Condition-based prognosis of machine health

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Abstract

Modern machines are complex and often required to operate long hours to achieve production targets. The ability to detect symptoms of failure, hence, forecasting the remaining useful life of the machine is vital to prevent catastrophic failures. This is essential to reducing maintenance cost, operation downtime and safety hazard. Recent advances in condition monitoring technologies have given rise to a number of prognosis models that attempt to forecast machinery health based on either condition data or reliability data. In practice, failure condition trending data are seldom kept by industries and data that ended with a suspension are sometimes treated as failure data. This paper presents a novel approach of incorporating historical failure data and suspended condition trending data in the prognostic model. The proposed model consists of a FFNN whose training targets are asset survival probabilities estimated using a variation of Kaplan-Meier estimator and degradation-based failure PDF estimator. The output survival probabilities collectively form an estimated survival curve. The viability of the model was tested using a set of industry vibration data.

Key words: Artificial neural networks, condition-based maintenance, prognostics, reliability.

1. Introduction

Condition-Based Maintenance (CBM) is a philosophy of maintaining engineering assets based on non-intrusive measurements of their condition as well as on maintenance logistic. Recent advances in condition monitoring (CM) technologies have given rise to a number of prognostic models that attempt to forecast machinery health based on condition data. Most of the existing models for machinery prognostics can be divided into two main categories: physics-based models and data-based models. Reviews of these prognostic models can be found in [1, 2]. Basically, physics-based models attempt to combine system-specific mechanistic knowledge, defect growth formulas and CM data to predict the propagation of a fault. They generally require less failure histories than data-driven models and can be very accurate provided that the fault physics remain consistent across systems. It has also been reported that defect growth is not a deterministic process [3] and that wear of rotating machinery is still not fully understood at present [4,5]. Data-driven approaches attempt to derive models directly from the acquired CM data. These models may often be the more available solution in many practical cases where it is easier to gather data than to build accurate system physics models.

Nevertheless, several aspects of the data-driven approach need to be further investigated: (a) both reliability information and CM data need to be effectively integrated to enable longer-range prognosis, (b) suspended CM data of historical units that did not undergo failure have not been directly modelled and fully utilized, and (c) the nonlinear relationship between an asset's actual survival status and the measured CM indices need to be deduced.

This paper presents an approach for addressing the above challenges. Instantaneous reliability of historical items is first calculated using a variation of the Kaplan-Meier (KM) estimator and a degradation-based failure Probability Density Function (PDF). The estimated reliability will be used as the training targets for a Feed-Forward Neural Network (FFNN). The trained network will be capable of estimating the future survival probability of a monitored item given the corresponding CM indices. A study using pump vibration data from Irving Pulp and Paper mill[1] verified that the proposed model performs better than similar methods that neglect population characteristics and/or suspended data in prognosis.

2. Proposed Prognostic Model

The proposed prognostic model takes advantage of statistical models' ability to extract population characteristics and reliability, and of an Artificial Neural Network (ANN)'s ability to recognise nonlinear relationships between an asset's future health and a given series of prognostic information.

2.1 Architecture of ANN

The ANN used in this work is a FFNN with one hidden layer and is shown in Figure 1. The number of network inputs is $d+1$, where d the number of network delays is. Therefore, the input vector consists of the latest condition index of the monitored item plus d previous indices. Note that if inspection intervals are not equally-spaced, interpolation can be carried out to evenly space data points with an interval of Δ.

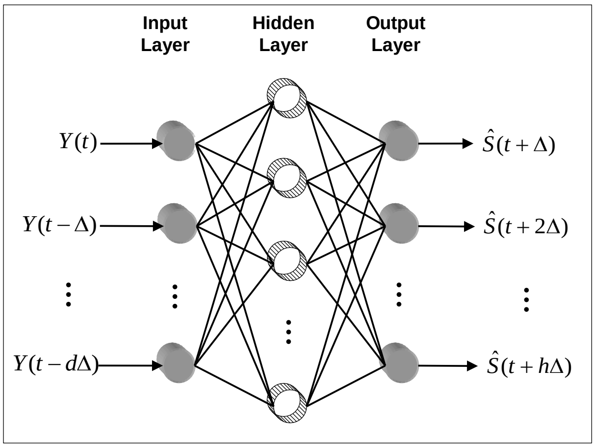

Figure 1. Architecture of the FFNN used in the proposed prognostic model

Let S denote probability of survival or reliable operation, t denote the current or latest time, Δ the fixed time interval between measurements, n the number of future interval that the n th output node represents and $n = 1,2,3,\ldots,h$. The activation of the n th output node is trained with and interpreted as $\hat{S}_{t+n\Delta}$, which is the probability of the item surviving up to the n th next time interval. The training targets for the FFNN are estimates of the survival probabilities of each monitored item in the train data set. The methods for

[1] Data courtesy of the Center for Optimization & Reliability Engineering (C-MORE), University of Toronto, and Irving Pulp and Paper, Saint John, Canada.

estimating these survival probabilities are presented in the following section.

