Improving data-driven prognostics by assessing predictability of features.

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ABSTRACT

Within condition based maintenance (CBM), the whole aspect of prognostics is composed of various tasks from multi-dimensional data to remaining useful life (RUL) of the equipment. Apart from data acquisition phase, data-driven prognostics is achieved in three main steps: features extraction and selection, features prediction, and health-state classification. The main aim of this paper is to propose a way of improving existing data-driven procedure by assessing the predictability of features when selecting them. The underlying idea is that prognostics should take into account the ability of a practitioner (or its models) to perform long term predictions. A predictability measure is thereby defined and applied to temporal predictions during the learning phase, in order to reduce the set of selected features. The proposed methodology is tested on a real data set of bearings to analyze the effectiveness of the scheme. For illustration purpose, an adaptive neuro-fuzzy inference system is used as a prediction model, and classification aspect is met by the well known Fuzzy C-means algorithm. Both enable to perform RUL estimation and results appear to be improved by applying the proposed strategy.

1. INTRODUCTION

Due to rapid growth in industrial standards, effective maintenance support systems are main area of focus nowadays. Different strategies have been adapted to assess machinery condition in real time and to avoid costly maintenance procedures. In this context, Condition Based Maintenance (CBM) strategy facilitates the competitive needs of industry by preventing costly maintenance activities, and thus, improving availability, reliability and security of machinery (Tobon-Mejia et al., 2011). In CBM, researchers show keen interest in less developed phase of prognostics that determines or predicts the remaining useful life (RUL) of a system (machinery) under certain operational conditions (Jardine et al., 2006). However, accurate prognostic systems are still scarce in the industry and need for an improvement is inevitable.

Prognostics can be categorized mainly into three approaches: experience based, model based and data driven methods (Heng & Zhang, 2009; Lebold & Thurston, 2001b; Ramasso & Gouriveau, 2010). Among these approaches data driven methods are considered to be a trade-off between experience based and model based approaches. They are increasingly applied to machine prognostics due to their effectiveness and ability to overcome limitations of latter categories (El-Koujok et al., 2008).

Mainly, the degradation process of a system (component) is reflected by features that are extracted from a sensor signal. These features are main source of information for prognostics model to estimate RUL. So, most importantly, in existing data-driven procedure of prognostics, critical phase of prediction should be met in appropriate manner for further classification and RUL estimation. However, from afore said procedure two issues can be pointed out. Firstly, there is no unique way to select most relevant features that are predictable and contribute for better RUL estimation. Secondly, the predictability should be assessed according to prediction model as well as horizon of prediction. This paper contributes to extend the existing approach by proposing a slight modification of features selection phase on the basis of predictability.

This paper is organized as follows. Section 2. discusses data-driven prognostics approach and points out the importance of the prediction accuracy. Following that, section 3. presents an improved framework for feature selection, based on the predictability assessment of features. Section 4. aims at defining the whole prognostics model that is employed in this paper. Both aspects of multi-steps ahead prediction and of health

state classification are considered. Section 5. deals with simulation and results discussion. Finally, section 6. concludes this research work.

2. DATA-DRIVEN PROGNOSTICS

2.1 Prognostics process flow

In maintenance field, prognostics considered as a key task within CBM that predicts RUL of machinery under certain operational modes and facilitates decision making. Thereby, the main objective of prognostics is to estimate RUL of system (component) before occurrence of failure state. Therefore, within CBM concept, the whole aspect prediction and failure can be viewed as set of certain activities that must be performed in order to accomplish predictive maintenance procedures (Lebold & Thurston, 2001a).
Mainly, data-driven methods alter raw (unprocessed) data into useful information and forecast global performance of the system. In order to deduce RUL, prognostic task is applied by performing forecasts in time and further analyzing them by classification module to approximate most probable states of the system (Fig. 1 and 2). More precisely, in a first stage, data acquisition from sensor sources is performed, and further preprocessed before feeding prediction model. The second stage of data-preprocessing is composed of two distinct phases i.e., feature extraction module, that is accomplished by signal processing techniques and feature selection module that depends on data mining approaches. Finally, in third stage of prognostics, prediction module forecasts observations in time, that are further analyzed by the classifier module to determine most probable states of the system. Lastly, RUL is derived by he estimated time to attain the failure state.

