Features Selection Procedure for Prognostics: An Approach Based on Predictability

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Abstract: Prognostic aims at estimating the remaining useful life (RUL) of a degrading equipment, i.e at predicting the life time at which a component or a system will be unable to perform a desired function. This task is achieved through essential steps of data acquisition, feature extraction and selection, and prognostic modeling. This paper emphasizes on the selection phase and aims at showing that it should be performed according to the predictability of features: as there is no interest in retaining features that are hard to be predicted. Thereby, predictability is defined and a feature selection procedure based on this concept is proposed. The effectiveness of the approach is judged by applying it on a real-world case: through comparison is made in order to show that the better predictable features lead to better RUL estimation.

Keywords: PHM, data-driven prognostics, predictability, connexionist systems.

1. INTRODUCTION

In order to avoid high costs while increasing safety and availability of equipments, researchers and industrials show a keen interest in concepts of condition based maintenance (CBM). More precisely, "prognostic" becomes a major area of focus nowadays. The core process of prognostic is to estimate the remaining useful life (RUL) of a system before a failure occurs (ISO13381-1 (2004); Jardine et al. (2006)). It is thereby a promising activity that benefits in form of planning, safety, availability and maintenance cost reduction (Brotherton et al. (2000)). However, real prognostic systems are scarce in industry. Indeed, there is still a vacuum that is yet to be filled: nobody is able to *a priori* ensure that an accurate prognostic model can be built (according to a specific problem). In other words, the applicability of a prognostic approach is still an open area, mainly because of the predictability of future. This is a central point of this paper.

Three main categories of prognostic approaches are generally distinguished: experience-based, model-based, and data-driven approaches (Byington et al. (2002); Heng et al. (2009); Vachtsevanos et al. (2006)). Briefly, experience-based approaches are used in statistical reliability applications to predict failure probability at any time. Model-based methods suppose that the degradation process can be formalized in a mathematical form. Data-driven approaches aim at transforming raw *in situ* data into appropriate information by performing a non-linear modeling of real systems. These approaches are notably suitable when physics of failure is hard to be modeled, or in absence of prior knowledge or human experts. Therefore, they are increasingly applied to machine prognostics.

As for data-driven approaches, the underlying assumption is that the degradation process can be reflected by features that are extracted from sensor signal. These features are considered as being the main source of information to represent the current health state of a component/system. Following that, the RUL can be estimated by forecasting in time a set of features that have been selected. However, a critical problem can be addressed: there is no way to ensure that the most relevant features (the ones that contain the main information among all features) are those that will be best predicted. This is the issue of the paper: in order to directly go through a suitable prognostic model, the feature selection phase should consider the features that are better predictable and can contribute to prognostic modeling. An additional problem appears: predictability should be clearly defined and assessed according, firstly to the prediction model one aims to use, and secondly, to the horizon of prediction that is required. Assuming that, an extension to existing data-driven procedure is proposed in this paper. The main purpose of this method is to reconsider the learning phase of data-driven approaches by considering both steps "feature selection" and "prognostic modeling" as complementary and closely related.

The paper is organized in three main parts. First, classical data-driven prognostics procedure is replaced within CBM concept and predictability problem is pointed out. This concept is thereby defined according to existing works. Following that, a novel features selection procedure based on predictability is proposed in section 3. Also, assuming that predictability relies on the capability of forecasting tools, two connexionist systems are introduced as a set of "potential model" to perform multi-step ahead predictions. Lastly, in section 4, the whole procedure is applied and discussed on a real-world prognostics problem related to the health of a degrading engine.

2. PROGNOSTIC AND PREDICTABILITY

2.1 Prognostic within CBM architecture

Prognostic can not be seen as a single task: the whole aspects of failure analysis and prediction must be viewed as a set of activities that are necessary to be performed. This aspect is highlighted within the Condition-Based Maintenance (CBM) concept. According to CBM practitioners, various activities, ranging from data collection through the recommendation of specific maintenance actions, must be carried out to perform predictive maintenance (and thereby improve maintenance's performances). Generally, a CBM system is seen as the integration of seven layers, one of them being that of "prognostic" (see Fig. 1 for a distributed CBM architecture).

