basic components to form different PHM workflows and another PHM Cloud module that can be supplied with a virtual machine server as a PHM server for a new user:

- Prepare and customize PHM workflow.
- Create a virtual machine (PHM server) for the current user.
- Output PHM results to the Web server (User Application).

In [3], this article presents at first an approach based on mobile agents for predictive maintenance in cloud manufacturing. As an emerging technique, the mobile agent approach allows a new paradigm for predictive maintenance as remote services instead of the conventional centralized approach and provides distributed maintenance services in the manufacturing enterprises. In addition, the mobile agent can flexibly deploy different services (e.g. signal processing algorithms) to adapt the changes of different operations and tasks in a dynamic manufacturing environment.

To evaluate the efficiency of the presented mobile agent paradigm, six induction motors with different failure modes in a motor-tested system are used to imitate distributed manufacturing processes. Mobile agents distribute signal-processing algorithms (e.g. feature extraction) to cloud nodes instead of transmitting raw detection measurements to the central server, and can significantly reduce the traffic load on the network.

In [26], authors have almost proposed PHM framework based on Cloud, but the aim here is to maximize the overall efficiency of the hardware. The paper details the agent-based adaptive implementation method. The advantages offered by this proposal are:

- The factory managers are aware of the state of operation of the entire plant at anytime and anywhere.
- Provide data support to make equipment prognostics and estimate RUL.

The idea of using the Data Agent is to acquire device data and pre-process data, and then decide what data will be transferred to Cloud.

To validate the approach proposed in work [1], the authors have applied it in [27] to the raw data collected from sewing machines.

In this case study, three band saws of different sizes and configurations (two horizontal saws and one vertical) were installed at different geographical locations.

During sawing, data is acquired from the machines by both additional sensors and controller signals. At the end of each cut, a row of characteristic values is sent to the database in the cloud and triggers the adaptive prognosis algorithm.

In [28], this article discusses the trends and advances in machine monitoring systems and offers a cloud-based machine monitoring platform that seamlessly integrates PHM technology with the cloud computing infrastructure. To illustrate cloud-based machine monitoring and prognostics, a tool condition monitoring (TCM) program in a machine tool is used as a case study. For this, a PHM system was developed to estimate the condition of the component i.e. the cutting tool, using analytic tools such as those found in the Watchdog Agent developed by the Center for Intelligent Maintenance Systems.

In the other hand, they concentrate in the PHM system and the method's implementation.

In [29], a data driven method for RUL prediction based on Bayesian approaches is proposed. The method builds on unsupervised selection of interesting variables from the input offline signals. It constructs representative features that can be used as health indicators. The method represents the current status of the online signals as well as the uncertainty about the predictions in a probabilistic form. Two real-life data sets were used in the experiments: a turbofan engine data sets and a lithium-ion battery aging. The performance of the prediction is enhanced by integrating two models, namely, k-NN and GPR. The selected variables are shown to be interesting. Moreover, the prediction results show low MAPE error for both applications and the turbofan engine results outperform the prediction of another method.

In [30], the objective is devoted to the detection of a degradation, to the estimation of the duration of operation by giving the preventive action before being a failure; and classification of failures after failure by giving the action of diagnosis and/or maintenance. For this, the authors propose a new Neuro-Blur system of prediction aid based on the Recognition of Forms (RdF) and called 'NFPROG' (Neuro Fuzzy PROGnosis). NFPROG is an interactive simulation software, developed within the Laboratory of Automation and Productivity-University of Batna Algeria. It is a fuzzy perceptron of four layers whose architecture is based on Elman neural networks.

This system is applied to the clinkerization workshop (cement oven) in the cement manufacturing process (baking process) at the CIMENT Company of Batna (Algeria). And since the latter has an installation and

Table 1. Comparison between works.

