Prognosis of a Degradable Hydraulic System: Application on a Centrifugal Pump

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ABSTRACT

This article proposes a preliminary diagnostic/prognostic method for the identification of a critical system, undergoing a continuous evolutionary degradation, in a production area, and the determination of the component responsible for its degradation, called the failing element. Using for this, a model based on learning by multilayer perception (*MLP*). The purpose of this paper is to provide a modeling approach that makes it possible to determine the level of degradation reached by the system at any given point of time, in a precise way. Thus, the horizon of the failure will be produced with a minimum error compared to the discrete jump model used in the literature. The proposed approach consists of using a neural network with fewer layers and optimal computing time. We performed data learning (tests) in order to illustrate a regression of good correlation of these data (tests) on a centrifugal pump with satisfactory performance parameters and compared it with other commonly used methods.

1. INTRODUCTION

Today, the maintenance responsibility professions are undergoing unprecedented development. The maintenance manager must have, whenever possible, the means and tools capable of providing alarming signals, prior to the occurrence of the failure, in order to meet a certain number of constraints and expectations. In parallel with this recent years' evolution, various techniques and strategies have been developed in the concept of *PHM* "Prognostics and Health Management" (Soualhi et al, 2019) which makes it possible to better predict the future of the physical state and make feasible and better informed maintenance decisions (Tiddens et al, 2018; Tagawa et al, 2020). These techniques differ in terms of the data being used, the assumptions related to the failure and the operating mode of the system and the calculation models to remedy certain constraints (Aggab et al, 2015).

In most rotating systems, the problems encountered are the phenomena of wear of the rotating elements and vibrations. These types of deterioration are justified in (El Adraoui et al, 2020). Two studies have been conducted, the objective of which is to verify and validate the influence of vibrations and wear on the remaining service life of the system, by following its behavior over time. Most of these constraints and expectations in terms of performance related to the productivity, quality, reliability and the system/equipment's availability have led maintenance strategies to become the top priority to guarantee higher availability based on the anticipation of the degradation caused during operation. The implementation of so-called "predictive" maintenance seems to be the most appropriate to meet the objectives of current needs. It's based on different architectures supporting these activities which have been established according to several literatures (Aggab et al, 2015; Krishnakumar et al., 2018).

In this direction, several studies have been approached to resolve the problem of availability, namely (Aggab et al, 2015). The latter modeled a controlled system that is a pump to circulate a fluid between two reservoirs (Nguyen, 2015) whose gain is subject to degradation, in order to predict the state of health before failure by using an observer, based on the Hidden Markov Model (*HMM*) to visualize the behavior of a system in a severe environment. By exploiting the model of (Aggab et al, 2015), this work focuses on a field study to detect critical equipment. Then, it makes a prognosis of this critical equipment, by proposing a structured approach, based on the use of an artificial intelligence fuzzy neural network model under Matlab.

The key point focuses on a projection of the previous model on a real system through simulation. The latter leads to an inverse relationship to determine the remaining useful life

(*RUL*) for the future operation. The reason behind using the fuzzy neural network with multilayered perception, is for it being an effective tool to estimate the level of degradation of an industrial system with better performances.

This work is organized as follows:

We started with the presentation of a global diagnosis in the context of discriminated equipment detection. Then, we devote ourselves to the architecture of the proposed approach with literature included and to presenting the different stages of the adopted approach. Afterwards, we present and illustrate the results and performances of our approach to the system that will finally allow us to draw conclusions on the work presented as well as on some perspectives.

2. STUDIED SYSTEM

Most of the problems faced by industrialists within the company come together in the production area, namely hydraulic machines (pumps), fans, reducers, etc... According to field statistics, pumps represent the most essential installations, thanks to their intrinsic and primordial roles in the production series. Since they are subject to evolutionary degradations, which directly influence the efficiency and profitability of production within companies.

2.1. The system's definition

The pumps, in Fig.1 and Fig.2, are mechanical systems (hydraulic machines) which generate a pressure difference ΔP between the inlet and outlet tubulars.

Figure 1. Centrifugal pump installed in an OCP-Morocco production area.

According to the normal standards of use, these machines communicate to the fluid, generally a liquid, either the gravity energy E_p, or the kinetic energy by the setting in motion of the fluid E_c (Adamt, 1976; ENSPM Formation Industry, 2005).

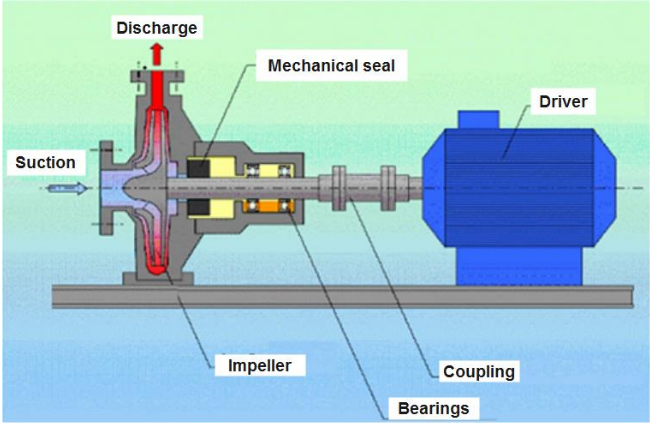


Figure 2. Essential components of a centrifugal pump.

