Development of a prognostic tool to perform reliability analysis.

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Mohamed El-Koujok, Rafael Gouriveau & Noureddine Zerhouni
FEMTO-ST Institute, UMR CNRS 6174 - UFC / ENSMM / UTBM
Automatic Control and Micro-Mechatronic Systems Department, Besançon, France

ABSTRACT: 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. Within this frame, neuro-fuzzy systems are well suited for practical problems where it is easier to gather data (online) than to formalize the behavior of the system being studied. In this context, and according to real implementation restrictions, the paper deals with the definition of an evolutionary fuzzy prognostic system for which any assumption on its structure is necessary. The proposed approach outperform classical models and is well fitted to perform *a priori* reliability analysis and thereby optimize maintenance policies. An illustration of its performances is given by making a comparative study with an other neuro-fuzzy system that emerges from literature.

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 (Muller et al. 2008; Iung et al. 2003). 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 (Byington et al. 2002; Jardine et al. 2006; Vachtsevanos et al. 2006). 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 (Wang et al. 2004; Yam et al. 2001; Zhang et al. 1998). In this context, the paper deals with the definition of an evolutionary fuzzy prognostic system for which any assumption on its structure is necessary. This 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, prognostic is briefly defined and positioned within the maintenance strategies, and the relationship between prognostic, prediction and online reliability is explained. Following that, the use of Takagi-Sugeno neuro-fuzzy systems in prognostic applica-

tions is justified and the ways of building such models are discussed. Thereby, a NF model for prognostic is proposed. In the third part, an illustration of its performances is given by making a comparative study with an other NF system that emerges 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 (*a posteriori* comprehension), 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" and which is the object of this paper. Prognostic reveals to be a very promising maintenance activity and industrials show a growing interest in this thematic which becomes a major research framework; see recent papers dedicated to condition-based maintenance (CBM) (Jardine et al. 2006; Ciarapica and Giacchetta 2006). The relative positioning of detection, diagnosis, prognostic and decision / scheduling can be schematized as proposed in Fig. 1. In practice, prognostic is used to be performed after a detection step: the monitoring system detects that the equipment overpass an alarm limit which activates the prognostic process.

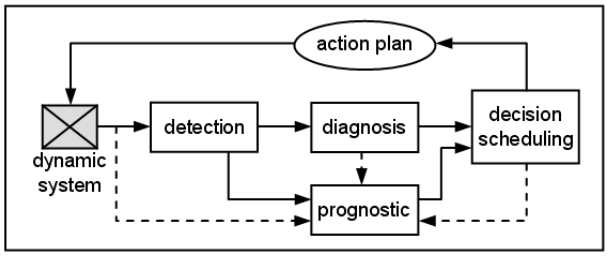

Figure 1: Prognostic within maintenance activity

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" (ISO 13381-1 2004). In this acceptation, 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 (Jardine et al. 2006). Thereby, two salient characteristics of prognostic appear:

- prognostic is mostly assimilated to a prediction process (a future situation must be caught),
- prognostic is based on the failure notion, which implies 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 equipment. In other words, 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. Next section of this paper emphasizes on this step of prognostic.

2.3 From prediction to reliability

As mentioned earlier, an important task of prognostic is to predict the degradation of equipment. Following that, prognostic can also be seen as a process that allows the *a priori* reliability modeling.
Reliability ($R(t)$) is defined as the probability that a failure does not occur before time t. If the random variable ϑ denotes the time to failure with a cumulative distribution function $F_\vartheta(t)$=$Prob(\vartheta \leq t)$, 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 (Fig. 2). At any time t, the failure probability can be predicted as follows:

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

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 can be expressed as follows:

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

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 (tp) and the time to underpass a reliability limit (R_{lim}) fixed by the practitioner (see Fig. 2).

These explanations can be generalized with a multidimensional degradation signal. See (Chinnam and Pundarikaksha 2004) or (Wang and Coit 2004) for more details. Finally, the *a priori* reliability analysis can be performed if an accurate prognostic tool

is used to approximate an predict the degradation of an equipment. This is the purpose of next sections of this paper.