2.2 Statistical modelling of survival probabilities

The target survival probabilities for ANN training are computed by taking into account the actual survival status of the historical item at the time of measurement, as well as how the health of this historical item compared to the health of the entire population at a similar operating age.

2.2.1 Training targets for complete datasets

A historical dataset is considered *complete* if the monitored item has reached failure when removed from operation. Let $i = 1,2,\ldots,m$ and m represents the number of monitored historical items. If item i has reached failure before repair or replacement, its survival probabilities is assigned with a value of “1” up until its failure time step, T_i, and a value of “0” thereafter:

$$S_{KM,i}(t) = \begin{cases} 1, & 0 \le t < T_i \\ 0, & t \ge T_i \end{cases} \tag{1}$$

Note that we consider all functions discussed here to be the true function estimated from the given degradation datasets and drop the hat “^” for notational clarity.

2.2.2 Training targets for suspended datasets

A historical dataset is considered *suspended* if the item has not reached failure when repaired or removed from operation. For such suspended datasets, the survival probability is similarly assigned a value of “1” up until the time interval in which survival was last observed. Survival probabilities for the following time intervals are computed using a variation of the KM estimator [6] based on the survival rate of the complete datasets from this moment onwards, the modified KM estimator tracks the cumulative survival probability of the suspended unit i as follows:

$$S_{KM,i}(t) = \begin{cases} 1, & 0 \le t < L_i \\ \mu_i, & t = L_i \\ \mu_i \cdot \prod_{L_i \le t_j \le t} \left(1 - \frac{d_j}{n_j}\right), & t > L_i \end{cases} \tag{2}$$

where d_j is the number of failures up to time step t_j, n_j is the number of units at risk just to time t_j, L_i denotes the time interval in which historical unit i observed to be still surviving and μ_i is the health index estimated based on the fault severity of the unit at repair/replacement and $0 \le \mu_i \le 1$.

2.2.3 Failure PDF estimation based on degradation data

In classical reliability theory, the population characteristics are commonly expressed through the overall probability density estimated from all historical failure times. These historical failure times can be defined as the horizontal intersections of the condition indices with the failure threshold (see Figure 2). The reliability function is the probability distribution of random variable, T, which represents an item’s operating time to failure, $f(t)$ is the PDF of T, and is defined here as:

$$S(t) = \Pr[T > t] = \int_t^{\infty} f(t)dt \quad (3)$$

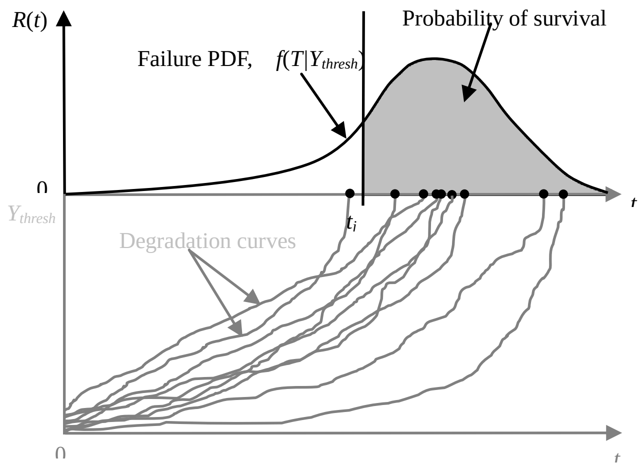

Figure 2. Conventional failure PDF estimated from historical failure events

A main deficiency of the classical reliability approach is that it only provides an overall reliability estimate for the whole population of items. Maintenance personnel would be more interested in the specific reliability information of a particular piece of component currently in operation. A more "condition-based" approach to estimating reliability is then based on the degradation data of historical items and their change over time [7], and is shown in Figure 3.

