From monitoring data to remaining useful life: an evolving approach including uncertainty

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Abstract

Although prognostic activity is nowadays recognized as a key feature in maintenance strategies, real prognostic systems are scarce in industry. That can be explained from different aspects, one of them being the lack of knowledge on the monitored system that impedes the development of classical dependability analysis (based on statistical data for example). Within this frame, the general purpose of the work is to propose a prognostic system that starts from monitoring data and goes through provisional reliability and remaining useful life by characterizing the uncertainty following from the degradation process. More precisely, the paper emphasizes on the development of an evolving neuro-fuzzy predictor that, not only "gives" an approximation of the degradation of an equipment but also associates to it a confidence measure.

Keywords: Prognostic, Degradation, Reliability Modeling, Evoloving Neuro-Fuzzy System, Uncertainty.

1. Introduction

The growth of reliability, availability and safety of a system is a determining factor in regard with the effectiveness of industrial performance. As a consequence, the high costs in maintaining complex equipments make necessary to enhance maintenance support systems and traditional concepts like preventive and corrective strategies are progressively completed by new ones like predictive and proactive maintenance. Thereby, prognostic is considered as a key feature in maintenance strategies as the estimation of the provisional reliability of an equipment as well as its remaining useful life allows avoiding inopportune spending.
From the research point of view, many developments exist to support the prognostic activity [1, 2, 3]. However, in practice, choosing an efficient technique depends on classical constraints that limit the applicability of the tools: available data-knowledge-experiences, dynamic and complexity of the system, implementation requirements (precision, computation time, etc.), available monitoring devices... Moreover, implementing an adequate tool can be a non trivial task as it can be difficult to provide effective models of dynamic systems including the inherent uncertainty of prognostic. That said, developments of this paper are founded on the following two complementary assumptions. 1) On one hand, real systems increase in complexity

and their behavior is often non-linear, which makes harder a modeling step, even impossible. Intelligent Maintenance Systems must however take it into account. 2) On the other hand, in many cases, it is not too costly to equip dynamic systems with sensors, which allows gathering real data online. Furthermore, monitoring systems evolve in this way.

According to all this, neuro-fuzzy (NF) systems appear to be very promising prognostic tools: NFs learn from examples and attempt to capture the subtle relationship among the data. Thereby, NFs are well suited for practical problems, where it is easier to gather data than to formalize the behavior of the system being studied. Actual developments confirm the interest of using NFs in forecasting applications [4, 5, 6].

In this context, the paper deals with the definition of a prognostic system for which any assumption on its structure is necessary: it starts from monitoring data and goes through provisional reliability and remaining useful life by characterizing the uncertainty following from the degradation process. More precisely, the paper emphasizes on the development of an evolving neuro-fuzzy predictor that, not only "gives" an approximation of the degradation of an equipment but also associates to it a confidence measure. The model is well adapted to perform *a priori* reliability analysis and thereby optimize maintenance policies.

The paper is organized in three main parts.

In the first part, the concept of "prognostic" is clarified and replaced within the maintenance strategies. The relationship between prognostic, prediction and online reliability is also explained: the efficiency of a prognostic system is highly dependent on its ability to perform "good" predictions as reliability indicators follow from it. This is a central point of the work. Following that, the use of Takagi-Sugeno neuro-fuzzy systems in prognostic applications is justified and the ways of building such models are briefly discussed in the second part. An evolving neuro-fuzzy model for prognostic is thereby proposed and presented. Unfortunately, neuro-fuzzy predictors do not provide uncertainty indicators. Thus, in the third part, statistical estimation techniques are adapted to the evolving neuro-fuzzy predictor in order to provide a confidence measure on prediction and thereby enable reliability analysis. The whole is illustrated with an example extracted from literature.

2. Prognostic and reliability

2.1 From maintenance to prognostic

Maintenance activity combines different methods, tools and techniques to reduce maintenance costs while increasing reliability, availability and security of equipments. Thus, one usually speaks about fault detection, failures diagnosis, and response development (choice and scheduling of preventive and/or corrective actions). Briefly, these steps correspond to the need, firstly, of "perceiving" phenomena, secondly, of "understanding"' them, and finally, of "acting" consequently. However, rather than understanding a phenomenon which has just appeared like a failure, it seems convenient to "anticipate" its manifestation in order to take adequate actions as soon as possible. This is what could be defined as the "prognostic process". The relative positioning of detection, diagnosis, prognostic and decision / scheduling can be schematized as proposed in Figure 1.