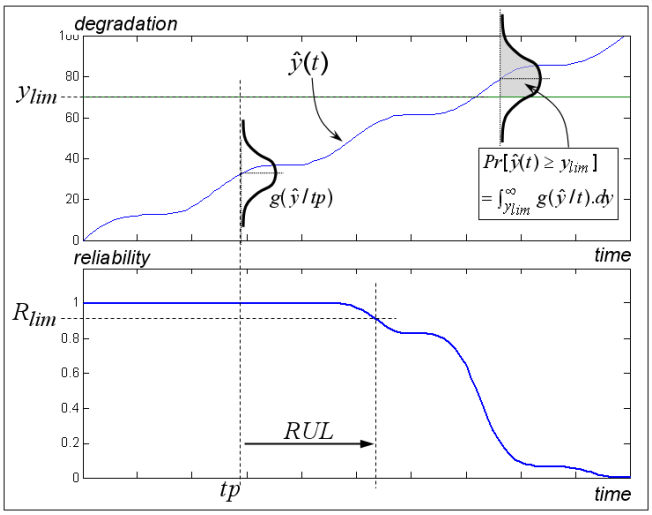

Figure 2: Prediction and reliability modeling

3 FUZZY MODELS FOR PREDCITION

3.1 Takagi-Sugeno system: a fitted prediction tool

Various prognostic approaches have been developed ranging in fidelity from simple historical failure rate models to high-fidelity physics-based models (Vachtsevanos et al. 2006; Byington et al. 2002). Similarly to diagnosis, these methods can be associated with one of the following two approaches, namely model-based and data-driven. That said, 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.

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 evolve and it is now quite esay 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 (Zhang et al. 1998), 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 (Wang et al. 2004). Thereby, they can perform the degradation modeling step of prognostic.

3.2 Takagi-Sugeno models: principles

a) The inference principle

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 approximation is a combination of the whole rules: a TS model can be seen as a multi-model structure consisting of linear models that are not necessarily independent (Angelov and Filev 2004).

Consider Fig. 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. That said, a TS model can be generalized to the case of n inputs and N rules (see here after).

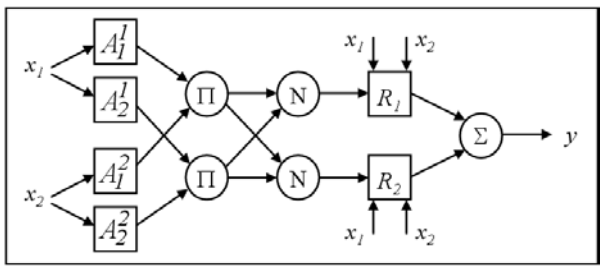

Figure 3: First order TS model

The rules perform a linear approximation of inputs as follows:

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

where R_i is the ith fuzzy rule, N is the number of fuzzy rules, $X = [x_1, x_2, \ldots, x_n]^T$ is the input vector, A_i^j denotes the antecedent fuzzy sets, $j = [1, n]$, y_i is the output of the ith linear subsystem, and a_{iq} are its parameters, $q = [0, n]$.

Let assume Gaussian antecedent fuzzy sets (this choice is justified by its generalization capabilities

and because it covers the whole domain of the variables) to define the regions of fuzzy rules in which the local linear sub-models are valid:

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

where $(\sigma_j^i)^2$ is the spread of the membership function, and x^{i*} is the focal point (center) of the ith rule antecedent.

The firing level of each rule can be obtained by the product fuzzy T-norm:

$$\tau_i = \mu_{i1}(x_1) \times \ldots \times \mu_{in}(x_n) \quad (6)$$

The normalized firing level of the ith rule is:

$$\lambda_i = \tau_i / \sum_{j=1}^{N} \tau_j \quad (7)$$

The TS model output is calculated by weighted averaging of individual rules' contributions:

$$y = \sum_{i=1}^{N} \lambda_i y_i = \sum_{i=1}^{N} \lambda_i x_e^T \pi_i \quad (8)$$

where $\pi_i = [a_{i0} a_{i1} a_{i2} \ldots a_{in}]$ is the vector parameter of the ith 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 equation 5 has two parameters: its center x^* and its spread deviation σ). This kind of parameter are referred to as premise or antecedent parameters. The second type of parameters are the linear ones that form the consequent part of each rule (a_{iq} in equation 4).

b) Identification of TS fuzzy models

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:

- the design of the structure (number and type of membership functions, number of rules),
- the optimization of the model's parameters.