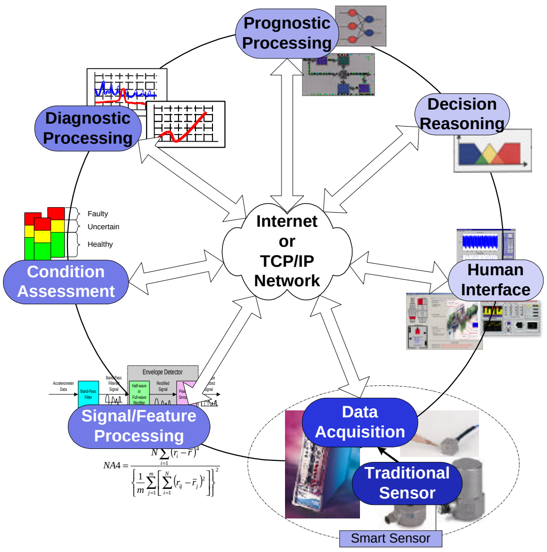

Fig. 1. Architecture of CBM (Lebold and Thurston (2001))

When focusing on the prognostic process, one can underline a flow that goes from multidimensional data through the remaining useful life of a system. This procedure consists of three main phases (Fig. 2). Data are first acquired from sensor sources, and are then pre-processed before feeding a prognostic model. The pre-processing step is composed of a features extraction module based on signal processing techniques, and of a features selection module that relies on data mining approaches. The prognostic phase is also composed of two complementary modules. A prediction engine forecasts observations in time. These predictions are then analyzed by a classifier which provides the most probable state of the system. The RUL is finally deduced thanks to the estimated time to reach the failure mode. Obviously, prediction phase is critical and must be dealt in an appropriate manner in order to provide accurate predictions and thereby, to achieve better RUL estimation.

2.2 Predictability concept

Predictability is not a well defined concept. In general, predictability attributes to the capability in making predictions of future occurrence on the basis of past information. It should depict a goodness of predictions, so that

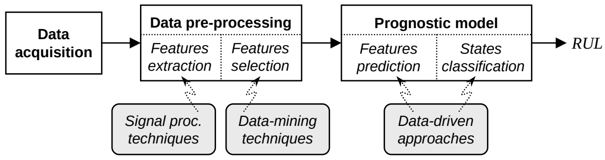

Fig. 2. Prognostics process flow

undesirable events can be avoided by making accurate forecasts in a timely manner. Predictions can be incorrect; therefore, it is important to understand their quality in a framework that is dependent on the considered time series. In addition, predictability can be affected by different factors that vary from event to event and make modeling process more complicated (Wang et al. (2008)).

Accurate time series models. Predictability states for the degree of correctness in forecasting or shows the usefulness of a forecasting method (Abbas and Arif (2006)). In this context, it must be considered that up to what extent accurate predictions of a given time series can be provided by an applied modeling approach. Therefore, metrics are required in order to show significance of accurate prediction modeling. Remarkably, there are few works that focus on the predictability aspect by considering modeling accuracy. Wang et al. used seasonally adjusted coefficient of efficiency to evaluate predictability of univariate stream flow process (Wang et al. (2008)). However, in this study need of a suitable forecasting approach as well as model performance measure is highlighted for a particular domain. (Kaboudan (1999)) presented a quantitative metric to measure time series predictability using genetic programming. (Duan (2002)) provided an improvement of those developments. (Teodorescu and Fira (2008)) defined metrics to determine suitable predictors for genomic sequence: quantitative metrics that depict the ability of time series to be predicted by a particular approach. However, they were useful for single step-ahead forecasting methods.

Accuracy over horizon. Accuracy of prediction is greatly affected by horizon of prediction. A time series can be well predicted over a short horizon but difficult to be predicted for a long term horizon. As error grows with increasing horizon, consequently prediction accuracy is reduced, and this denotes low predictability of a time series. In accordance to that, (Diebold and Kilian (2001)) proposed a general measure of predictability to measure relative accuracy over different horizons for macroeconomic application. (Abbas and Arif (2006)) presented new metrics for predictability that were applied to multi-step ahead predictions of surrogated time series. However, no consensual point of view appears in existing contributions.

Defining predictability. As a synthesis, either considering correctness or horizon of prediction, literature points out that predictability is closely related to accuracy of predictions that are judged against certain error tolerance. In others words, assessing a prognostic model requires the user to be able to define the limit of prediction he would like to obtain, as well as the performance of prediction that follows from that. This all enables us to explicitly state that predictability is closely related not only to the type of prognostic model one mean to use, but also to the horizon of prediction that is judged as useful (short-

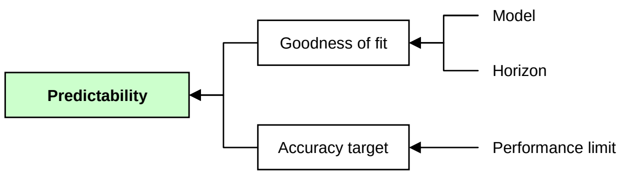

Fig. 3. Compounds of predictability concept

term, mid-term, long-term). Also it depends on a limit of accuracy one means to reach (Fig. 3).