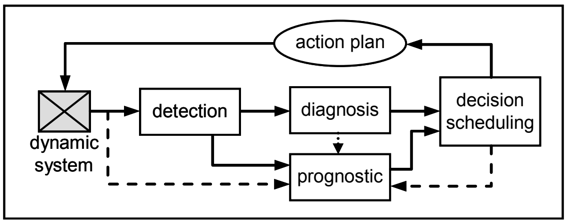

Figure 1. Prognostic within maintenance activity.

2.2 From prognostic to prediction

Although there are some divergences in literature, prognostic can be defined as proposed by the International Organization for Standardization: "prognostic is the estimation of time to failure and risk for one or more existing and future failure modes" [7]. Prognostic is also called the "prediction of a system's lifetime" as it is a process whose objective is to predict the remaining useful life (RUL) before a failure occurs given the current machine condition and past operation profile [2]. Thereby, two salient characteristics of prognostic appear: (1) prognostic is mostly assimilated to a prediction process (a future situation must be caught), (2) prognostic is based on the failure notion, which implies that it is associated with a degree of acceptability. A central problem can be pointed out from this: the accuracy of a prognostic system is related to its ability to approximate and predict the degradation of an equipment: starting from a "current situation", a prognostic tool must be able to forecast the "future possible situations" and the prediction phase is thereby a critical one.

2.3 From prediction to reliability

As mentioned earlier, an important task of prognostic is to predict the degradation of an equipment. Following that, prognostic can also be seen as a process that allows the a priori reliability modeling. Reliability ($R(t)$) is classically defined as the probability that a failure does not occur before time t. If the random variable ϑ denotes the time to failure and $F_{\vartheta}(t) = Pr(\vartheta \leq t)$ its cumulative distribution function, then:

$$R(t) = 1 - F_{\vartheta}(t) \tag{1}$$

Let assume now that the failure is not characterized by a random variable but by the fact that a degradation signal (y) overpass a degradation limit (y_{lim}), and that this degradation signal can be predicted ($\hat{y}$) with a degree of uncertainty (Figure 2). At any time t, the failure probability can be predicted as follows:

$$F(t) = Pr\left[\hat{y}(t) \geq y_{lim}\right] \tag{2}$$

Let note $g(\hat{y}/t)$ the probability distribution function that denotes the prediction at time t. Thereby, by analogy with reliability theory, the reliability modeling is:

$$R(t) = 1 - Pr\left[\hat{y}(t) \geq y_{lim}\right] = 1 - \int_{y_{lim}}^{\infty} g(\hat{y}/t).dy \tag{3}$$

The remaining useful life (RUL) of the system can finally be expressed as the remaining time between the time in which is made the prediction (t_p) and the time to underpass a reliability limit (R_{lim}) fixed by the practitioner. This can be generalized with a multi-dimensional degradation signal. See [8] or [9] for more details.

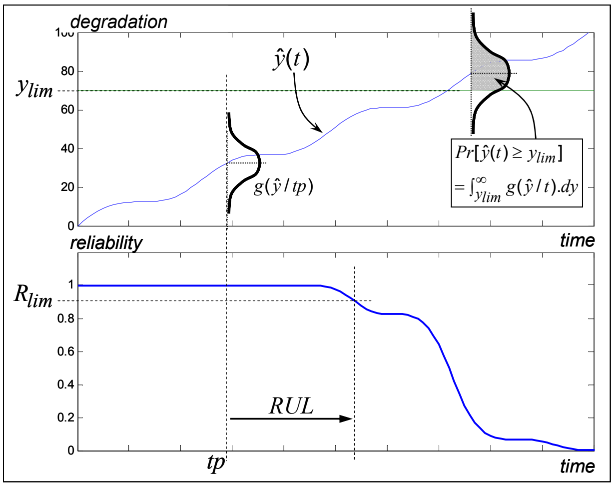

Figure 2. Prediction and reliability modeling.