Centrifugal pumps are hydraulic machines that have been around for quite some time and have, more or less, ruled the pumping function in several applications for decades. They are known for being "pressure generators". Centrifugal pumps contain one or more rotating elements, which help expel energy to the fluid which, in turn, is guided to discharge by a component known as the manifold. The fact that centrifugal pumps have dominated the fluid motion industry as a whole is enough to understand how invaluable they are for a mix of applications spanning different industries. Here is a closer look to different uses of centrifugal pumps:

- To provide water for daily use,
- To increase the pressure: Centrifugal pumps,
- To pump water for domestic applications,
- To help fire protection setups,
- To aid the circulation of a fluid,
- To ensure drainage of the sump,
- To regulate the boiler water.

2.2. Studied system's defects

In an industrial production sector, specifically, in the OCP-Morocco production area, we have tried to quantify equipment failures on an annual basis, by trying to trace equipment, then the organs that represent criticality. Pumps were found to represent a maximum frequency of *460* and a percentage of *35.28%* (see Fig.3 and Fig.4), compared to the other equipment used in the process, mentioning as example motors, reducers, couplers, turbines, agitators, etc. This frequency classification came down from constraints that were applied by the pump's working environment (speed of rotation, nature of circulating fluid, pressure, environment, etc…). To determine the major problems which lead to the deterioration of the mechanical state and their impact on the gain of the pumps, based on a field study in the Company Central Workshops (CCW), using history data and data for a given period to extract our graphical results.

Fig.3 and Fig.4 illustrate the different types of failures encountered during operation, namely the failure of the mechanical seals, which is significant compared to other failures with a criticality of *22* as illustrated in Fig.5.

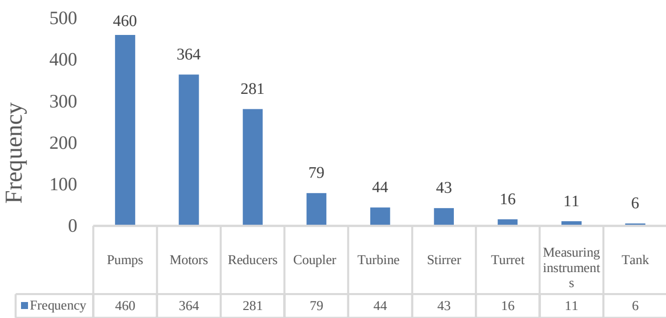


Figure 3. Frequency of equipment failure in the production area.

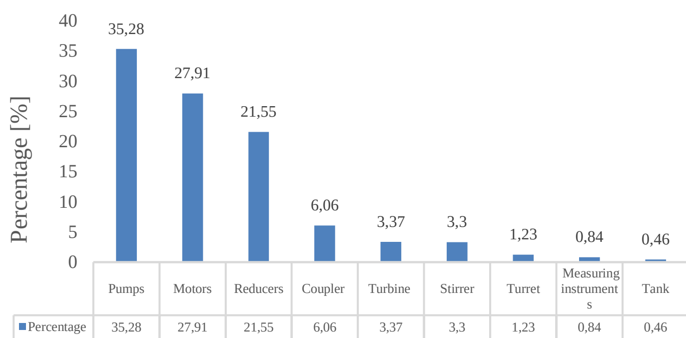


Figure 4. Percentage of equipment failure in the production area.

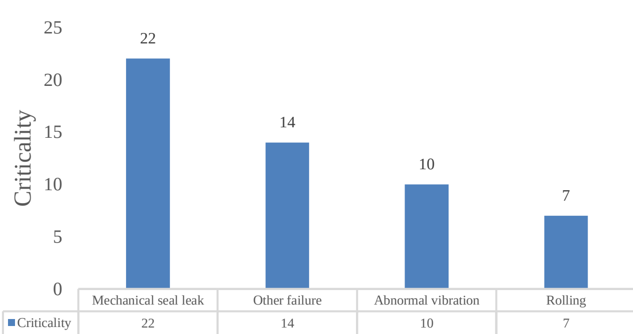


Figure 5. Failing pump components criticality in descending order.

These results can be interpreted as a lack of monitoring of maintenance operations and operating conditions. So, we conclude from this diagnostic analysis that data plays an important role in determining the critical factors that anticipate the impact of the gain of the pumps, namely: wear of the packing, abnormal vibrations, cavitation, damage to bearings, etc., which requires an intelligent strategy to minimize this criticality.