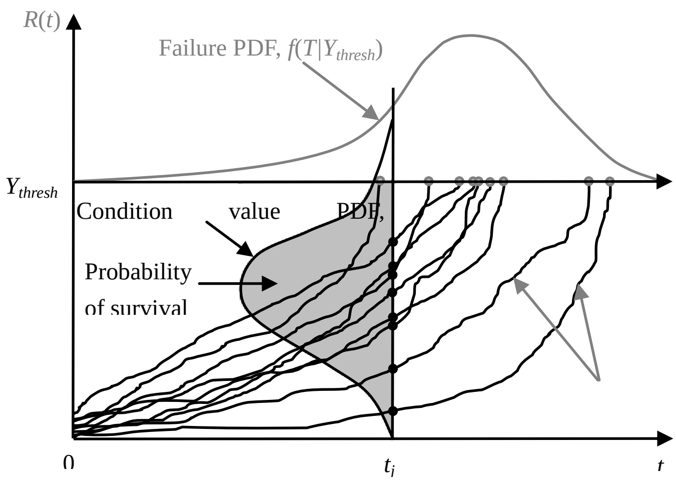

Figure 3. Instantaneous reliability based on historical degradation processes

Let $Y_i(t)$ be the *condition* value of all historical events from items, i = 1 to m and at operating age t. The probability of the condition indices not exceeding failure threshold is defined by the following equation:

$$\Pr[Y(t) < Y_{thresh}] = \int_0^{Y_{thresh}} f(Y \mid t)dY \quad (4)$$

In the case considered, this overall probability of condition values not exceeding failure threshold is also the overall probability of survival:

$$S(t) = \Pr[Y(t) < Y_{thresh}] = \int_0^{Y_{thresh}} f(Y \mid t)dY \tag{5}$$

The above equation shows that reliability function can be estimated by taking into consideration the mechanism of change in the condition of each historical item.

To estimate specific survival probability for each historical unit i for the purpose of generating training targets for the FFNN, we successively multiply the probability of the surviving units having condition indices higher than the observed index of unit i but lower than the threshold (Note that we consider that the condition value, which represents degradation of the corresponding asset, will not decrease. This is an assumption that will yield us a conservative estimate of survival probability). Let $k = 1,2..$, and setting the constraint to be such that the historical condition index at $t+k\Delta$ is the conditional probability of a unit i surviving interval $t+k\Delta$ is [2],

$$S_{PDF,i}(t+k\Delta) = \prod_{j=1}^{k} \frac{\int_{y_{i,t+j\Delta}}^{y_{thresh}} f\left(y \mid t+j\Delta\right)dy}{\int_{y_{i,t+j\Delta}}^{\sim} f\left(y \mid t+j\Delta\right)dy} \tag{6}$$

The numerator is the integral of the PDF between the observed degradation index of item i and the threshold (illustrated in Figure 4) with dash-dot line representing the degradation data of item i); and the denominator is the integral of the PDF over all possible values equal to or higher than the observed degradation index of item i (illustrated in Figure 5).

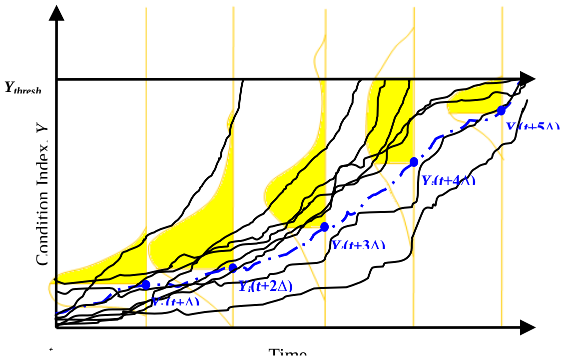

Figure 4. Integral of the PDF between the observed degradation value of item *i* and the threshold value

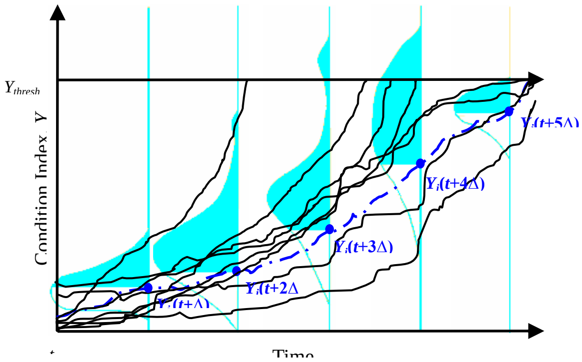

Figure 5. Integration of the PDF over all probable values equal to or higher than the observed degradation values of item *i*

2.24 Final target outputs for ANN training

The final estimated survival probability of item i at interval t is then the mean of the two survival probability estimates:

$$S_i(t) = mean\left[S_{KM,i}(t), S_{PDF,i}(t)\right] \tag{7}$$

The training target vector for historical item i consists of the estimated survival probability in the h successive intervals, given by $S_i(t+h\Delta)$. The input vector is given by $Y_i(t+h\Delta)$. During training, the input and target vectors of the training sets are repetitively presented to the neural network. The network attempts to produce output values that are as close to the target vectors as possible. After training, when a series of condition indices at the current time t and d previous time steps, the network will produce an output vector:

$$O(t) = \begin{bmatrix} \hat{S}(t+\Delta) \\ \hat{S}(t+2\Delta) \\ \vdots \\ \hat{S}(t+h\Delta) \end{bmatrix} \tag{8}$$

The output can be plotted as the survival curve for that unit, estimated at time t. As the next set of input values becomes available, a new updated output vector will be produced, generating a new survival probability curve.