Finally, in order to perform *a priori* reliability analysis, an effective prognostic tool should provide the probability distribution function of prediction for time t. Moreover, this would enable to build confidence intervals on predictions, which can help practitioners in judging from the degradation state of the system and thereby, in taking adequate decisions. This point is again discussed in part 4.

3. Fuzzy models for prediction

3.1 Takagi-Sugeno system: a fitted prediction tool

According to some authors, the methods presented in this section are sometimes labeled as "prognostic techniques". However, most of them refer to what, in this paper, is called "prediction". Note that the aim of this part is not to dress an exhaustive overview of prediction techniques but to explain the orientations of works that are taken. Various prognostic approaches have been developed ranging in fidelity from simple historical failure rate models to high-fidelity physics-based models [1, 3]. Briefly, similarly to diagnosis, prognostic methods can be associated with one of the following two approaches, namely model-based and data-driven.

Model-based methods assume that an accurate mathematical model for the analyzed system can be constructed. The main advantage of these approaches is their ability to incorporate physical understanding of the system. 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.

Data-driven approaches use real data (like online gathered with sensors or operator measures) to approximate and track features revealing the degradation of components and to forecast the global behavior of a system. The strength of data-driven techniques is their ability to transform high-dimensional noisy data into lower dimensional information for prognostic decisions: in many applications, measured input/output data is the major source for a deeper understanding of the system degradation.

Real systems are complex and their behavior is often non linear, non stationary. These considerations make harder a modeling step, even impossible. Yet, a prediction computational tool must deal with it. Moreover, monitoring systems have evolved and it is now quite easy to online gather data. According to all this, data-driven approaches have been increasingly applied to machine prognostic. More precisely, works have been led to develop systems that can perform nonlinear modeling without a priori knowledge, and that are able to learn complex relationships among "inputs and outputs" (universal approximators). Indeed, artificial neural networks (ANNs) have been used to support the prediction process [6], and research works emphasize on the interest of using it. Nevertheless, some authors remain skeptical as ANNs are "black-boxes" which imply that there is no explicit form to explain and analyze the relationships between inputs and outputs. According to these considerations, recent works focus on the interest of hybrid systems: many investigations aim at overcoming the major ANNs drawback (lack of knowledge explanation) while preserving their learning capability. In this way, neuro-fuzzy systems are well adapted. More precisely, first order Tagaki-Sugeno (TS) fuzzy models have shown improved performances over ANNs and conventional approaches [4]. Thereby, they can perform the degradation modeling step of prognostic.

3.2 Takagi-Sugeno models: principles

A first order TS model provides an efficient and computationally attractive solution to approximate a nonlinear input-output transfer function. TS is based on the fuzzy decomposition of the input space. For each part of the state space, a fuzzy rule can be constructed to make a linear approximation of the input. The global output is a combination of the whole rules. In others words, a TS model can be seen as a multi-model structure consisting of linear models that are not necessarily independent [10].
Consider Figure 3 to explain the first order TS model. In this illustration, two inputs variables are considered, two fuzzy membership functions (antecedent fuzzy sets) are assigned to each one of them, and the TS model is finally composed of two fuzzy rules. (Note that a TS model can be generalized to the case of n inputs and N rules).

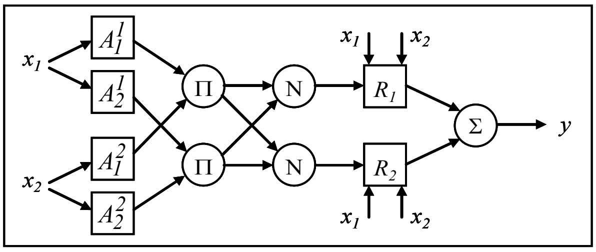

Figure 3. First order TS model.