Finally, we define predictability as:

- the ability of a given time series TS to be predicted with an appropriate modeling tool M that facilitates future outcomes over a specific horizon H and with a desired performance limit L.

Formally, we propose to formulate it as:

$$Pred\left(TS/M, H, L\right) = exp^{-\left| ln\left(\frac{1}{2}\right) . \frac{MFE^{H}_{TS/M}}{L} \right|} \quad (1)$$

where, H states for the horizon of prediction, L is the limit of accuracy that is fixed, and MFE is the mean forecast error in between the actual values of TS and the predicted ones (thanks to M):

$$MFE^{H}_{TS/M} = \frac{1}{H} . \sum_{i=1}^{H} e_{i} = \frac{1}{H} . \sum_{i=1}^{H} \left(M^{i} - TS^{i}\right) \quad (2)$$

Perfect value for MFE is 0. $MFE > 0$ indicates under forecast and $MFE < 0$ over forecast. Predictability has an exponential form (Fig. 4) and is as higher (maximum=1) as the MFE is lower. A TS can be considered as predictable if its predictability coefficient is in between 0.5 and 1, i.e., if the MFE is in between 0 and the limit value L chosen by the user.

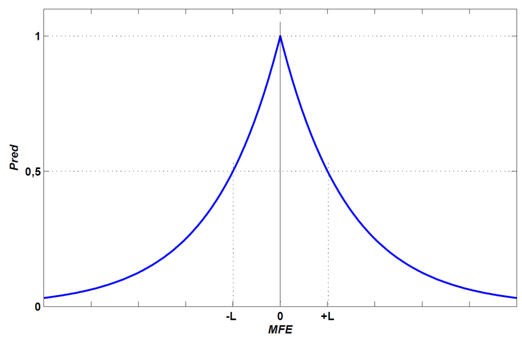

Fig. 4. Illustration of predictability measure

3. PREDICTABILITY DRIVEN PROGNOSTICS

3.1 Selection procedure based on predictability

As stated before, (and illustrated in Fig. 2) the prognostic model uses a set of selected features to provide an estimation of the RUL. The learning phase of the model has to be reiterated until suitable prognostic performances are obtained ("try and error approach"). However, this can be a waste of time, because some features can be very hard (even impossible) to be predicted, i.e., since there is no certainty that an accurate prognostic model can be provided. In other words, there is no interest in retaining features that cannot be forecasted in time. Therefore, learning phase of a prognostic model should be extended to the selection of features: not only the user aims to build the model for prognostic, but he also has to define the appropriate set of features that can be more accurately predicted over different horizons. Following that, the "features selection" phase should be performed while building the prognostic model. On this basis, features set obtained from classical data-mining techniques can be further reduced to final set of predictable features in accordance to learned prediction models. Consider Fig. 5 as for an illustration of such a methodology. The depicted procedure aims first at defining which features are predictable (according to a model and a horizon of prediction). This enables either to retain or reject each potential couple of "feature-model" to be used for prognostics.

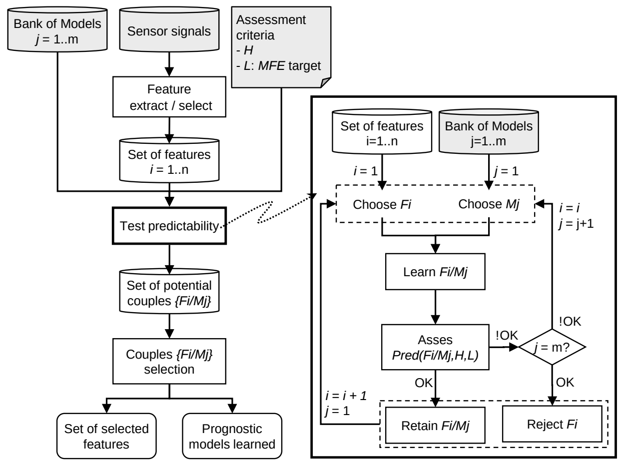

Fig. 5. Selection procedure based on predictability

3.2 Long term predictions with connexionist systems

The aforementioned procedure assumes that various forecasting models are available. Let introduce two connexionist systems as for multi-steps ahead prediction tools.