		Criteria					
Papers	Case study	Cloud computing	RUL estimation	Virtualization	Scalability	Distributed solution	Performance
[1]	/	✓	x	✓	✓	✓	x
[3]	Six Induction Motors	x	✓	x	x	✓	x
[26]	Swivel Bearingin industrial robots	✓	✓	✓	x	x	x
[27]	Sawing machine	✓	✓	✓	✓	✓	x
[28]	TCM program	✓	✓	✓	x	x	x
[29]	Turbofan engine and Lithium-ion battery	x	✓	x	x	x	x
[30]	The clinkerization workshop (cement oven)	x	✓	x	x	x	x
Our proposed approach	Aircraft engines fleet	✓	✓	✓	✓	✓	✓

configuration of programmable logic controllers from Siemens S7-400, the authors chose PCS7 as the programming platform for their system.

While developing a Software as a Service, the performance is very important factor to consider. However, all the mentioned works does not deal with the performance of prognostic systems. Table 1 summarizes the previous related works and shows the comparison between them and our proposed approach based on some important criteria.

5. Prognostic as a service approach

5.1. Proposed approach

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

- An ubiquitous access and the maintenance availability at any time and everywhere.
- A big infrastructure for running solutions and big memory space for storage data.
- The communication between factories who have many distributed sites and sharing the experiences that can be easily reused by other industrial users who have similar needs.
- Multi-tenant application, an architecture where a single application instance will serve multiple clients (tenants), to reduce maintenance costs and improve scalability.
- The security of maintenance's data and user's.

To satisfy these requirements, we switched to an IT-based solution by introducing the cloud computing paradigm. Technological advances and the new ideology, namely X as a Service, brought by the emerging cloud computing paradigm are opening new opportunities to tackle existing hurdles for implementation of PHM systems.

However, we have designed and implemented an architecture as shown in Figure 3 that defines an approach 'Prognostic as a Service' (Prognostic-aaS). It will provide a suitable and efficient PHM solution as a service, on demand of a client, in accordance with an SLA (Service Level Agreement) contract drawn up in advance to ensure a better QoS and pay this service per use (pay as you go).

This approach has many advantages that are:

- Facilitate the maintenance process and the availability. (estimation of the RUL leads us to take the maintenance decision at the right time and thus avoid the failure).
- Ensure the continuity of the machines operation.
- 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.
- Offer the prognostic as a service in the cloud computing.

By using this system, the company no longer owns the used server because it is made available by its provider. However, it can progressively access many services without having to manage the underlying infrastructure, which is often complex (database maintenance, data backup, software update, server maintenance, etc.). Applications and data are no longer on the local computer, but on the 'cloud' which is a set of interconnected remote servers using high-performance internet links essential to the fluidity of the system. Access to the service is through a software application or an internet browser on the company's computers and easily available.