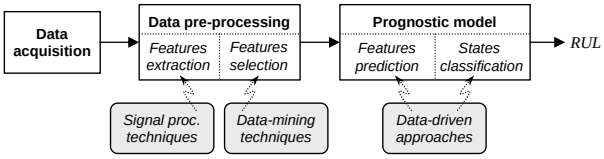

Figure 1. Prognostics process flow

2.2 Underlying predictability problem

From data-driven approaches, artificial intelligence (AI) based tools like artificial neural networks and neuro-fuzzy (NFs) have successfully been employed to perform non-linear modeling of prognostics (W.Q. Wang et al., 2004; Lebold & Thurston, 2001a). The standard of AI approaches is divided into two phases, i.e., learning phase and testing phase. As, monitored input/output data is the main source of information for prediction model, therefore, firstly the behavior is learned by monitored data and secondly, the test phase uses learned model to predict current and future states of degrading equipment.

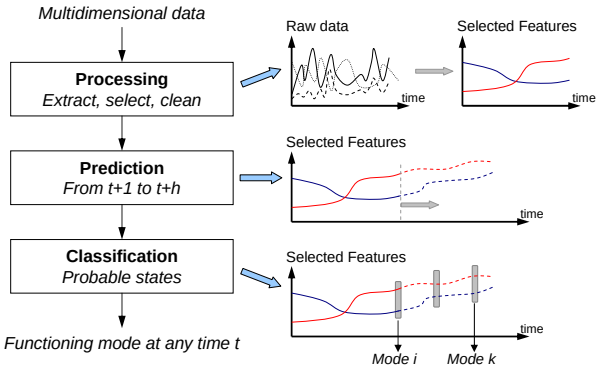

Figure 2. From data to RUL

In classical way prognostics model is learned by set of features that are acquired by sensor signal. Thereby, the model must be retrained upon these features, until significant performance level is achieved. This approach can be time expensive because some of the features can be very hard to be predicted. In other words, there is no use in retaining such features that are not predictable. So, the learning phase of prognostics modeling should consider the important steps of "feature selection" and "prediction modeling" in a simultaneous manner in order to retain or reject features on the basis of predictability. Thereby, this implies predictability to be defined (next section).

3. SELECTION OF PREDICTABLE FEATURES

3.1 Accuracy vs predictability

Predictability attributes to the significance in making predictions of future occurrence on the basis of past information. It is important to understand the prediction quality in a framework that is dependent on the considered time series predictability. As, predictability in terms of given time series is not a well defined terminology for real-world processes, few works focus on the predictability aspect (Kaboudan, 1999; W. Wang et al., 2008; Diebold & Kilian, 2001). Assuming that, in order to determine prediction quality, predictably can be measured on the basis of forecast error based approach. Various measures have been reported in literature to judge the quality of prediction or selecting a prediction model (Saxena et al., 2008, 2009, 2010; Monnet & Berger, 2010). See Eq. (1) for a set of potential metrics that can be used to assess predictability:

$$\begin{aligned} \text{MSE} &= \frac{1}{N} \times \sum_{i=1}^{N} \left(y^i_{pred} - y^i_{act} \right)^2 \\ \text{MAPE} &= \frac{100}{N} \times \sum_{i=1}^{N} \left| \left(y^i_{pred} - y^i_{act} \right) / y^i_{act} \right| \\ \text{RMSE} &= \sqrt{\text{MSE}} \\ \text{CVRMSE} &= \text{RMSE}/\mu_y \\ \text{MFE} &= \frac{1}{N} \times \sum_{i=1}^{N} \left(y^i_{pred} - y^i_{act} \right) \end{aligned} \quad (1)$$

From these measures MSE, MAPE and RMSE are most common accuracy measures for prediction, whereas CVRMSE and MFE can be employed to model selection. However, there is no general measure that can be explicitly employed to predictability factor of prognostics.
Generally, any type of signal will not be predicted with the same accuracy at different horizons of prediction. So, assuming that, the critical prediction phase in prognostics must be met accurately in order to provide efficient information. Therefore, predictability in prognostics not only is closely related to prediction model but also to the horizon of prediction that is judged as useful. On this basis, a new measure is proposed in this paper to assess predictability in prognostics.

3.2 Defining the predictability concept

Assessing the prognostics model requires the user to be able to define a suitable limit to prediction for the desired performance. According to author's knowledge, the predictability concept is not well described. So, it can be defined 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 desired performance limit L". Formally we propose it as:

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

where, Eq. (2) shows the emperical formulation in which $\text{MFE}_{TS/M,H}$ represents the mean forecast error Eq. (1), that measures average deviation of predicted values from actuals. The ideal value for this criteria is 0, if the value of $MFE > 0$ then prediction model tends to underforecast, else if the value of $MFE < 0$ then prediction model tends to overforecast. Moreover, the fixed limit of accuracy is denoted by L (chosen by the user). The exponential form of predictability can attain maximum value "1" as MFE is minimizes, and a given TS is considered predictable, if the coefficient of predictability ranges between [0.5, 1] (Fig. 3).