2.3. Discussion

In this section, we will present a diagnostic method based on the equipment failure history to finally justify our path choice, which generally focuses on hydraulic machines, namely pumps.

We approached our problem with a histogram representing all the equipment and the study of their criticality, and then we found that the critical equipment is the pump, which is subject to failure favored by several factors. The detection of the discriminated / critical equipment allowed us to develop a model to estimate the state of health. This model is an accessible tool capable of determining the level of degradation at any time point to make the intervention decision before the failure.

3. PROGNOSIS OF THE STUDIED SYSTEM

3.1. Typology of degradation models

Sometimes, the authors model the degradation in a discrete manner. This discrete degradation model makes it possible to model the degradation in staircase fashion. It's essentially based on the notion of accumulation of a set of damages whose system in degradation passes from a state E_i to a state E_{i+1} according to a jump behavior.

In the literature, (Nachlas, 2005; Nakagawa, 2007) distinguish between two large families of damage models. The first family lists standard cumulative damage models. In these models, the system is considered failed when the evolution of the shocks reaches the permitted degradation threshold. The second family is dismayed at the independent damage models whose shocks are no longer extensive.

We define the damage model as a model carrying a double stochastic process which describes a phenomenon produced at random times t_i, $i = (1{:}\ N)$, so that each instant t_i is associated with a shock of amplitude A_i (see Fig.6) with the assumptions:

$$\begin{cases} A_0 = 0 \\ A_i \succ 0 \quad ; i \geq 1 \quad , A_i \neq A_{i+1} \end{cases} \tag{1}$$

for any identically distributed *i*.

So, the total damage is calculated by the following formula:

$$D(t) = \sum_{i=0}^{N(t)} A_i \tag{2}$$

where *N (t)* denotes the numbers of shock events predicted before time *t*.

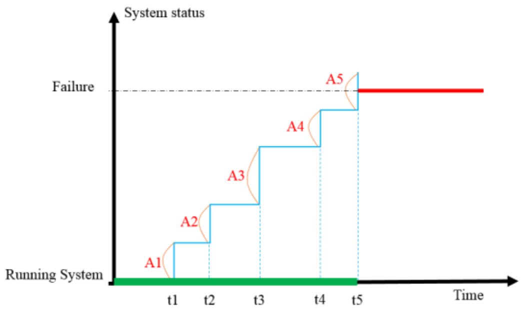


Figure 6. Cumulative damage model.

In the independent damage model, the system failure date corresponds to the first occurrence of a shock that exceeds the threshold condition. This model is generally applied in fragile materials, namely glass, which manifests itself through a strong shock or electronic components, which are damaged quickly, due to an overload that exceeds the threshold, imposed by the manufacturer (Letot, 2013). This damage model is cited by the following formula:

$$D(t) = \min_i (t_i \mid A_i \geq threshold) \tag{3}$$

This kind of model (see Fig.7) is generally based on the knowledge of laws of evolution of the degradation between two successive events. The power of this model is generally apparent in its ability to determine degradation at any desired time. The application of this model is found in systems that require a precise forecast to ultimately avoid any kind of failure that can cause a great loss in the production system and a difficulty in recovery to good health.

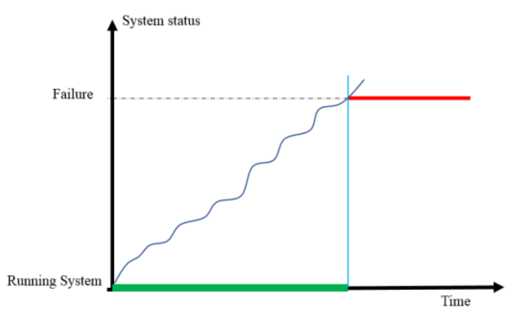


Figure 7. Continuous degradation model.

This model is based on the time-to-delay approach with a conditional residual survival law (time elapsed between any instant and the failure of the system if it is not subject to any maintenance) is readjusted at each inspection by following recursive filtering the system's current state and the history of the maintained process (Christer and Wang, 1992).

In the literature, (Saxena et al, 2008; Saxena , 2009) consider performance as a metric that is supposed to be judged if the prognosis made is executed at a certain targeted level, the desired prediction error must be less than the value set by the neural network. For this, there are two criteria to take into account (Aggab, 2016):

- First criterion: The accuracy of the prediction made must always remain below a fixed threshold. The latter is defined by the parameter $\alpha \times 100\%$.
- Second criterion: It is linked to the concept of time. It is defined by the time of detection of a fault tad over a time horizon provided by the parameter λ, until the manifestation of the fault at time T_d.