The rules perform a linear approximation of inputs as follows:

$$R_i : if\ x_1\ is\ A_i^1\ and\ ...\ and\ x_n\ is\ A_i^n\ \ THEN\ \ y_i = a_{i0} + a_{i1}.x_1 + ... + a_{in}.x_n \quad (4)$$

where R_i is the i^{th} fuzzy rule, N is the number of rules, $X = [x_1, x_2, ..., x_n]^T$ is the input vector, A_i^j denotes the antecedent fuzzy sets, $j = [1, n]$, y_i is the output of the i^{th} linear subsystem, and a_{iq} are its parameters, $q = [1, n]$. Let assume Gaussien antecedent fuzzy sets (this choice is justified by its generalization capabilities) to define the regions of fuzzy rules in which the local linear sub-models are valid:

$$\mu_j^i = exp^{-(4\left\| x - x^{i*} \right\|_j)/((\sigma_j^i)^2)} \quad (5)$$

where σ_j^i is the spread of the membership function, and x^{i*} is the focal point (center) of the i^{th} rule antecedent. The firing level (τ_i) and the normalized firing level (λ_i) of each rule are obtained as follows:

$$\tau_i = \mu_{i1}(x_1) \times ... \times \mu_{in}(x_n), \quad \lambda_i = \tau_i \Big/ \sum_{j=1}^{N} \tau_j \quad (6)$$

The model output is the weighted averaging of individual rules' contributions:

$$y = \sum_{i=1}^{N} \lambda_i y_i = \sum_{i=1}^{N} \lambda_i x_e^T \pi_i \quad (7)$$

where $\pi_i = [a_{i0}, a_{i1}, \ldots, a_{in}]$ is the vector parameter of the i^{th} sub-model, and $x_e = [1\ X^T]^T$ is the expanded data vector.

A TS model has two types of parameters. The non-linear parameters are those of the membership functions (a Gaussian membership like in eq. (5) has two parameters: its center $x*$ and its spread deviation σ). These kinds of parameter are referred to as premise or antecedent parameters. The second types of parameters are the linear ones that form the consequent part of each rule (a_{iq} in eq. 4).

3.3 Choosing a TS system: exTS for prognostic application

Assuming that a TS model can approximate an input-output function (previous section), in practice, this kind of model must be tuned to fit to the studied problem. This implies two task to be performed: (1) the design of the structure (number and type of membership functions, number of rules), (2) the optimization of the model's parameters. For that purpose, different approaches can be used to identify a TS model (mosaic scheme: by an expert [11], gradient descent [12], genetic algorithms [13], clustering methods [14], evolving algorithms [15, 16]). All approaches can not be detailed in the paper, so that the following paragraphs only briefly justify the choice of a prediction technique.

According to the degradation modeling problem, a prediction technique for prognostic purpose should not be tuned by an expert as it can be too difficult to catch the behavior of the monitored equipment. Thereby, the first approach for identification (mosaic scheme) should be leaved aside. Descent gradient and genetic algorithms approaches allow updating parameters by a learning process but are based on a fixed structure of the model, which supposes that an expert is able to indicate the adequate architecture to be chosen. Unfortunately, the accuracy of predictions is fully dependent on this. In opposition, clustering approaches require less *a priori* structure information as they automatically determine the number of membership functions and of rules. However, in practical applications, the learning process is effective only if sufficient data are available. In addition to it, when trained, such a TS model is fixed and if the behavior of the monitored system changes (like in a degradation phase), predictions can suffer from the lack of representative learning data.

Considering the applicative restrictions that supposes the implementation of a prognostic tool, evolving TS models appear to be the more promising for prognostic applications. Firstly, they are able to update the parameters without the intervention of an expert. Secondly, they can be trained in online mode as they have a flexible structure that evolves with the data gathered from the system: data are collected continuously which enables to form new rules or to modify an existing one. This second characteristics is very useful to take into account the non-stationary aspect of degradation. According to all this, an accurate TS prediction technique for online reliability modeling is the evolving one. A particular model is this one proposed by [17]: the "evolving eXtended Takagi-Sugeno" system (exTS).

3.4 Learning procedure of exTS

The learning procedure of exTS is composed of two phases: (1) an unsupervised data clustering technique is used to adjust the antecedent parameters, (2) the supervised recursive least squares learning method is used to update the consequent parameters.

3.4.1 Clustering phase: partitioning data space.

In opposition to other approaches, the exTS clustering phase processes on the global input-output data space: $z=[x^T, y^T]^T$, $z \in R^{n+m}$, where $n+m$ defines the dimensionality of the input/output data space. Each one of the sub-model of exTS operates in a sub-area of z.