For that purpose, different approaches can be used to identify a TS model. In all cases, the consequent parameters of the system are tuned by using a least squares approach.

Mosaic or table lookup scheme. It is the simplest method to construct TS fuzzy system as the user defines himself the architecture of the model and the antecedents parameters values (Espinosa et al. 2004).

Gradient Descent (GD). The principle of the GD algorithm is to calculate the premise parameters by the standard back-propagation algorithm. GD has been implemented in a special neuro-fuzzy system: the ANFIS model (Adaptive Neuro-Fuzzy Inference System) proposed by (Jang and Sun 1995).

Genetic Algorithms (GAs). GAs are well known for their optimization capabilities. The GAs are used by coding the problem into chromosomes and setting up a fitness function. Since the consequent part of a TS model can be calculated by using a least squares method, only the premise part of the model is coded into chromosomes and optimized by the GAs.

Clustering methods (CMs). The basic idea behind fuzzy clustering is to divide a set of objects into self-similar groups (cluster). The main interest of this type of methods is that the user does not need to define the number of membership functions, neither the number of rules: CMs adapt the structure of the TS model by the learning phase.

Evolving algorithms. These algorithms are based on CMs and therefore, do not require the user to define the structure of the TS model. In opposition to all previous approaches, they do not need a complete learning data set to start the identification process of the TS model (start from scratch): they are online algorithms with self constructing structure. These approaches were recently introduced (Angelov and Filev 2003; Kasabov and Song 2002).

3.3 Discussion: exTS for prognostic application

The selection of an identification approach for TS model depends obviously on the prediction context. 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 (table lookup 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. However, the accuracy of predictions is fully dependent on this, and such identification techniques suffer from the same problems as ANNs. Yet, the ANFIS model is known as a fitted tool for time-series prediction and has been used for prognostic purpose (Goebel and Bonissone 2005; Wang et al. 2004).

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. Thereby, if the behavior of the

monitored system changes significantly (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 (evolving systems with regard to the parameters). 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 (Angelov and Zhou 2006): the "evolving eXtended Takagi-Sugeno" system (exTS). The way of learning this type of model is presented in next section and the interest of using it is illustrated in section 4.2.

3.4 Learning procedure of exTS

The learning procedure of exTS is composed of two phases:
- Phase A: an unsupervised data clustering technique is used to adjust the antecedent parameters,
- Phase B: the supervised Recursive least squares (RLS) learning method is used to update the consequent parameters.

a) Clustering phase: partitioning data space

The exTS clustering phase processes on the global input-output data space: $z = [x^T, y^T]^T$; $z \in R^{n+m}$, $n+m$ 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 TS model is based on the calculus of a "potential" (see after) which is the capability of a data to form a cluster (antecedent of a rule).
The clustering procedure starts from scratch assuming that the first data point available is a center of a cluster: the coordinates of the first cluster center are those of the first data point $(z_1^* \leftarrow z_1)$. The potential of the first data point is set to the ideal value: $P_1(z_1) \rightarrow 1$. Four steps are then performed for each new data gathered in real-time.

Step 1. Starting from $k = 2$, the potential P_k of the data point z_k is recursively calculated at time k:

$$P_k(z_k) = \frac{k-1}{k-1+\sum_{n+m}^{j=1}\sum_{k-1}^{i=1}\|z_i - z_k\|_2^j} \tag{9}$$

Step 2. The potential of the cluster/rule centers is recursively updated:

$$P_k(z^*) = \frac{(k-1)P_{k-1}(z^*)}{k-2+P_k(z^*)+P_k(z^*)\sum_{j=1}^{n+m}\|z^* - z_{k-1}\|_j^2} \tag{10}$$

Step 3. The potential of the data point (step 1) is compared to boundaries issued from the potential of the cluster centers (step 2):

$$\left(\underline{P} \leq P_k(z_k) \leq \overline{P}\right) \tag{11}$$

where $(\overline{P} = max_{i=1}^N \{P_i(z^*)\})$ is the highest density/potential, $(\underline{P} = min_{i=1}^N \{P_i(z^*)\})$ is the lowest density/potential and N is number of centers clusters $(x^{i*}, i = [1, N])$ formed at time k.