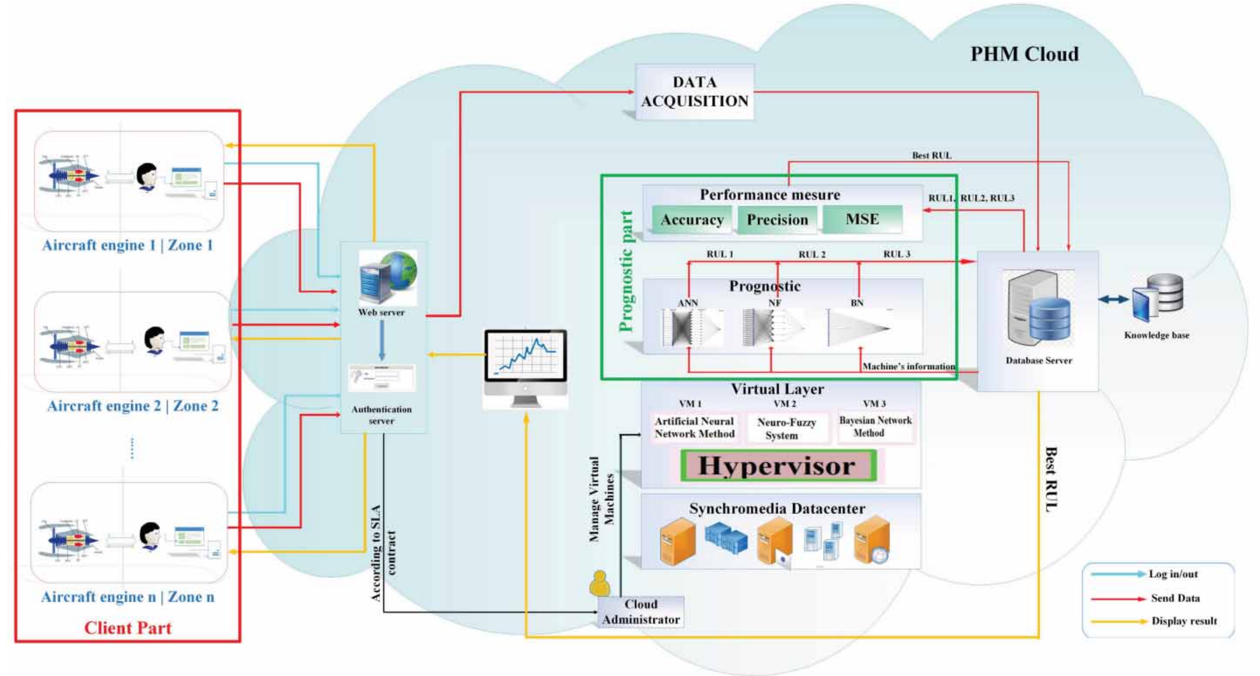

Figure 3. Proposed architecture (Prognostic as a Service).

The proposed architecture is composed of two parts:

- PHM-Client side

This side represents the consumer services offering by cloud providers (Prognostic as a Service), in general is the factory. In this approach, we supposed to have many engines geographically distributed that can communicate with 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. He also benefits characteristics of PHM-Cloud Side by sending the necessary data recovered from local Databases to the cloud Databases and enjoy the PHM technical assistance.

- 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 based on the elasticity principle, allows a strong and real-time PHM computing level.

In this side, we have the Cloud Administrator that represents the traditional cloud administrator [14,31]; he has the complicated task of cloud management and monitoring. He provides the virtual machines and deploys the available services (Prognostic SaaS, Prognostic PaaS, and Prognostic IaaS) to a client (factory).

5.2. Communication process

The SLA contract is established between the service provider and the client by specifying all the levels of services mentioned previously to be provided by the service provider to the client.

After authentication, the client sends the necessary data recovered from machines to databases in the PHM-Cloud side by using a set of protocols and technics to ensure the connection.

When a client sends his task (prognostic task), if a Physical Machine with sufficient space capacity is found, the task is provisioned immediately. Otherwise, the task will subdivide and so the system is able to adapt to these demands by automatically provisioning and distributing resources so that the resources provided are consistent with the system's demand.

Then the Cloud Administrator treats recovered data, calculates the RUL on the virtual machine with the selected method, and displays the results of calculated RUL and best RUL to the client. The cost of service and terms of payment are predefined in the contract.

This scenario is summarized in the sequence diagram shown in Figure 4.

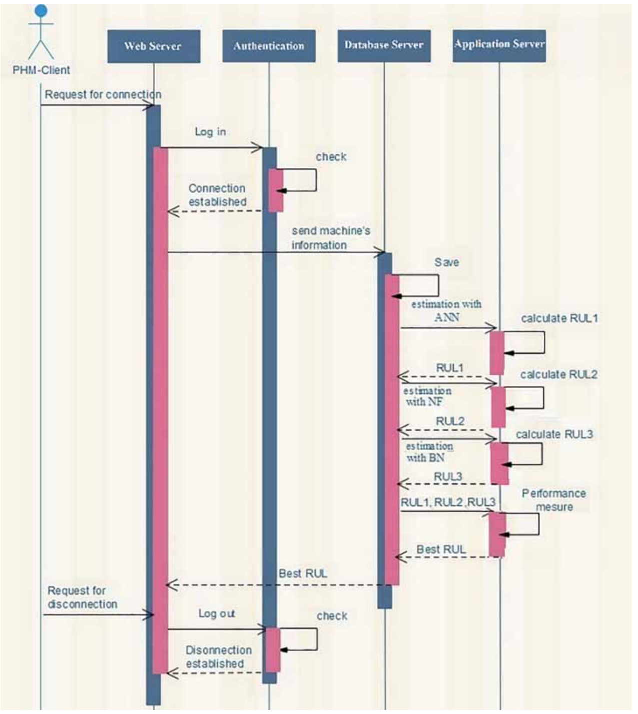

Figure 4. The sequence diagram of the proposed system.