It turns out that there is no measure that meets the criteria of relevance, ease of calculation and limit of use. The measure used to assess the quality of the prediction is the absolute mean percentage error. It offers the advantage of considering the order of magnitude of the prediction error. The degradation of the system can be seen by the deterioration of the problematic actuator (pump). Indeed, the partial loss of *G* or the total capacity of an actuator can introduce a loss of the system's performance in the sense that it varies its behavior compared to the desired behavior (Aggab, 2016):

$$G(t) = G_{init} - D(t) \tag{4}$$

where:

- *G(t)*: Capacity at time *t*,
- G_{init}: Initial capacity of the pump,
- *D(t):* Degradation of the pump accumulated at time *t*.

Equation *(4)* explains that the gain at time *t* is the initial gain at time t_0 minus a relative degradation at time *t*.

3.2. Modeling approach

Artificial intelligence (*AI*) is a powerful tool for prediction and universal approximation (Jang et al, 1997; Zhang, 2019). Its fundamental structure of a neural network system consists of a transformation of a partially fuzzy input using transfer functions, namely: Identity function, Walking function, sigmoid function, hyperbolic tangent function, etc...); then, from a relationship constructed using a set of rules, the determination of values and finally their transformations into output values according to the application considered. (Salvail-Bérard, 2012) defines classical regression as a tool that uses a "*box*" made up of a linear combination of relevant elementary functions and the adjustment simply consists of optimizing the coefficients of this linear combination. Neural networks are an example of such complex models that have proven themselves in several fields such as fraud detection or handwriting recognition. The behavior of the neural network, therefore, depends on the w_j (see Fig.8 and Fig.9) which are used to weight the contributions of the nodes from one layer to the next, and also on the activation thresholds of each node. A data set called a training set should be used to optimize the parameters (w_j and r_i) in order to minimize the network prediction error. The neural network system uses a learning mechanism based on techniques and models. One of the most used models is that of Takagi and Sugeno (Takagi & Sugeno, 1985). In this model, a fuzzy rule is constructed using a weighted linear combination of the digital inputs rather than a fuzzy set. Generically for two fuzzy If-Then rules, is defined as follows:

If x_1 and x_2 are two inputs to neuron 1 and r_1 is its bias, then:

$$y_1 = w_1x_1 + w_2x_2 + r_1 \quad (5)$$

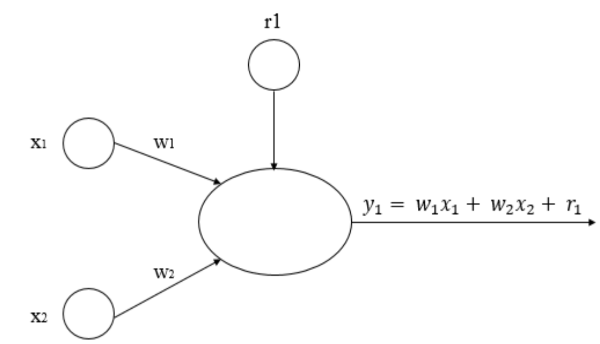


Figure 8. Representation of a formal neuron with two inputs.

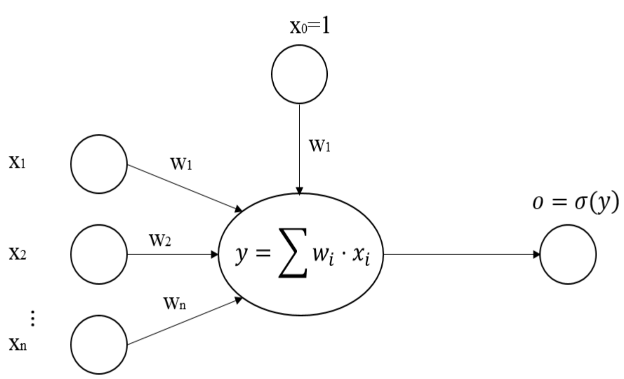


Figure 9. Hidden layer of a neuron with *n* inputs.

with:

- $x_0 = 1$: Bias, represents the activation threshold of the neuron,
- x_i $(i = 1{:}\ n)$: Inputs,
- w_i : Synaptic coefficients,
- y : Weighted sum,
- o : Network output.

Learning consists in recovering class centers. Its realization requires the knowledge of the number of classes. This number is fixed, in a way that the learning of the model is possible in reasonable computation time (Welte, 2008). All of the data consists of *35* degradation tests (see Fig.10) until the pump fails for missions with two set points with a random evolution.

In our case, according to (Vrignat et al, 2015; Mustafaraja et al, 2011), the gain G_a of the pump decreases compared to its nominal gain according to a random shock process. The shock arrival process is a Poisson process with the parameter $\lambda = 10^{-3}\ arrival.s^{-1}$ and $\Delta = 0.5$.