Step 4. If, the new data point has a potential in between the boundaries (11) any modification of the rules is necessary. Else, they are two possibilities:

1. if the new data point is closed to an old center $(min_i^N \left\|x_k - x^{*i}\right\|_j < \frac{\sigma_j^i}{2})$, then the new data point (z_k) replaces this center $(z_j^* := z_k)$,
2. else, the new data point is added as a new center and a new rule is formed $(N = N+1; x_N^*)$.

Note that, the exTS learning algorithm presents an adaptive calculation of the radius of the clusters (σ_j^i). See (Angelov and Zhou 2006) for more details.

b) RLS phase: update of the consequent parameters

The exTS model is used for on-line prediction. In this case, equation (8) can be expressed as follows:

$$\hat{y}_{k+1} = \sum_{i=1}^N \lambda_i y_i = \sum_{i=1}^N \lambda_i x_e^T \pi_i = \psi_k^T \hat{\theta}_k \tag{12}$$

$\psi_k = [\lambda_1 x_e^T, \lambda_2 x_e^T, \ldots, \lambda_n x_e^T]_k^T$ is a vector of the inputs, weighted by normalized firing (λ) of the rules, $\hat{\theta}_k = [\pi_1^T, \pi_2^T, \ldots, \pi_N^T]_k^T$ are parameters of the sub-models.

The following RLS procedure is applied:

$$\hat{\theta}_k = \hat{\theta}_{k-1} + C_k \psi_k (y_k - \psi_k^T \hat{\theta}_{k-1});\ k = 2, 3, \ldots \tag{13}$$

$$C_k = C_{k-1} - \frac{C_{k-1}\psi_k \psi_k^T C_{k-1}}{1+\psi_k^T C_{k-1}\psi_k} \tag{14}$$

with initial conditions

$$\hat{\theta}_1 = [\hat{\pi}_1^T, \hat{\pi}_2^T, \ldots, \hat{\pi}_N^T] = 0,\ C_1 = \Omega I \tag{15}$$

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 COMPARATIVE STUDY OF ANFIS AND exTS

4.1 exTS versus ANFIS

To illustrate the performances of exTS, this model is compared to the ANFIS model (Adaptive Neuro-Fuzzy Inference System) proposed by (Jang and Sun 1995) that emerges from literature: ANFIS shown improved performance over conventional method and Wang demonstrates that it is a robust machine health condition predictor (Wang et al. 2004).

The whole learning algorithm of ANFIS can not be fully presented here (see referenced authors for more explanation). In a few words, ANFIS uses an hybrid algorithm which is the combination of the gradient descent (that enables the updating of the antecedent parameters) and of the least squares estimate (that optimizes the consequent parameters).
A specificity of ANFIS can be pointed out: ANFIS is fully connected which implies that if M membership functions are assigned to each one of the n inputs variables, then the ANFIS is composed of $N = M^n$ rules (see Fig. 4 for an example). As a consequence, many parameters must be updated but, when well trained, ANFIS may perform good predictions.

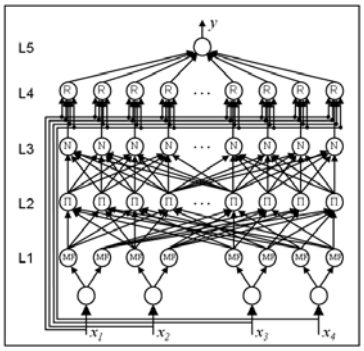

Figure 4: Architecture of an ANFIS with 4 inputs

4.2 Experimental data sets

Two real experimental data sets have been used to test the prediction performances of ANFIS and exTS. In both cases, the aim of these predictions is to approximate a physical phenomenon by learning data gathered from the system. That can be assimilated to the prediction step of the prognostic process.