5.3. Databases

Aircraft engines are designed to be used during several tens of years [14]. Predicting the progression of damage in aircraft engine turbo machinery is very important task for condition-based maintenance planning [32].

In the present work, we have used PHM08 Challenge Data Set of Aircraft Engine. System monitored data of an aircraft engine is taken from National Aeronautics and Space Administration (NASA) Prognostics Center of Excellence Data Repository.

Data sets consist of multiple multivariate time series. Each data set is further divided into training and test subsets. 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 that 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 [32].

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

- The first one is current age (ti),
- Three (3) are operational conditions,
- Twenty -one (21) are sensor measurements.

In this work, we will calculate the RUL. It is the percentage residual life (Rl) of engine calculated using

Table 2. The cloud infrastructure characteristics.

	Servers		
Features	Web	Application	Database
OS		Ubuntu 14.04	CentOS 7
CPU (Core)		4	6
RAM (Gb)		3	
Hypervisor		Xen	
HDD (Gb)		1000	

Equation (1):

$$Rl = \frac{\text{Time To Failure} - \text{Current Age}}{\text{Time To Failure}}. \tag{1}$$

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 (component is new) and the unit is failed when the residual life percentage reaches the value 0.

The MSE is evaluated according to Equation (2):

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{i=N}(t_i - a_i)^2, \tag{2}$$

$$\text{where} \left\{ \begin{array}{c} t_i \rightarrow \text{Predicted value} \\ a_i \rightarrow \text{Real value} \\ N \rightarrow \text{Number of data points} \end{array} \right\}.$$

6. Experimental study

To implement our solution, we developed a cloud prognostic application using three data driven methods: ANN, NFS and BN.

In addition, we have hosted our cloud infrastructure in a cloud environment of Synchromedia laboratory Datacenter of the Department of Automation Engineering at the École de téchnologie supérieure of University of Québec [33].

The cloud infrastructure characteristics are reported in Table 2.

Forecasting is the process of estimating unknown situations in the future. In another way, it is the process of estimating the RUL of a system.

To estimate the RUL of an aircraft engine, we have implemented the three following methods.

6.1. ANN method

We will use in this experiment The Nonlinear AutoRegressive neural network method with eXternal input (NARX) with the Levenberg Marquardt algorithm (LMA) can learn to predict one time series given past values of the same time series, the feedback input, and