Choice of an ANN and a NFS. Among different prognostics approaches, data-driven methods have great potential due to their ability to learn from examples and to model non-linear phenomena. Also, input-output data set is main source of information to develop better understanding of systems current health state (Huang et al. (2007)). Therefore, machine-learning methods are of great interest for prognostics. Within these techniques, adaptive networks like artificial neural networks (ANN) and neuro-fuzzy systems (NFS) are increasingly used for prediction problems (Chinnam and Baruah (2004); Gomes de Freitas et al. (1996); Wang (2007)). These connexionist systems are capable to capture complex relationship among inputs and outputs and have good approximation capability for non-linear modeling of real systems. Also, they have shown good performances in prognostic applications (El-Koujok et al. (2008); Wang and Vachtsevanos (2001); Wang et al. (2004); Yam et al. (2001)).
As for illustration purpose, let consider a feedforward ANN

and a first-order NFS in this paper. The ANN is assumed to be tuned (learning phase) thanks to Levenberg-Marquardt algorithm that is considered to be faster and more effective as compared to other techniques (Hagan and Menhaj (1994)). The adaptive neuro-fuzzy inference system (ANFIS) proposed by (Jang and Sun (1995)) is also considered to be a potential approach for forecasting in maintenance applications (El-Koujok et al. (2008)). Besides this, each approach has its own benefits as well as limitations, which are not deeply presented here, but interested reader can refer to (Hagan et al. (1996); Li and Cheng (2007)) for more theoretical details.

General formalization. Connexionist systems like artificial neural networks or neuro-fuzzy systems aim at approximating an input-output function. This kind of systems must be tuned to fit to the studied problem thanks to a learning phase of parameters. Let $[X]$ be the input data set, $[Y]$ the output data set. With these notations, the approximation function can finally be formalized as:

$$[\hat{Y}] = f([X], [\theta]) \tag{3}$$

where $[\hat{Y}]$ states for the estimated output set $[Y]$, and $[\theta]$ for the set of parameters that have to be tuned during the learning phase.
In a similar manner, let now formalize the problem of connexionist-based multi-steps ahead prediction of an univariate time series (like a feature for prognostic). A univariate time series TS_t is a chronological sequence of values describing a physical observation made at equidistant intervals: $TS_t = \{x_1, x_2, \ldots, x_t\}$ (where t states for the temporal index variable). With these notations, the multi-steps ahead prediction problem consists in estimating a set of future values of the time series: $[\hat{X}_{t+1\to t+H}] = [\hat{x}_{t+1} , \hat{x}_{t+2} , \hat{x}_{t+3} , \ldots , \hat{x}_{t+H}]$ where H states for the final prediction horizon. According to eq. 3, this approximation can be expressed as:

$$[\hat{X}_{t+1\to t+H}] = msp([X_t]) \tag{4}$$

where, "*msp*" states for "multi-steps ahead prediction", and $[X_t] \in TS_t$ is know as the set of regressors used (for example $[X_t] = [x_t , x_{t-1} , x_{t-2}]$).

Multi-steps predictions with an iterative approach. The multi-steps ahead prediction model "*msp*" can be obtained in different manners and by using different connexionist tools (structure + learning algorithm). (Gauvain et al. (2011)) dress an overview of those approaches. According to this work, the iterative approach is the most common one. Multi-step predictions are provided by using a single tool (an ANN or a NFS) that is tuned to perform a one-step ahead prediction $\hat{x}_{t+1}$. This estimated value is used as one of the regressors of the model to estimate the following ones and the operation is repeated until the estimation of $\hat{x}_{t+H}$. The procedure is illustrated in Fig 6. Formally:

$$\hat{x}_{t+h} = \begin{cases} \text{if } h = 1, f^1\left(x_t, \ldots, x_{t+1-p}, [\theta^1]\right) \\ \text{elseif } h \in \{2, \ldots, p\}, \\ f^1\left(\hat{x}_{t+h-1}, \ldots, \hat{x}_{t+1}, x_t, \ldots, x_{t+h-p}, [\theta^1]\right) \\ \text{elseif } h \in \{p+1, \ldots, H\}, \\ f^1\left(\hat{x}_{t+h-1}, \ldots, \hat{x}_{t+h-p}, [\theta^1]\right) \end{cases} \tag{5}$$

where $\{f^1, [\theta^1]\}$ states for the one-step ahead prediction model (ANN or NFS) with its parameters set calculated during the learning phase, p the number of regressors used, i.e. the number of past discrete values used for prediction. Note that from the time $h > p$, predictions are made only on evaluated data and not on observed data. This