Industrial dryer data set. The first data set is issued from an industrial dryer. It has been contributed by Jan Maciejowski[1] from Cambridge University. This data set contains 876 samples. Three variables (fuel flow rate, hot gas exhaust fan speed, rate of flow of raw material) are linked with an output one (dry bulb temperature).
For simulations, both ANFIS and exTS have been used with five inputs variables. Predictions were made at different horizons h. Assuming that t denotes the current time, the TS models were build as follows:
- input 1: $x_1(t)$ - fuel flow rate,
- input 2: $x_2(t)$ - hot gas exhaust fan speed,
- input 3: $x_3(t)$ - rate of flow of raw material,
- input 4: $x_4(t)$ - dry bulb temperature,
- input 5: $x_5(t-1)$ - dry bulb temperature,
- output 1: $\hat{y}(t+h)$ - predicted dry bulb temperature.

Air temperature in a mechanical system. The second data set is issued from an hair dryer. It has been contributed by W. Favoreel[2] from the KULeuven University. This data set contains 1000 samples. The air temperature of the dryer is linked to the voltage of the heating device.
For simulations, both ANFIS and exTS have been used with five inputs variables. Predictions concern the air temperature, and the TS models were build as follows:
- input 1 to 4: air temperature at times $(t-3)$ to (t),
- input 5: $x_5(t)$ - voltage of the heating device,
- output 1: $\hat{y}(t+h)$ - predicted air temperature.

4.3 Simulations and results

In order to extract more solid conclusions from the comparison results, the same training and testing data sets were used to train and test both models. Predictions were made at $(t+1)$, $(t+5)$ and $(t+10)$ in order to measure the stability of results in time. The prediction performance was assessed by using the root mean square error criterion (RMSE) which is the most popular prediction error measure, and the Mean Absolute Scaled Error (MASE) that, according to (Hyndman and Koehler 2006), is the more adequate way of comparing prediction accuracies.
For both data sets, the learning phase was stopped after 500 samples and the reminding data served to test the models. Results are shown in table 1.

4.4 Discussion

a) Accuracy of predictions
According to the results of table 1, exTS performs better predictions than ANFIS model. Indeed, for the industrial dryer (data set 1), both RMSE and MASE are minors with exTS than with ANFIS. An illustration of it is given in Fig. 5.
However, in the case of the air temperature data set, exTS do not provide higher results than ANFIS (RMSE and MASE are quite the same). Moreover, as it is shown in Fig. 6, the error spreadings of both model are very similar. Yet, one can point out that exTS only needs 6 fuzzy rules to catch the behavior of the studied phenomenon (against 32 for the ANFIS

[1] ftp://ftp.esat.kuleuven.ac.be/sista/data/process_industry

[2] ftp://ftp.esat.kuleuven.ac.be/sista/data/mechanical

Industrial Dryer		ANFIS	exTS
$t+1$	Rules	32	18
	RMSE	0.12944	0.01569
	MASE	16.0558	2.16361
$t+5$	Rules	32	17
	RMSE	0.84404	0.05281
	MASE	114.524	7.38258
$t+10$	Rules	32	17
	RMSE	1.8850	0.18669
	MASE	260.140	27.2177
Air temperature		ANFIS	exTS
$t+1$	Rules	32	4
	RMSE	0.01560	0.01560
	MASE	0.4650	0.47768
$t+5$	Rules	32	6
	RMSE	0.13312	0.12816
	MASE	2.01818	1.97647
$t+10$	Rules	32	6
	RMSE	0.23355	0.22997
	MASE	3.66431	3.66373