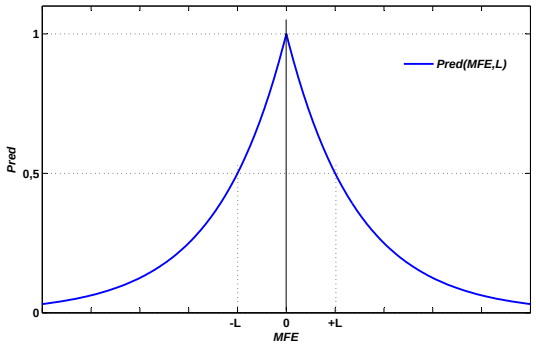

Figure 3. Illustration of predictability measure

4. Prognostics Modeling

4.1 Multi-steps ahead prediction

In prognostics, forecasting the global health state of a system is difficult task to achieve due to inherent uncertainity. However, from the category of data driven prognostics, AI based approaches like ANN and NFs can be quiet easily applied to such complex and non-linear environment.
Such connexionist systems have good capability to learn and adapt from environment and capture complex relationship among data. They are increasingly applied to prediction problems in maintenance field (Yam et al., 2001; Chinnam & Baruah, 2004; El-Koujok et al., 2011). They appear to be potential tools, in order to predict degrading behavior, and thus forecast the global state of the system.
Multi-step ahead (MSP) modeling can be achieved different ways by using connexionist tools. However, in this case, the most common MSP model can be achieved via iterative approach. MSPs are obtained using a single connexionist tool that is tuned for single-step ahead prediction $\hat{x}_{t+1}$. The predicted value is further utilized as one of the regressors of prediction model, and this process is followed in an iterative way until estimation $\hat{x}_{t+H}$, as shown in Fig. 4. Formally:

$$\hat{x}_{t+h} = \begin{cases} * \text{ if } h = 1, \\ \quad f^1\left(x_t, \ldots, x_{t+1-p}, [\theta^1]\right) \\ * \text{ elseif } h \in \{2, \ldots, p\}, \\ \quad f^1\left(\hat{x}_{t+h-1}, \ldots, \hat{x}_{t+1}, x_t, \ldots, x_{t+h-p}, [\theta^1]\right) \\ * \text{ elseif } h \in \{p+1, \ldots, H\}, \\ \quad f^1\left(\hat{x}_{t+h-1}, \ldots, \hat{x}_{t+h-p}, [\theta^1]\right) \end{cases} \quad (3)$$

where, t denotes temporal index variable, p is for number of regressors used and H states the horizon of prediction. Whereas, $\left\{f^1, [\theta^1]\right\}$ states for single-step ahead prediction model, with its parameter calculation performed during learning phase.
In this paper the Adaptive Neuro-Fuzzy Inference System (ANFIS) is used as a the one step-ahead prediction model. A detailed description of this tool can not be given in the paper. One can cite to (Jang, 1993; Li & Cheng, 2007) for theoretical background.

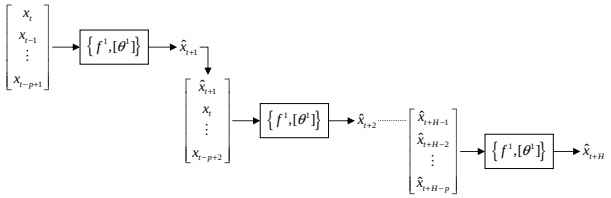

Figure 4. Multi-steps ahead predictions with iterative model

4.2 Classification step

The main aim of the classification phase is to determine most probable states of the degrading system, and thus providing a snapshot of time from projected degradations. In this phase, the temporal predictions made by the prediction module are analyzed by classifier module to determine most probable functioning modes of system (component). Most importantly, reliable and effective classification results better RUL estimation (Fig. 5). However in this case, due to the absence of ground-truth information the classification phase is met by well known Fuzzy C-Means (FCM) approach to illustrate our concept.