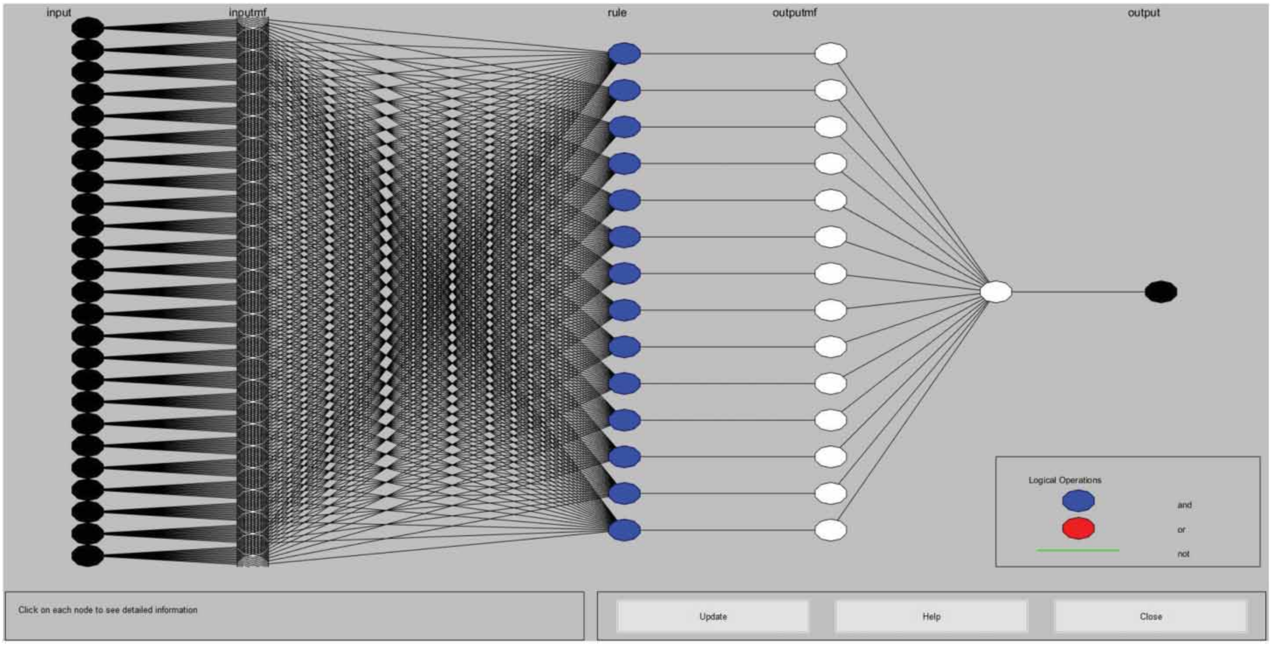

Figure 5. ANFIS model structure.

another time series, called the external or exogenous time series. LMA is used to solve nonlinear least squares problems. These minimization problems arise especially in the least squares curve fitting. It is a data-driven approach that learns from historical data.

We have used three layers: one input layer, one hidden layer and one output layer.

In the hidden layer, we have used 10 neurons and Hyperbolic Tangent Sigmoid Transfer Function. In the output layer, we have used Linear Transfer Function. We have used 10 epochs.

6.2. Neuro-Fuzzy system

We used the NFS, it is a combination between two computing tools: ANN and Fuzzy Logic. It is a data-driven approach that learns from historical data. NFSs are used to solve problems of classification of failures. But when a monitoring method estimates the future conditions of a system from its present state, it is called prognostic [30].

There are different NFS architectures, in our experiment we used ANFIS system (Adaptive Network-based Fuzzy Inference System) that is based on TAKAGI SUGENO approach. This syntax is the major training routine for Sugeno-type fuzzy inference systems. ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least squares method and the backpropagation gradient descent method for training FIS membership function parameters to emulate a given training data set. ANFIS can also be invoked using an optional argument for model validation. The type of model validation that takes place with this option is a checking for model over fitting, and the argument is a data set called the checking data set.

As shown in Figure 5, we have used five layers. The used system is composed of 25 inputs with one output (RUL) and 14 MFs (membership functions) to each input. The MFs input type is Gaussian and the MFs output type is linear. We have used 10 epochs.

6.3. BN method

The Bayes Net Toolbox (BNT) is an open-source Matlab package for directed graphical models. BNT supports many kinds of nodes (probability distributions), exact and approximate inference, parameter and structure learning, and static and dynamic models. For training, we have used the function Bayesian regularization back propagation (trainbr): trainbr can train any network as long as its weight, net input, and transfer functions have derivative functions. Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination so that at the end of training the resulting network has good generalization qualities.

We have used a Static BN. We have used Directed Acyclic Graph with 25 Gaussian continues observable nodes (input) and one continues hidden node (output). We have used the method of maximum likelihood. We have used the junction-tree algorithm for inference.

6.4. Results

We estimated the RUL of 218 aircraft engines using the three previous methods. We can display the RUL of several machines but that may not be clear and readable. For this reason, we chose to display and compare the RUL of three aircraft engines.

Each among Figures 6–8 shows three graphs representing RUL estimation of three engines.

In each graph, we have two axes:

- The horizontal axis represents the age of the machine, its values are between 0 and 250 cycles.
- The vertical axis represents the RUL estimated by the selected method, its values are between 0 and 1 (percentage).