Table 1: Simulation results

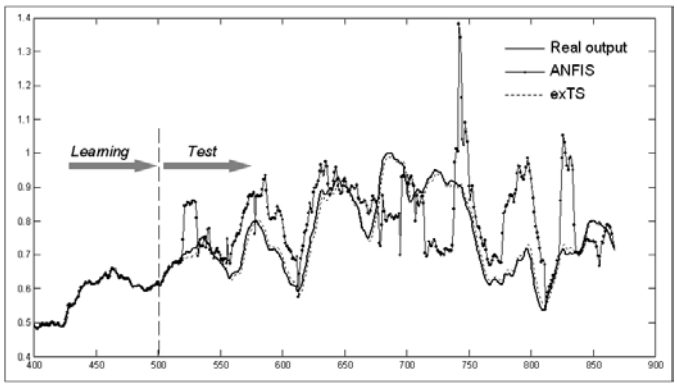

Figure 5: Predictions - Industrial Dryer, $t+1$

model). This lead us to consider the complexity of the structure of both prediction systems.

b) Complexity of the prediction systems

Let take the example of the last line of table 1 to compare the structures of the ANFIS and exTS models. The number of parameters for both systems is detailed in table 2.

As there are 5 inputs for the Air Temperature application (see 4.2), and assuming Gaussian membership functions for the antecedent fuzzy sets, the ANFIS model is composed of 212 parameters. Following that, with a more complex application than that of the benchmark studied in the paper, an ANFIS system can be quickly limited by the number of inputs (because the numbers of parameters to be updated increases). In addition, classically, one says that the number of learning samples for the ANFIS model must be more than five times the numbers of parameters, which can be critical for industrial

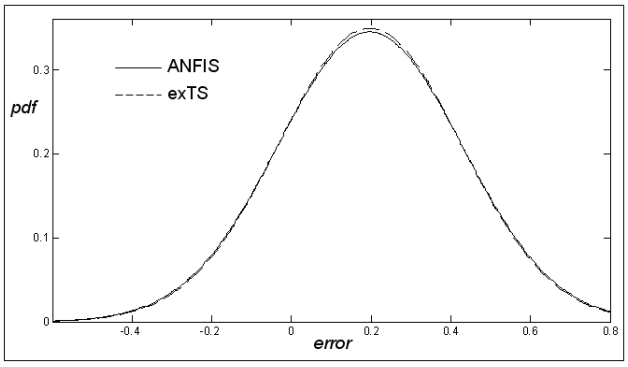

Figure 6: Pdf error - Air temperature, $t+10$

practitioners.

In opposition, exTS evolves only if there are significant modifications on the input-output variables as it has an on-line learning process: exTS start from scratch with a single rule and modifications or additions of rules are made only if relevant. As a consequence, for the same prediction purpose, an exTS system can have the same prediction accuracy that an ANFIS model but with less rules (6 vs 32 in the case considered in table 2). This complexity reduction of the prediction system can also be pointed out by considering the total number of parameters (96 vs 212).

c) Computation efficiency

Finally, although it can not be fully developed in the paper, exTS is much more computationally effective than the ANFIS system. This can be explained from two complementary point of views. Firstly, as stated before, an exTS system can perform predictions with a slightly structure that the ANFIS, which implies that fewer parameters have to be updated. Secondly, when using an exTS system, all learning algorithms are recursive ones which allows the on-line use of the system and ensure the rapidity of treatments.

Structural properties for the Air Temperature benchmark at $t+10$		
Criteria	ANFIS	exTS
nb inputs	5	5
nb rules	32	6
type of mf	Gaussian	Gaussian
antecedent parameters		
mf/input	2	= nb rules = 6
tot. nb of mf	2×5	6×6
parameters/mf	2	2
ant. parameters	$2\times2\times5=20$	$2\times6\times5=60$
consequent parameters		
parameters/rule	6 (5 inputs + 1)	6
cons. parameters	$6\times32=192$	$6\times6=36$
parameters	**20+192=212**	**60+36=96**

Table 2: Complexity of the prediction systems

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. Following that, prognostic can also be seen as a process that allows the reliability modeling. In this context, the purpose of the work reported in this paper is to point out an accurate prediction technique to perform the approximation and prediction of the degradation of an equipment.