This clustering algorithm is based on the calculus of a "potential" which is the capability of a data to form a cluster (antecedent of a rule). The procedure starts from scratch and, as more data are available, the model evolves by replacement or upgrade of rules [17]. This enables the adjustment of the antecedent parameters (the non-linear ones): the center x^* and the spread deviation σ of the membership functions (eq. 5).

3.4.2 RLS phase: update of the consequent parameters.

The exTS model is used for online prediction: at prediction time k, eq. 7 can be expressed as follows:

$$\hat{y}_{k+1} = \sum_{i=1}^{N} \lambda_i y_i = \sum_{i=1}^{N} \lambda_i x_e^T \pi_i = \psi_k^T \hat{\theta}_k \tag{8}$$

$\psi_k^T = [\lambda_1 x_e^T, \lambda_2 x_e^T, ..., \lambda_n x_n^T]_k^T$ is a vector of the inputs, weighted by normalized firing (λ) of the rules, $\hat{\theta}_k = [\hat{\pi}_1^T, \hat{\pi}_2^T, ..., \hat{\pi}_N^T]_k^T$ are parameters of the sub-models.
The following RLS procedure is applied:

$$\hat{\theta}_k = \hat{\theta}_{k-1} + C_k \psi_k (y_{k+1} - \psi_k^T \hat{\theta}_{k-1}); k = 2,3,... \quad (9)$$

$$C_k = C_{k-1} - C_{k-1}\psi_k \psi_k^T C_{k-1} \big/ 1 + \psi_k^T C_{k-1} \psi_k \quad (10)$$

with initial conditions $\theta_1 = [\pi_1^T, \pi_2^T, ..., \pi_N^T]_k^T = 0, C_1 = \Omega I$, where Ω is a large positive number, C_1 is a $R(n+1) \times R(n+1)$ co-variance matrix, and $\hat{\theta}_k$ is an estimation of the parameters based on k data samples.

4. Including uncertainty to exTS prediction model

4.1 Principles

Unfortunately, neuro-fuzzy predictors do not provide uncertainty indicators. Thus, in this part, a way to adapt statistical estimation techniques to the evolving neuro-fuzzy predictor (exTS) is proposed in order to supply a confidence measure on prediction and thereby enable reliability analysis.

As explained before, an exTS model can predict the degradation state of an equipment: in this way, exTS approximate an input-output function by optimizing non-linear and linear parameters. Yet, a modeling error must be taken into account:

$$y_{k+1} = f(X_k, \lambda^*, \theta_k^*) + \varepsilon_{k+1} \quad (11)$$

where, y_{k+1} is the real degradation situation, X_k is the input vector at prediction time k, λ^* is the optimal vector of the normalized firing level of the rules that depends on the non-linear parameters, θ_k^* is the optimal vector of the linear parameters, and ε_{k+1} traduces the modeling error of the exTS system. ε_{k+1} is assumed to be independently and identically distributed following a Gaussian distribution $N(0, s^2)$ with mean zero and variance s^2 [18].
The prediction error ($\hat{\varepsilon}_{k+1}$) can be expressed as the difference between the real degradation (y_{k+1}) and the output of the exTS predictor ($\hat{y}_{k+1}$):

$$\hat{\varepsilon}_{k+1} = y_{k+1} - \hat{y}_{k+1} = f(X_k, \lambda^*, \theta_k^*) + \varepsilon_{k+1} - \hat{y}_{k+1} \quad (12)$$

$\hat{\varepsilon}_{k+1}$ is assumed to be distributed following a normal distribution $N(0, \sigma^2_{\hat{\varepsilon}_{k+1}})$.

Thereby, a confidence interval of the prediction error can be expressed as:

$$-\varphi_{\alpha/2}.\sigma_{\hat{\varepsilon}_{k+1}} \leq \hat{\varepsilon}_{k+1} \leq +\varphi_{\alpha/2}.\sigma_{\hat{\varepsilon}_{k+1}} \quad (13)$$

where, $\varphi_{\alpha/2}$ is the inverse of the normal cumulative distribution function for the confidence bounds α. Following that, the real degradation can be bounded:

$$\hat{y}_{k+1} - \varphi_{\alpha/2}.\sigma_{\hat{\varepsilon}_{k+1}} \leq y_{k+1} \leq \hat{y}_{k+1} + \varphi_{\alpha/2}.\sigma_{\hat{\varepsilon}_{k+1}} \quad (14)$$