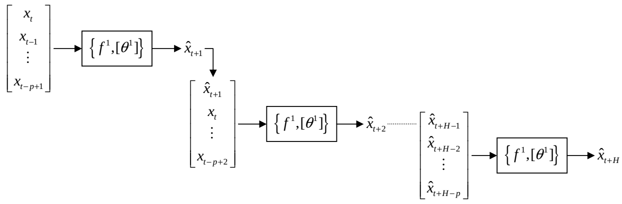

Fig. 6. Iterative model for multi-steps predictions

multi-steps prediction technique has been used to forecast features on time in order to illustrate the procedure of feature selection based on predictability concept.

4. EXPERIMENTS AND DISCUSSION

4.1 Data sets and simulation settings

Data sets. The proposed developments are applied on the challenge data set of diagnostics and prognostics of machine faults from first international conference of prognostics and health management (Saxena et al. (2008)). This data set consists of multivariate time series signals (26 features) from different degrading instances and contaminated with measurement noise. Each set of time series comes from a different engine of a same fleet. Each engine starts from different initial conditions and manufacturing conditions are not known to the user. Each engine begins from a normal state but, due to some fault occurrence, starts to degrade. Thus the fault magnitude increases with time until failure state takes place.

Simulations settings. From the dataset, among 26 available features, 8 were pre-selected in a previous work thanks to information theory and Choquet Integral (Ramasso and Gouriveau (2010)). These 8 features (F1 to F8) are used as a starting point to illustrate the proposed approach of "predictability-based" feature selection (section 3.1).
Experiments are performed by using an ANN and a NFS as potential tools for feature predictions. Each tool is tuned according to parameters shown in table 1. The training of each model is met by data sets of 40 multivariate time series, whereas 5 multivariate time series data are used to perform tests. Multi-step ahead predictions are performed from time $t = 50$ till the end of degradation, using iterative approach (section 3.2.3).

Table 1. Prediction models - Settings

ANN-Parameters	**Settings**
In. / Hidden / Out. layer neurons	3 / 5 / 1
Hidden / Output layer Act. ftn.	sigmoidal / linear
Training Algorithm	Levenberg-Marquardt
ANFIS-Parameters	**Settings**
Input / Output layer neurons	3 / 1
Number / type of input memb. ftn	3 / Pi-shaped
Rules / FIS	27 / First order Sugeno
Defuzzification method	Weighted Average
Training Algorithm	Hybrid Method

Prediction results obtained from each case are thoroughly tested on predictability criteria to retain or reject each couple of potential "feature-model" to be used for prognostics. In order to validate our proposed methodology, for each test, RUL is estimated with all features and with selected ones. This task was performed through classification step by considering Fuzzy-Cmeans clustering algorithm (Bezdek (1981)). However, details of classification step are not presented here. Following that, all the obtained RUL estimates are compared throughly.

4.2 Results and discussion

Predictability results. As stated before, in order to exclude unpredictable features, predictability analysis is performed on each test case of multivariate time series. For illustration, simulation results from a single test are reported in table 2 over different horizon indexes for better understanding.

Table 2. Predictability results on a single test

	Approach	H=t+50	H=t+120	H=t+134
F1	ANFIS	0,934	0,606	0,504
	ANN	0,770	0,762	0,6173
F2	ANFIS	0,005	0,0002	4,8e-05
	ANN	0,017	9,0e-06	4,6e-07
F3	ANFIS	0,0025	0,0025	5,2e-05
	ANN	0,0023	2,6e-14	3,09e-17
F4	ANFIS	0,965	0,870	0,841
	ANN	0,982	0,876	0,840
F5	ANFIS	0,915	0,8925	0,925
	ANN	0,904	0,592	0,507
F6	ANFIS	0,943	0,9908	0,957
	ANN	0,947	0,995	0,963
F7	ANFIS	0,993	0,927	0,904
	ANN	0,966	0,907	0,888
F8	ANFIS	0,187	0,540	0,888
	ANN	0,970	0,637	0,360

The obtained results show that features F2, F3 do not satisfy predictability criteria neither by ANN nor by ANFIS, as it is clearly indicated by their lower values of predictability ($Pred < 0.5$). Similar findings about F2 and F3 are obtained from other test cases as well, by applying both connexionist tools.

Moreover, ANFIS shows better performance with higher predictability values as compared to ANN for most of the simulations. This phenomena is shown in Fig. 7, that depicts a global picture of features predictability over prediction horizon $t + 134$ steps ahead in accordance to tool of prediction.