The straight represents the real RUL of the engine, and the curved one represents the estimated RUL using our methods.

When the engine starts to work, it is in good state (when the RUL is equal to 1 i.e. the engine is new) and, over time, we notice clearly the decrease of the RUL it means the degradation of the engine until failure (when the RUL reaches the value 0 i.e. the engine has failed).

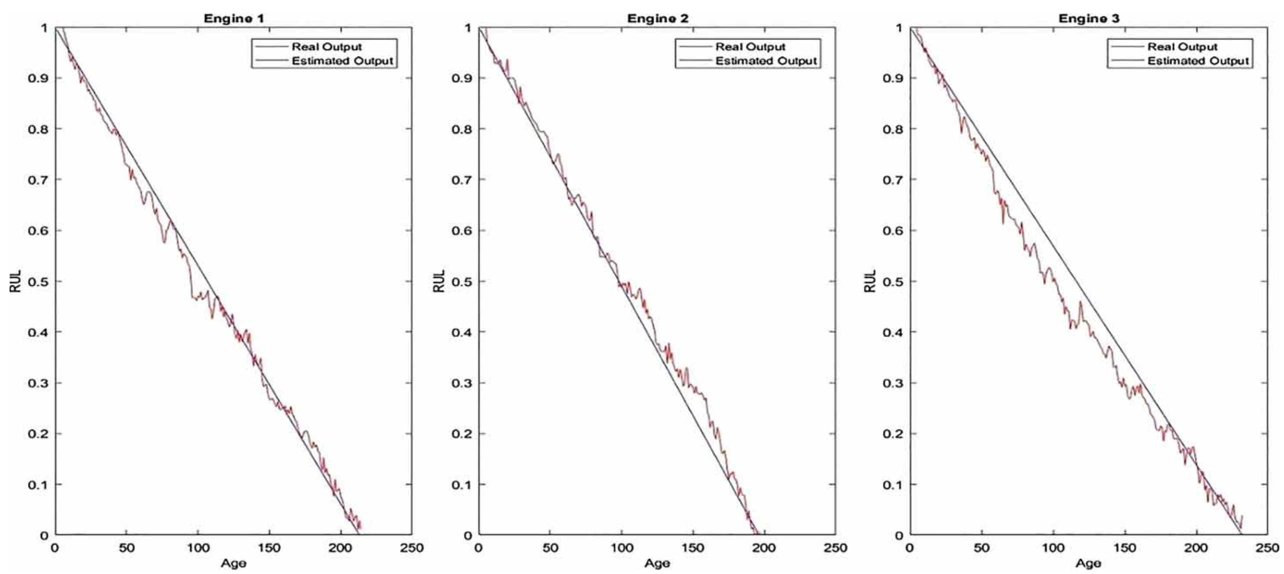

Figure 6. RUL estimation with ANN method.