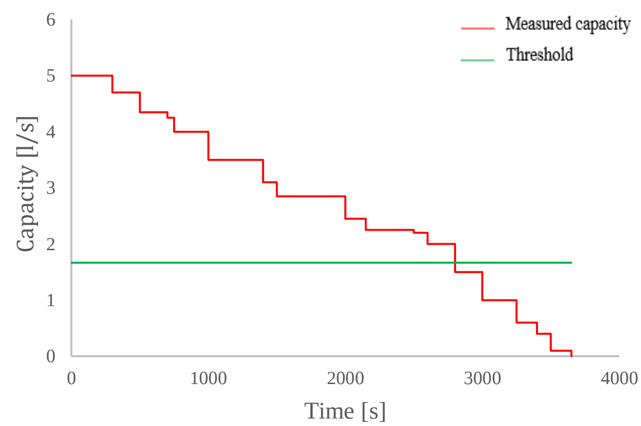


Figure 10. Trajectory of pump capacity as a function of time.

In neural networks of the hidden layer, functions are often used, among which is the sigmoid function. The name *"sigmoid"* comes from its *S* shape. Several authors use a neural network to model physical behavior, thanks to its performance to predict the value of a quantity, a parameter or a variable within a complex system: the interior temperature of a complex building (Mustafaraja et al, 2011).

In (Msaaf & Belmajdoub, 2015), the authors define the activation function as a transfer function, which links the weighted summation to the output signal. There are several types of the activation function. Fig.11 illustrates the most used activation functions.

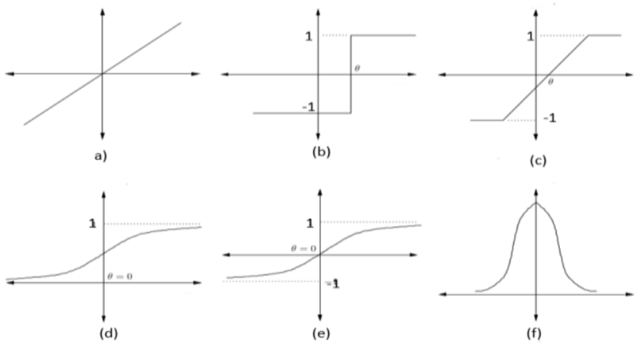


Figure 11. Most used output functions, (a) identity function, (b) threshold function, (c) piecewise linear function, (d) sigmoid function, (e) hyperbolic tangent function, (f) Gauss function.

- *Definition of the identity function*

An identity function is an affine function defined for every real *x* by:

$$id_X : X \to X$$
$$f : x \to x$$

• *Definition of the sigmoid function*

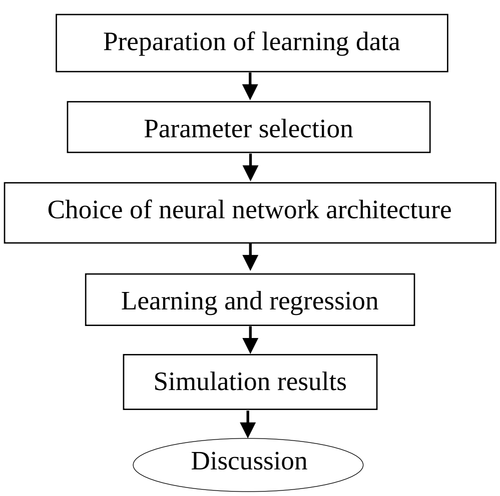
A sigmoid function *(also called S curve)* is defined by:

$$f(x) = \frac{1}{1+e^{-x}} \text{ For all real } x,$$

But we generalize for any function with the following expression:

$$f_\lambda(x) = f(\lambda x) = \frac{1}{1+e^{-\lambda x}}$$

The model, which we are going to adopt, aims to train the network with a set of representative data (*35* tests) to ensure fast and strong learning, and a correct generalization. This model consists of the following stages:



• *Adopted model*

To model our system, the object of study, based on a multilayer perception architecture (*MLP*) (McClelland et al, 1986; Koivo, 1994). That it is a set of perceptions divided into successive layers, namely: an input layer, several hidden layers and an output layer (see Fig.12).

Our architecture is made out of:

- Input x_i,
- 3 hidden layers:
  - 1st layer of 4 neurones,
  - 2nd layer of 7 neurones,
  - 3rd layer of output,
- Output y_i.

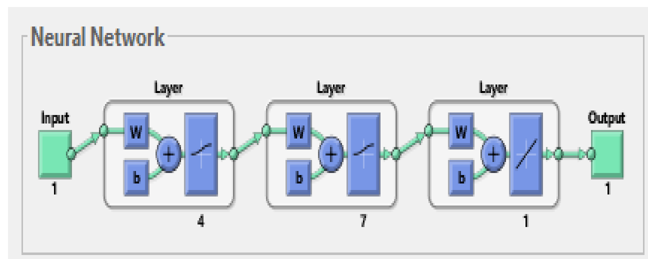


Figure 12. Neural network architecture adopted.