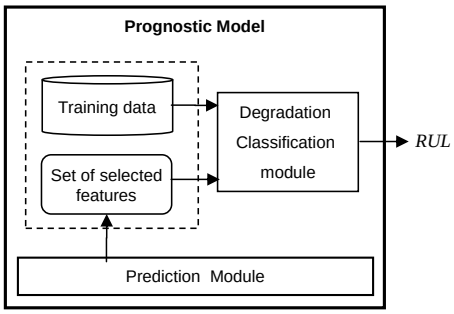

Figure 5. Classification Module

FCM is used as an unsupervised clustering approach that assigns temporal predictions to different classes based on fuzzy partitioning. In other words, a data point with a membership grade between [0, 1], can belong to various groups (Bezdek, 1981). Formally, the FCM clustering is attained by assigning membership to every data point that corresponds to each cluster center that is based on the measured distance between a data point and center of the cluster. Mainly, if a data point is closer to particular cluster center, therefore, a greater membership value is assigned. Moreover, the summation of membership grades from all data points correspond to a membership equal to '1'. Mainly, FCM aims to operate in an iterative manner to determine cluster centers that reduces following objective function:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{c} (u_{ij})^m . \| \mathrm{x}_i - \mathrm{v}_j \|^2 \qquad (4)$$

where, $\| \mathrm{x}_i - \mathrm{v}_j \|^2$ represents the euclidean distance between the i^{th} data point and the j^{th} cluster center, u_{ij} describes the membership of the i^{th} data point to the j^{th} centroid, and $m > 1$ is a weighting exponent.

5. Experiments and Discussion

5.1 Experimental setup

The proposed methodology for feature selection is illustrated by real data set of bearings form NASA data Repository. The data set consisted of multiple time series (variables) from different instances and contaminated with measurement noise (Fig. 6) i.e., representing history of fault degradation process. Moreover there is no information about the bearing condition and manufacturing variations. The simulation process is composed of three stages i.e., data-preprocessing, feature prediction and selection and health state classification to estimate RUL.

For experimental purpose, in the first stage only 8 variables (features F1-F8) are utilized from bearing data set, and filtered for noise removal.

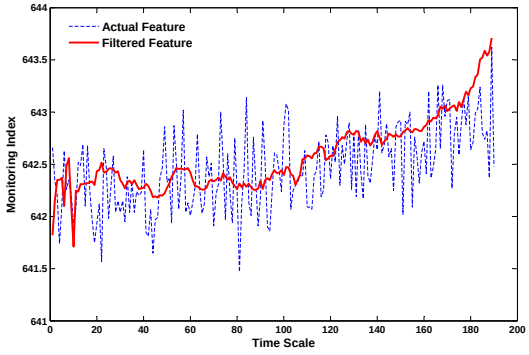

Figure 6. Filtered feature from bearing data set

The second phase corresponds to proposed feature selection methodology based on predictability. So, for illustration purpose ANFIS is used as potential connexionist tools to perform MSP. Each prediction model is tuned according to settings shown in Table 1. The training and testing data sets were composed of 40 bearings data each. However, to achieve MSP over different horizons, model training is met by a data set of 40 bearings, whereas, 5 test cases are employed for analysis purpose. All the predictions are analyzed by potential measures of accuracy (Eq. 1). In order to perform feature selection, proposed predictability measure is employed to validate our concept (Eq. 2).

ANFIS-Parameters	Settings
Input / Output layer neurons	3 / 1
Number of input membership functions	3
Type of input membership functions	Pi-shaped
Number of rules	27
Fuzzy Inference System	First order Sugeno
Defuzzification method	Weighted Average
Output Membership function	Linear
Learning Algorithm	Hybrid Method
Number of epochs	100
Training performance	MSE

Table 1. ANFIS model settings

Finally, classification phase partitions the temporal predictions into four modes of degradation, i.e., each mode repre-

sents fault progression toward end of life.
To show the concept of predictability for better classification and RUL estimation, simulations are performed on all features (F1-F8) and also with selected features that are predictable (excluding F2 and F3). Therefore, the obtained results from both cases give better perception of estimated RUL.

5.2 Prediction results

In the test phase, predictions are performed over different horizons (Fig 7). The horizon length for short term, mid-term and long term based on 35/80/140 steps ahead. The obtained outputs form each prediction tool are analyzed in a comprehensive manner using different performance metrics. To exemplify this scenario, a test case of bearing is presented in Table 2.