$\sigma_{\hat{\varepsilon}_{k+1}}$ can be calculated at each prediction step:

$$\sigma^2_{\hat{\varepsilon}_{k+1}} = \sigma^2[f(X_k, \lambda^*, \theta_k^*) + \varepsilon_{k+1} - \hat{y}_{k+1}] \quad (15)$$

Assuming that λ^* is tuned by the clustering phase of the learning process, the input-ouput function f is linear with regards to the consequent parameters θ_k^*. According to eq. 8, the degradation state is approximated as follows:

$$y_{k+1} = f(\psi_k, \theta_k^*) + \varepsilon_{k+1} = \psi_k^T \theta_k^* + \varepsilon_{k+1} \quad (16)$$

where, ψ_k is the vector of the inputs weighted by normalized firing proposed. Thus,

$$\sigma^2_{\hat{\varepsilon}_{k+1}} = \sigma^2[\psi_k^T \theta_k^* + \varepsilon_{k+1} - \hat{y}_{k+1}] = \sigma^2[\psi_k^T \theta_k^* + \varepsilon_{k+1} - \psi_k^T \hat{\theta}_k] \quad (17)$$

$$\sigma^2_{\hat{\varepsilon}_{k+1}} = \sigma^2[\psi_k^T(\theta_k^* - \hat{\theta}_k)] + \sigma^2[\varepsilon_{k+1}] = \sigma^2[\psi_k^T \hat{\theta}_k] + s^2 = \psi_k^T C_k \psi_k + s^2 \quad (18)$$

C_k and $\hat{\theta}_k$ are obtained with eq. 9 and 10. Further information can be found in [17].

As a synthesis, it is possible to provide the exTS output ($\hat{y}_{k+1}$) (eq. 8). In addition, the normal distribution of the prediction error ($\hat{\varepsilon}_{k+1}$) can also recursively be obtained (eq. 18). The whole permit: (1) to dispose from a distribution function of the prediction ($\hat{y}_{k+1} + \hat{\varepsilon}_{k+1}$) and thereby perform the reliability analysis (like proposed in section 2.3), (2) to build confidence intervals on the real degradation estimation and thereby take more reliable decisions (eq. 14). This proposition is illustrated in next sections.

4.2 Experimentations

A real experimental data set has been used to show the performance of exTS when used as a prediction system, and to illustrate the integration of the uncertainty to build the confidence interval. The aim of the predictions is to approximate a physical phenomenon by learning data gathered from the system. The data set is issued from an hair dryer. It has been contributed by W. Favoreel from the KULeuven University (ftp://ftp.esat.kuleuven.ac.be/sista/data/mechanical). This data set contains 1000 samples. The air temperature of the dryer is linked to the voltage of the heating device. For simulations, exTS has been used with five inputs variables. Predictions concern the air temperature and were made at different horizons h : at $t+1$, $t+5$ and $t+10$. Assuming that t denotes the current time, the model was built as follows:

– input 1 to 4: air temperature at times ($t-3$) to (t),
– input 5: voltage of the heating device at time (t),
– output 1: $\hat{y}(t+h)$ - predicted air temperature at time ($t+h$).

500 samples were used for both the training and testing data sets. The prediction confidence was set to 95% ($\alpha = 0,05$).

A first way of assessing the prediction performance is to use the root mean square error criterion (RMSE) which is the most popular prediction error measure, or the mean absolute scaled error (MASE) (table I). In order, to judge from the predictions, the confidence intervals were also dressed up by using the proposed methodology. The results are shown in Figure 4. For clarity, this figure is reduced to an extract of all the prediction times: from sample 450 to sample 600.