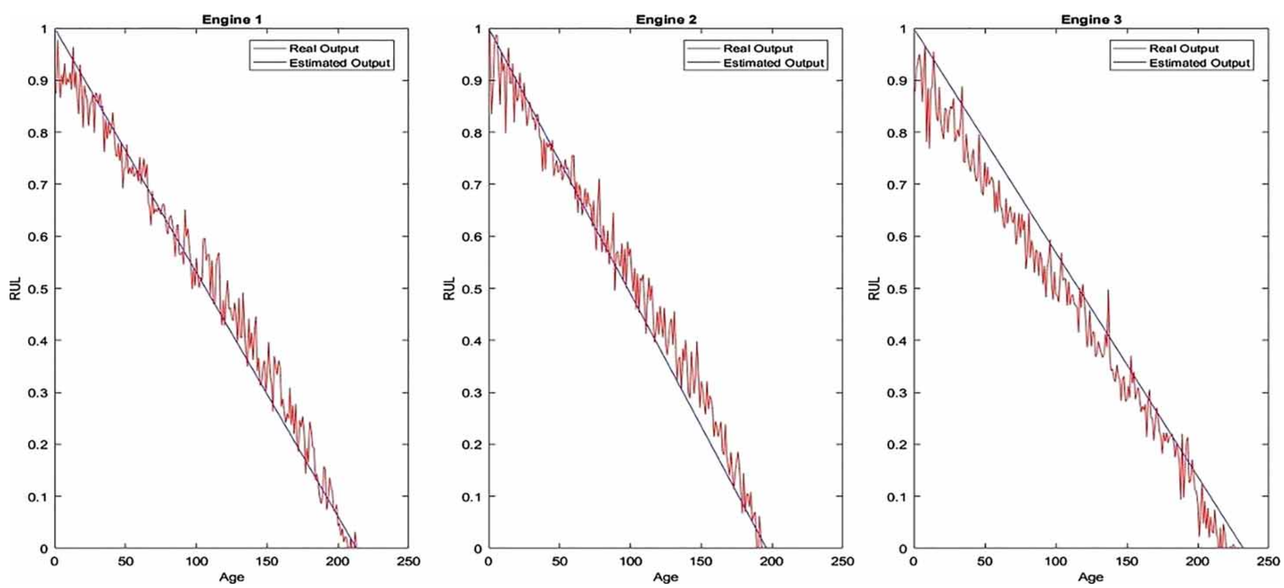

Figure 7. RUL estimation with NFS method.

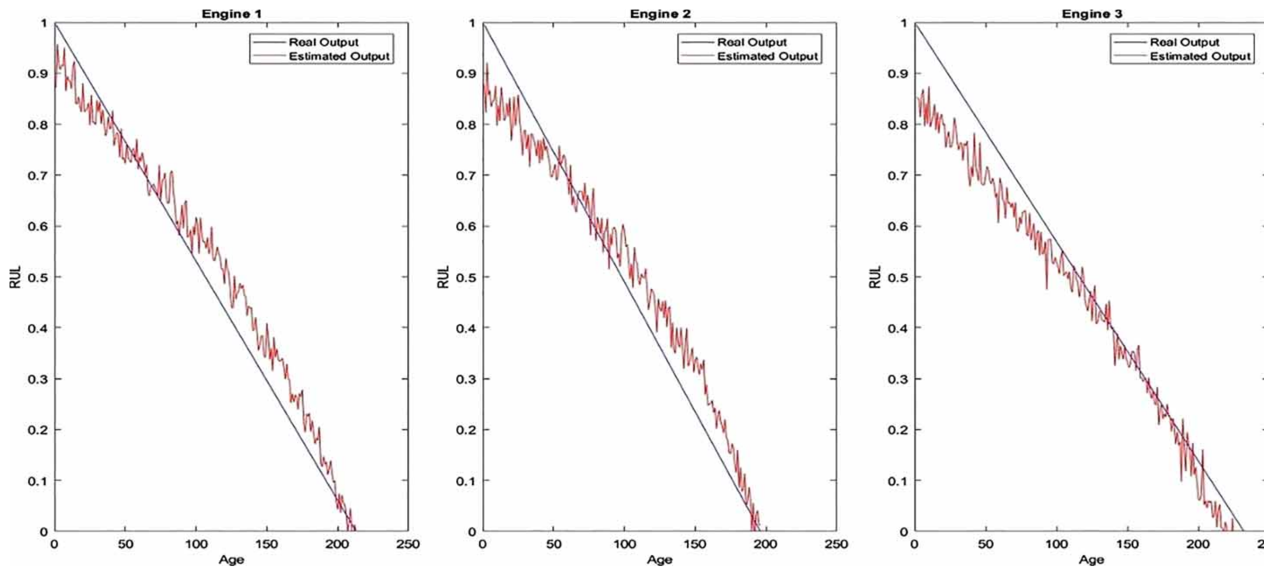

Figure 8. RUL estimation with BN method.

Table 3. The comparison between methods.

Comparison	Aircraft engine 1			Aircraft engine 2			Aircraft engine 3		
Methods	NFS	ANN	BN	NFS	ANN	BN	NFS	ANN	BN
Accuracy	0.9110	0.9696	0.8550	0.8940	0.9588	0.8470	0.9022	0.9625	0.8501
Precision	0.8780	0.9190	0.8610	0.8530	0.8996	0.8490	0.8650	0.9010	0.8575
MSE	0.0799	0.00109	0.0022	0.0822	0.00148	0.00267	0.0801	0.00121	0.00239

We can observe that the estimated RUL values are close to the real ones.