Several architectures in (Fatima & Hamid, 2009; Park et al, 2002; Msaaf & Belmajdoub, 2015; Krishnakumar et al, 2018) have been developed by authors who aim to make a comparison between the different types of neural networks. So we based on this literature to justify our choice of architecture for the model, which is a supervised learning architecture with several advantages such as a simple architecture, a global representation of the space, ability to accept noisy data and non-linear classification (Aggab, 2016).

4. RESULTS AND DISCUSSION

In this section, we estimate the lifetime before failure or the performance requirement of the system under study (pump), undergoing degradation, is no longer satisfied. This estimate is made based on a priori knowledge of operational conditions until t_s. The system is considered failed when the objectives concerning the system's performance (Gain) are no longer met. So, the actual gain of the system (pump) must be greater than a fixed value - the critical threshold - when designing the system, noted: $Ga_{critical}$. The value of the critical gain considered which describes the behavior of the system is of order: $\frac{G_{init}}{3}$.

The trajectory illustrated in Fig.13 correctly shows that the system responds satisfactorily to the desired performance constraint ($Ga_{critical}$) despite the incurred degradation of the gain of the pump, and this until the total failure. The deterioration favored during operation induces a decrease in gain continuously. This justifies all the factors mentioned in part (**2.2**) which directly affect the performance of the system.

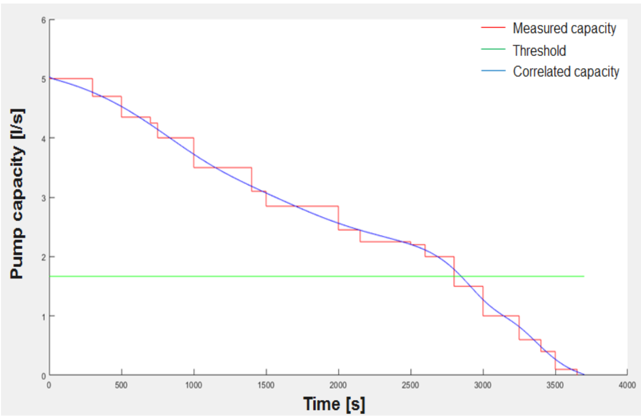


Figure 13. Established learning result.

Learning by the model based on the fuzzy neural network, multilayer perception (*MLP*) gives results close to reality compared to the shock model studied in (De Gooijer et al, 2006). The two models intersect with the threshold at the instant $t_s = 2800\ s$, but the model given by the fuzzy neural network remains close to the physical phenomenon of degradation which is manifested smoothly and continuously. We can judge the performance of a prediction method by different criteria commonly used, namely:

- The Mean squared error (MSE):

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\theta_{t_p+i} - \hat{\theta}_{t_p+i})^2} \tag{6}$$

- The correlation coefficient R:

$$R = \frac{\sum_{i=1}^{N}(\theta_{t_p+i} - \bar{\theta})(\hat{\theta}_{t_p+i} - \overset{*}{\theta})}{\sum_{i=1}^{N}(\theta_{t_p+i} - \bar{\theta})\sum_{i=1}^{N}(\hat{\theta}_{t_p+i} - \overset{*}{\theta})} \tag{7}$$

where $(\theta_{ti};\bar{\theta})$ and $(\hat{\theta}_{ti};\overset{*}{\theta})$ consecutively represent the value and the mean of the real and predicted values. N is the total number of samples.

The purpose of error measurement has been discussed in (Aggab, 2016). It appears that there is no measure satisfying the criteria of relevance, ease of calculation and limit of use at the same time. The measure used to assess the quality of the prediction is the mean square error (*MSE*). It offers the advantage of considering the order of magnitude of the prediction error (De Gooijer et al, 2006; Soualhi, 2013; Dragomir, 2008).

Our model, developed by multilayer perception (*MLP*) from the performance results obtained and illustrated in Fig.14, Fig.15 and Fig.16, is a strong and good learning model from a stand point of the mean square error (*MSE*) since we found a good value of order *0.03239* by *20* chosen epochs, and so for the correlation coefficient of the order of *0.99323*, this value tends towards *1*, which means a relatively perfect correlation for our model. In the end, the parameter result is of value *0.0001* for the *20* epochs which are generally weak.

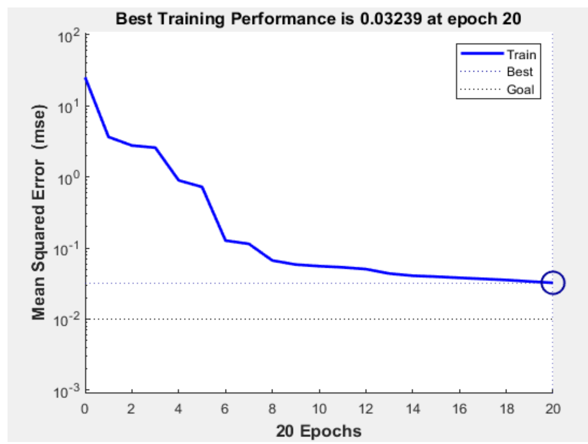


Figure 14. Mean squared error (*MSE*).