According to real implementation restrictions, neuro-fuzzy systems appear to be well suited for practical problems where it is easier to gather data (online) than to formalize the behavior of the system being studied. More precisely, the paper point out the accuracy of the exTS model in prediction. The exTS model has a high level of adaptation to the environment and to the changing data. It is thereby an efficient tool for complex modeling and prediction. Moreover, any assumption on the structure of exTS is necessary, which is an interesting characteristic for practical problems in industry. The exTS is finally a promising tool for reliability modeling in prognostic applications.

Developments are at present extended in order to characterize the error of prediction at any time and thereby provide confidence interval to practitioners. The way of ensuring a confidence level is also studied. This work is led with the objective of being integrated to an e-maintenance platform at a French industrial partner (em@systec).

REFERENCES

Angelov, P. and D. Filev (2003). On-line design of takagi-sugeno models. *Springer-Verlag Berlin Heidelberg: IFSA*, 576–584.

Angelov, P. and D. Filev (2004). An approach to online identification of takagi-sugeno fuzzy models. *IEEE Trans. on Syst. Man ad Cybern. - Part B: Cybernetics 34*, 484–498.

Angelov, P. and X. Zhou (2006). Evolving fuzzy systems from data streams in real-time. In *Proceedings of the Int. Symposium on Evolving Fuzzy Systems, UK*, pp. 26–32. IEEE Press.

Byington, C., M. Roemer, G. Kacprzynski, and T. Galie (2002). Prognostic enhancements to diagnostic systems for improved condition-based maintenance. In *2002 IEEE Aerospace Conference, Big Sky, USA*.

Chinnam, R. and B. Pundarikaksha (2004). A neuro-fuzzy approach for estimating mean residual life in condtition-based maintenace systems. *Int. J. materials and Product Technology 20:1-3*, 166–179.

Ciarapica, F. and G. Giacchetta (2006). Managing the condition-based maintenance of a combined-cycle power plant: an approach using soft computing techniques. *Journal of Loss Prevention in the Process Industries 19*, 316–325.

Espinosa, J., J. Vandewalle, and V. Wertz (2004). *Fuzzy Logic, Identification and Predictive Control (Advances in Industrial Control)*. N.Y., Springer-Verlag.

Goebel, K. and P. Bonissone (2005). Prognostic information fusion for constant load systems. In *Proceedings of 7th annual Conference on Fusion*, Volume 2, pp. 1247–1255.

Hyndman, R. and A. Koehler (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting 22-4*, 679–688.

ISO 13381-1 (2004). *Condition monitoring and diagnostics of machines - prognostics - Part1: General guidelines*. Int. Standard, ISO.

Iung, B., G. Morel, and J.B. Léger (2003). Proactive maintenance strategy for harbour crane operation improuvement. *Robotica 21*, 313–324.

Jang, J. and C. Sun (1995). Neuro-fuzzy modeling and control. In *IEEE Proc.*, Volume 83, pp. 378–406.

Jardine, A., D. Lin, and D. Banjevic (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mech. Syst. and Sign. Proc. 20*, 1483–1510.

Kasabov, N. and Q. Song (2002). Denfis: Dynamic evolvinf neural-fuzzy inference system and its application for time-series prediction. *IEEE Transaction on Fuzzy Systems 10-2*, 144–154.

Muller, A., M.C. Suhner, and B. Iung (2008). Formalisation of a new prognosis model for supporting proactive maintenance implementation on industrial sytem. *Reliability Engineering and System Safety 93*, 234–253.

Vachtsevanos, G., F.L. Lewis, M. Roemer, A. Hess, and B. Wu (2006). *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*. New Jersey, Hoboken: Wiley & Sons.

Wang, P. and D. Coit (2004). Reliability prediction based on degradation modeling for systems with multiple degradation measures. In *Proc. of Reliab. and Maintain. Ann. Symp. - RAMS*, pp. 302–307.

Wang, W., M.F. Goldnaraghi, and F. Ismail (2004). Prognosis of machine health condition using neuro-fuzzy systems. *Mech. Syst. and Sig. Process. 18*, 813–831.

Zhang, G., B.E. Patuwo, and M.Y. Hu (1998). Forecasting with artificial neural networks: the state of the art. *Int. Journal of Forecasting 14*, 35–62.