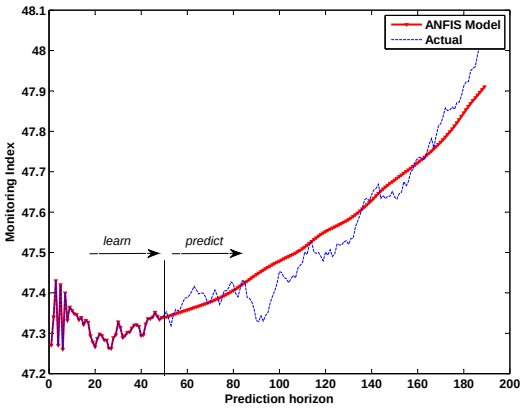

Figure 7. Example of predicted feature

In the selection phase, the outputs from selected models are assessed by MFE criteria and also with the proposed measure of predictability.
Among all features the MFE values for features F2 and F3 were not within bounds of desired performance criteria. Similar findings were achieved with the proposed measure of predictability Eq. (2). The validity of proposed measure can be clearly demonstrated by results from bearing test 1, as shown in Fig. 8. By these results it is well understood that F2 and F3 are not predictable according to defined predictability criteria. Therefore, better predictable features are F1, F4, F5, F6, F7 and F8, which can be selected for further classification to determine probable functioning modes of degrading asset.

5.3 Classification results

For illustration the temporal predictions from bearing test 1 are used for classification and RUL estimation. Therefore, the results are organized in two different cases for in an explicit manner for better perception and understanding (Fig. 9 and 10). In the first case classification is achieved with all features (F1- F8), whereas in the second case the classification is performed on predictable features only i.e.,excluding F2 and F3.

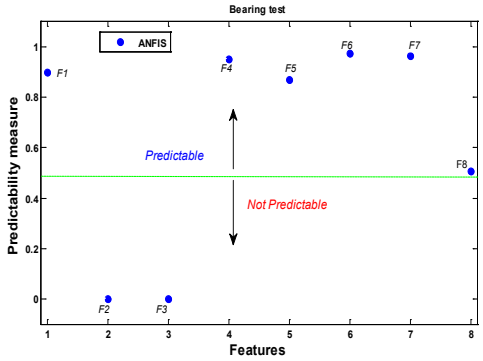

Figure 8. Predictable and not predictable feature set

It can be clearly judged from the results below that the first case shows inferior classification as compared to the classification performed by features that are selected on the basis of predictability. Moreover, the RUL deduced from second case of classifications is closer to the actual RUL, thus, validating better prognostics accuracy and improvements achived from proposed methodology.

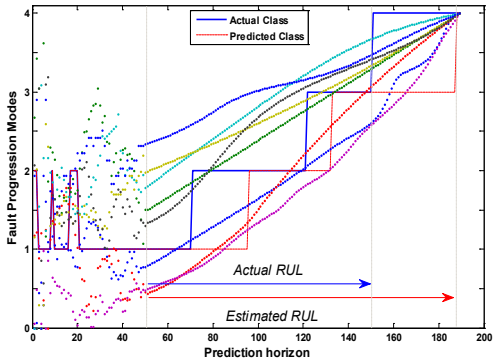

Figure 9. Classification with all features

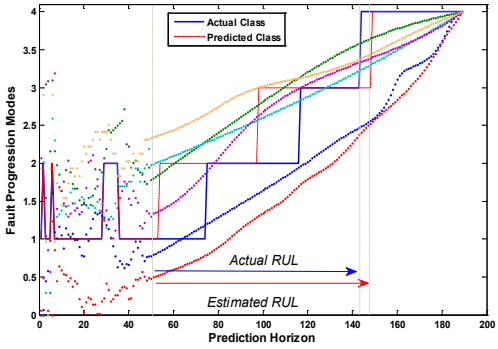

Figure 10. Classification with predictable features

	F1	F2	F3	F4	F5	F6	F7	F8
RMSE	0,111	2,3911	4,431681	0,0742	0,0495	0,0382	0,0334	0,507
MAPE	0,015	0,1166	0,219175	0,0024	0,0829	0,001	0,2909	0,103
CVRMSE	0,017	0,1503	0,314495	0,0031	0,1041	0,0016	0,3959	0,129
MFE	-0,083	1,5625	3,041406	0,0576	-0,008	0,0192	0,0237	0,013
$Pred$	0,682	0,0007	7,88E-07	0,7662	0,9648	0,9149	0,8961	0,944

Table 2. Predictability of bearing test(1) over long-term horizon

6. CONCLUSION

In this paper an improvement to existing data-driven prognostics approach has been presented. The proposition is based on the assessment of the predictability of features that impacts the accuracy of prognostics. The proposed methodology was met in three phases: 1) learning the prognostics model, 2) assessing temporal predictions on the basis of predictability, and 3) selecting those features that are better to be predictable. Mainly, multi-step ahead predictions were performed by ANFIS predictor. Lastly, set of predictable features were classified to determine possible fault modes, thanks to Fuzzy C-means clustering approach. The comparative analysis of classifications of test cases, show the efficiency of proposed methodology of "predictability based feature selection".

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