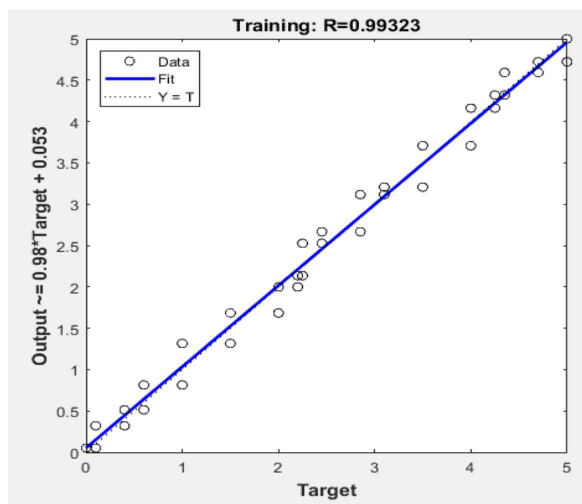


Figure 15. Correlation coefficient R.

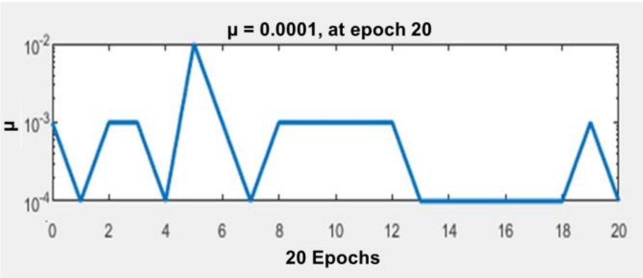


Figure 16. Coefficient of learning μ.

From these measurements, the performance of our model used for the estimation of the remaining useful life (*RUL*) gives satisfactory results:

- The value of the *MSE* is valid. The reason for working with it and not with *TLSM* is because it is a simple neural network with only one input and one output, for that it should be not a big prediction error,
- The value of the correlation coefficient is close to *1*,
- The μ coefficient tends towards 0 ($\mu = 0.0001$).

Note: The judgment of the prediction quality of the system is justified by values set by the designed neural network.

To make a comparison with the level of performance, this time we choose two other correlations, linear and polynomial. The objective of this choice is due, on one hand, to the simplicity of generation of the law, and on the other hand to the simple application of the approach.

The approach is used to generate an automatic regression of the processed data. Therefore, the data set regressions $A(t_i;G_i)$ for the different tests taken in our model are illustrated in the following two figures (see Fig.17 and Fig.18).

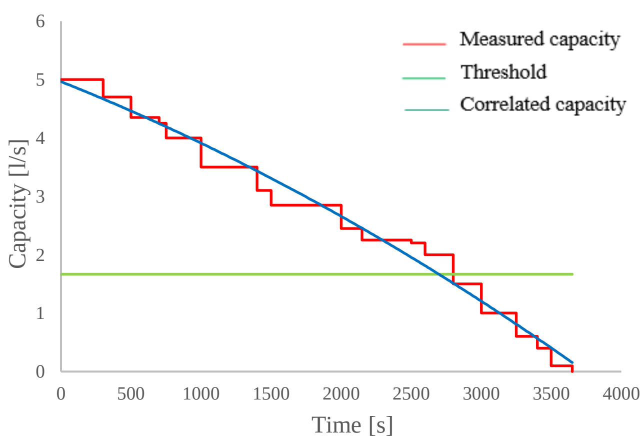


Figure 17. Regression by polynomial law.

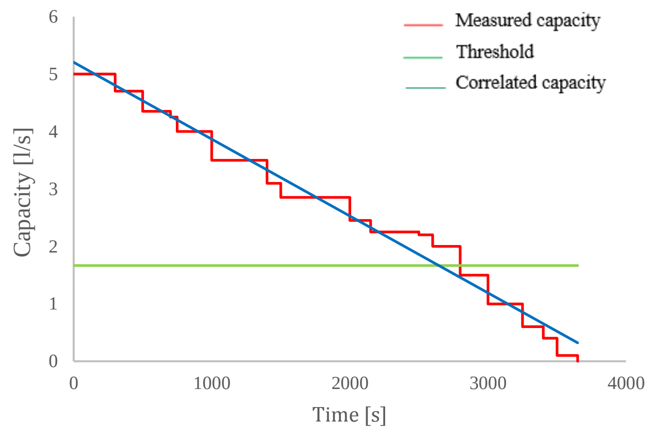


Figure 18. Regression by linear law.

Then, the correlation coefficient values obtained are presented in Table.1.

Table 1. Correlation coefficients of the *3* regressions.