We calculated the MSE of each method on these three engines. The MSE values are in Table 3.

The data for each engine is the same; it means the used data of the engines in the ANN method are the same data used for the other two methods. So comparing MSE on each method for each machine.

7. Performance measures of prognostic system of methods

To compare the previous methods and know which the effective one is, we have to study the performance of the prognostic system (Aircraft Engine) by calculating the accuracy and the precision that are mentioned below.

7.1. Accuracy

Accuracy measures the proximity of the expected failure date to the actual failure date. The calculation of this metric represents a critical point in the prognostic process. The calculation of this quantity is based on the existence of historical data on several components that have failed due to stresses experienced throughout a known period, which is not always possible.

If a set of N systems have failed (with associated prognostics), the accuracy is defined as Equation (3) [34]:

$$\mathrm{Acc} = \frac{1}{N}\sum_{t=1}^{N} e^{-\frac{E(t)}{\mathrm{RUL}_{\mathrm{real}}}}, \tag{3}$$

where $E(t)$ is the squared error and it is calculated with Equation (4):

$$E(t) = |\mathrm{RUL}_{\mathrm{real}}(t) - \mathrm{RUL}_{\mathrm{estimated}}(t)|^2. \tag{4}$$

The exponential function is used here to give a smooth monotonically decreasing curve. Accuracy is high (close to 1) when the predicted value is identical to the actual one and decreases when the predicted value deviates from the actual one [34].

7.2. Precision

Precision is a measure of dispersion of the RUL prediction. It allows how the predicted values are grouped around the interval in which the failure occurs. Precision depends strongly on the confidence level and distribution of predictions. It is defined in Equation (5) [34]:

$$\mathrm{Pr} = \left(\frac{1}{N}\sum_{i=1}^{N} e^{-(R_i/R_0)}\right)\left(e^{\frac{\frac{1}{N}\sum_{i=1}^{N}(E_i-\bar{E})^2}{\sigma_0}}\right), \tag{5}$$

$$\text{where } \bar{E} = \frac{1}{N}\sum_{i=1}^{N} E_i.$$

The sizes R_0, σ_0 are the normalization factors, and R_i is the prediction confidence interval for experimentation [34].

Similarly, an exponential function is used here to define the relation between the standard deviation of the prediction, confidence interval and precision. Precision has a value between 0 and 1 (1 indicating the highest precision and 0 the lowest one) [34].

8. Comparative study

To validate our system, we have compared the performance of our methods on three engines.

From Table 3, we can discuss the obtained results:

- Accuracy is very close to 1 in the ANN method that means its predicted values are the closest to the actual ones.
- The closest precision value to 1 is that of the ANN method that means it has the highest precision.
- The smallest MSE value is that of the ANN method so the smaller the error, the better the result will be.
- The shortest training time here is that of the ANN method therefore it is the fastest one.

From this discussion, we can observe clearly that the ANN method gives the best results on the level of three engines.

9. Conclusion

The PHM systems based on IT-solutions have not been widely seen in manufacturer's production floor, which is mainly caused by high costs for developing and maintaining PHM systems. To tackle this issue, we have presented a solution 'prognostic as a service' in order to switch to a cloud-based prognostic. We have proposed and detailed the different blocs of our architecture. As illustrated in the experimental study, we have chosen three data-driven methods (ANN, NFS, BN) in order to estimate the RUL of aircraft engines fleet. To discuss the performance of our system, a comparative study between methods for three engines has been conducted by calculating the accuracy, precision and MSE. To evaluate the proposed approach, we studied the QoS of the cloud prognostic system; the results show that it can provide the Prognostic aaS within reasonable QoS criteria.

As the future work, we will study the execution time and energy consumption in the Cloud Prognostic application. Additionally, we plan to ensure security of maintenance's and user's data in the cloud prognostic system.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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