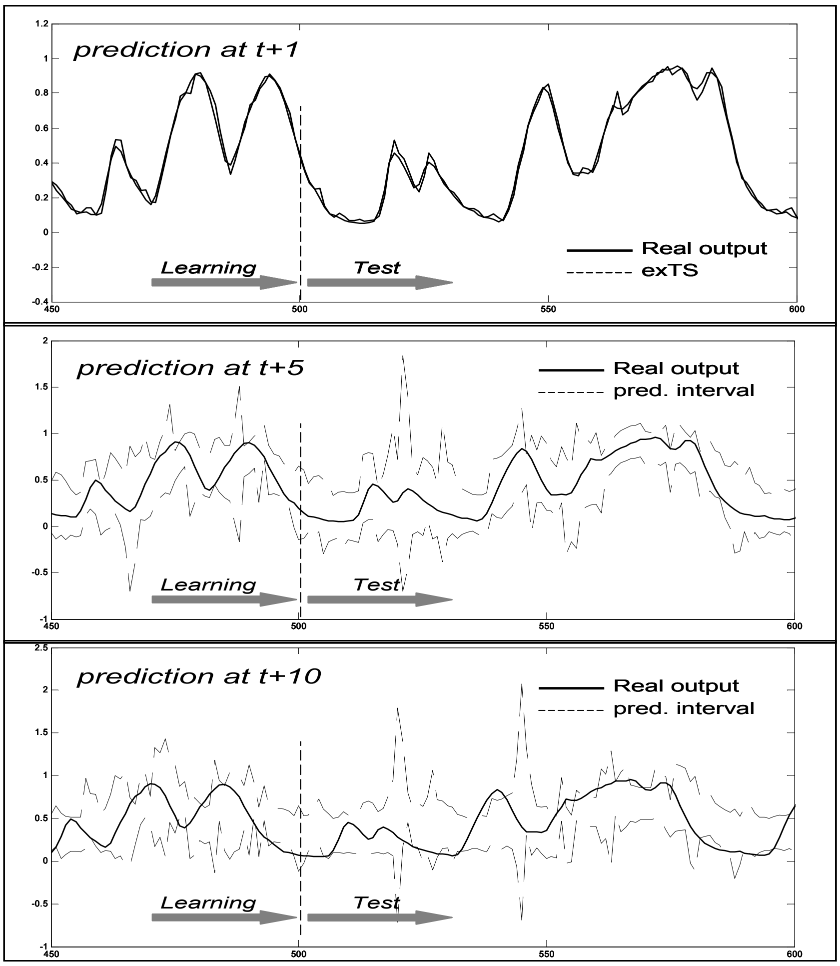

Figure 4. Accuracy of predictions and prediction intervals (95% confidence).

Table I: Simulation results - RMSE and MASE.

Prediction measure / horizon	$t+1$	$t+5$	$t+10$
RMSE	0,01560	0,12816	0,22997
MASE	0,47768	1,97647	3,66373

According to table I, exTS provides very good predictions, which illustrates the accuracy of this evolving neuro-fuzzy system. However, both RMSE and MASE increase with the horizon of prediction. Thus, these aggregated indicators are not sufficient to judge from the adequacy of the prediction system and thereby, from the opportunity of using it in prognostic applications. Yet, Figure 4 illustrates that the real output is almost in the confidence interval of predictions.
Finally, the exTS system improved by the methodology developed to build the confidence interval enable to make accurate predictions which is of good omen with regard to the online reliability estimation (as stated in part 2).

5. Conclusion

In maintenance field, prognostic is recognized as a key feature as the estimation of the remaining useful life of an equipment allows avoiding inopportune maintenance spending. However, it can be difficult to define and implement an adequate and efficient prognostic tool that includes the inherent uncertainty of the prognostic process. Indeed, an important task of prognostic is that of prediction since prognostic can also be seen as a process that allows the reliability modeling.
In this context, the paper deals with the definition of a prognostic system for which any assumption on its structure is necessary: it starts from monitoring data and goes through provisional reliability and remaining useful life by characterizing the uncertainty following from the degradation process. More precisely, the paper emphasizes on the use of the evolving neuro-fuzzy predictor exTS. A method to associate a confidence measure to the prediction is proposed and illustrated. This procedure is based on the adaptation of statistical techniques. The model is thereby well adapted to perform *a priori* reliability analysis since it provides the distribution functions of prediction.
Developments are at present extended in order to ensure a confidence level by modifying the learning algorithms. The underlying idea is that a compromise between generalization and approximation should be pursued: practitioners surly prefer a "well known constant" error than a "sometimes catastrophic ones". This work is led with the objective of being integrated to an e-maintenance platform at a French industrial partner (em@systec).

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