Regression	Correlation coefficient
Neural Network	**0.9932**
Polynomial law	0.9781
Linear law	0.9738

From these results, we found that regression by the neural network represents a better correlation coefficient of the order *0.9932* compared to others, that is to say a very good accuracy in terms of prediction, thus a good interpolation between two consecutive events A_i and A_{i+1}, which justifies our adopted model.

The sophisticated modeling method consists of learning from a discrete shock model, transforming it to a continuous model. The model obtained at the end, considers the good regression and the proximity to the physical nature, thanks to the performances found.

The neural network used has *3* internal layers, this number is justified by the results obtained during simulation in relation to a network of *2*, *4* or *5* layers, idem for the transfer functions used “*Sigmoid*” and “*identity*”.

The system has a supply current as input and a discharge capacity as its output. The model makes it possible to estimate the state of health of the system studied, which shows us the possibility of illustrating the interest of the method adopted within the framework of the process of evaluating the state of health of a hydraulic system and to determine the efficiency of maintenance activities and meet the constraints of the strategies developed in this area.

5. CONCLUSION AND PERSPECTIVES

In our paper, we treated an example of a mechanical system (centrifugal pump). This system represents a great variety of use in several fields. The study carried out showed us that it was possible to illustrate the advantage and the performance of the architecture by the proposed multilayer perception (*MLP*), to compare with other approaches and to estimate the duration of the remaining life of the system under study, undergoing a random degradation. The advantage of this model is to use, exploit and correlate data from several sources using fuzzy neural network artificial intelligence (*AI*). Our chosen type of modeling gives the advantage of an efficient interpretation concerning the meaning of health states in every moment. Moreover, it has been found that this type is the closest to physical reality, since it is continuously smooth.

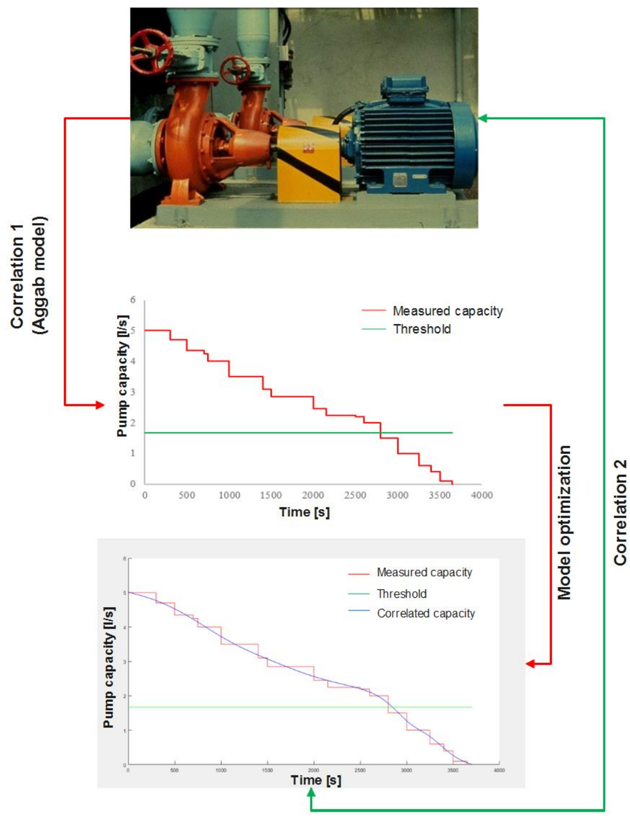


Figure 19. Research strategy developed and perspective.

In the health prognosis strategy presented (see Fig.19), the discrete model which has been treated in the literature is not realistic, therefore it remains insufficient to model the physical behavior of the studied system. In this sense, we have improved it by an approach based on a neural network model to make it a realistic model (correlation 1). The use of neural network is a powerful tool thanks to the results found during the research work carried out: ability to transform a discrete model to a continuous model, physical representation of behavior and very good *RMS*.

The result of the current work will be used to make a relation / function (correlation 2) in order to find the remaining lifetime (*RUL*) of the system under study. The time scale of the system behavior model has been reduced (*2800 s*). Otherwise the simulation time problem will be a constraint. So, we have accelerated the rate of degradation compared to what seems achievable at the simulation level. Then, a strategy towards solving the drawbacks related to the accuracy of the model to minimize the prediction error as long as it is a step towards a real scale (correlation 2).

NOMENCLATURE

$D(t)$	Degradation
A_i	State of degradation
$G(t)$	Pump capacity at time t
G_{init}	Initial pump capacity
$Ga_{critical}$	Critical pump capacity
$N(t)$	Numbers of shock events predicted
λ	Poisson coefficient
T_d	Failure time
x_0	Bias, represents the activation threshold of the neuron,
x_i	Network inputs
w_i	Synaptic coefficients
y	Weighted sum
o	Network output
MSE	Mean squared error
R	Correlation coefficient

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