Simulation also clearly show that predictability is highly dependent on the horizon of prediction and the results can vary from one prediction tool to another. As for an illustration, consider Fig. 8. The upper part of this figure depicts prediction results on feature F5 with both tools ANN and ANFIS. The lower part presents the corresponding predictability measures among the horizon of prediction. As expected, ANFIS shows better prediction and higher predictability as compared to ANN with changing horizon. In other words, predictability measure not only shows the significance of a tool but also gives confidence in making predictions over the increasing horizon. Thus, higher predictability values indicate greater confidence in predictions. Moreover, that strengthen the idea that the required horizon of prediction should be defined before building a prognostic model.

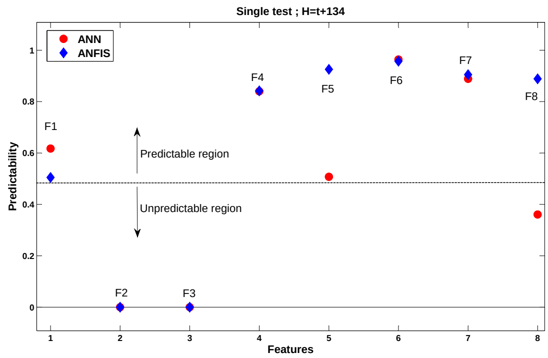

Fig. 7. Predictability of features ($H = t + 134$)

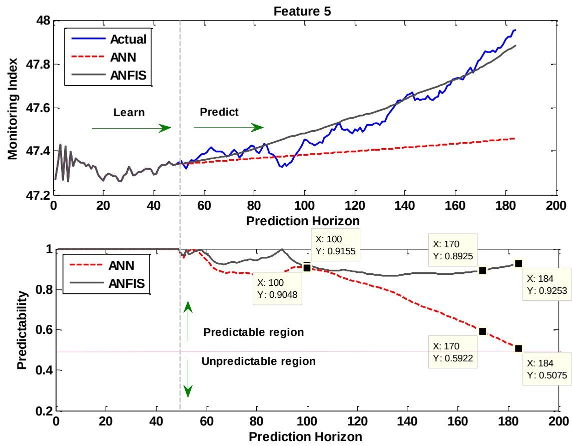

Fig. 8. Example of degrading feature prediction

Impact of predictability: Prognostics results. According to previous results, prognostics should be performed by using only predictable features, that leads to better RUL estimation i.e., with features {F1 ; F4 - F8}. Let validate this assumption by estimating the RUL for each multivariate time series test data set, by using, on one side, the whole set of pre-selected features {F1 - F8}, and on the other side, these final "predictability-based" selected features to make a comparison. As stated before (end of section 4.1), this part can not be fully described here, but RUL percentage errors obtained from simulations are summarized in table 3.

Table 3. RUL percentage error with ANFIS

Test	All features	Selected Features
1	7,096 %	0,636 %
2	11,83 %	1,898 %
3	24,34 %	1,265 %
4	15,95 %	0,6211 %
5	1,324 %	0,632 %
Mean % error	**12,10 %**	**1,01 %**

Above results arrangement show that for each test, percentage error of RUL by considering all features {F1 - F8} is much higher as compared to the case of selected features, i.e. excluding F2 and F3. As for a synthetic result, mean percentage error is divided by 12 when using the selected set of features. Also, results seem to be more stable among all tests when using the selected set of better predictable features. Finally, the features selection procedure based on predictability enhances significantly prognostics results.

5. CONCLUSION

The aim of this paper is to argue that the "selection" phase of prognostic should be performed accordingly to the predictability of features, since there is no interest in retaining features that cannot be forecasted in time. Discussion is based on the assumption that the "selection" and "prediction" phases both impact prognostic performances, and should thereby be considered simultaneously. Following that the concept of "predictability" is defined, and a novel features selection procedure based on this concept is proposed. In order to illustrate the developments, a multi-steps ahead prediction technique is presented and implemented on a real prognostic problem by using two type of connexionist systems for prediction purpose. Results show that "predictability" depends actually on the feature, but is also closely related to the type of prognostic model one means to use, and to the horizon of prediction that is judged as useful. Finally, developments are validated by performing RUL estimation via classification phase. Results show improvements by applying the proposed approach of "predictability-based" feature selection. However, for a large scale problems with high computational costs, different meta-heuristic techniques should be developed with regard to predictablity measuring criteria.

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