3. Results and Discussion

Vibration data and failure/suspension records of centrifugal pumps at Irving Pulp and Paper mill [8] were used for training, testing and comparing of the proposed model and two other models. Vibration signals are collected at 8 locations on the pump, before being pre-processed into 5 frequency bands, an overall summary of the 5 bands, and an acceleration value. For this case study, 32 histories were available (10 rolling element bearing failures, 6 mechanical seal failures, 14 calendar suspensions – pumps still operating normally when the data were obtained, and 2 informative suspensions with an estimated bearing health index of 0.5 and 0.4 respectively). As the failure mode to be considered in this study is bearing failure, the 6 seal failure datasets function as suspended datasets. The feature values were linearly interpolated so that the measurement points are equally spaced at 10 days. Three of the 10 failure datasets were reserved as test sets and the remaining datasets were assigned for modelling and network training. The FFNNs used for this real life data analysis had 11 input nodes, 15 hidden nodes and 5 output nodes (predicting 5 intervals ahead), and was trained with the gradient descent algorithm with momentum back propagation [9].

The three sets of prediction results from each of the 3 prognostic models were analysed individually. The prediction output of the proposed model is survival probabilities and not failure time. For evaluation purposes, the predicted failure time was identified by noting the first output unit that predicted a survival probability of less than 0.5 (the median survival time in KM estimator). As there are 3 models to be discussed and each model has 9 sets of prediction results (3 test-sets × 3 assessments), only the first test-set in Assessment I will be discussed in detail, consisting of all 6 complete histories and 16 suspended ones. The other results will be summarised and compared.

3.1 Proposed Model

As the prediction output of the proposed model is survival probabilities, the exact predicted failure times are not represented. For evaluation purposes, the predicted failure time was identified by noting the first output unit that predicted a survival probability of less than 0.5. Table 1 shows the prediction results of the 1st test set, in which the actual failure time was at t =600 days. The first output with a value below 0.5 was produced at t = 530 in the 5th row ("0.42", highlighted in Table 1) which means the bearing was forecasted to fail in the 5th next interval, i.e. t = 580 days. However, the failure did not occur till t = 600 days. The error is considered small in relation to the whole lifetime of the bearing ([600-580]/600 = 0.033 or 3.3%). Figure 6 shows the interpolated input data and the graphical representation of predicted survival probability at selected time steps.

The predicted survival probabilities closely matched the actual degradation trend. The survival probability was high and had a stable trend during earlier service of the bearing. The survival probability began to drop at an increasing rate around day 430, suggesting the initiation of a defect. It can also be seen in Figure 6 that, although the vibration RMS value temporarily stopped increasing at around t = 500 days and t = 560 days, the survival probability was still forecasted to drop at an increasing rate. This observation suggests that the prognostic model may have learned to capture the nonlinear relationship between the condition index and the actual health state of the monitored item. This capability makes such a model much more robust than models that directly use condition index to represent asset health.

Table 1. Prediction output of the proposed model.

	t=110	t=120	t=130	t=140	t=150	t=160	t=170	t=180	t=190
Survival Probability in1st following interval, $\hat{S}(t+\Delta)$ →	0.84	0.84	0.84	0.84	0.85	0.84	0.84	0.83	0.83
… 2nd following interval, $\hat{S}(t+2\Delta)$ →	0.83	0.83	0.83	0.83	0.84	0.84	0.83	0.82	0.82
… 3rd following interval, $\hat{S}(t+3\Delta)$ →	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.82	0.83
… 4th following interval, $\hat{S}(t+4\Delta)$ →	0.82	0.82	0.82	0.82	0.83	0.83	0.82	0.82	0.82
… 5th following interval, $\hat{S}(t+5\Delta)$ →	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.81	0.82

t=200	t=210	t=220	t=230	t=240	t=250	t=260	t=270	t=280	t=290	t=300	t=310	t=320	t=330	t=340	t=350
0.83	0.83	0.84	0.84	0.85	0.85	0.85	0.84	0.84	0.83	0.82	0.83	0.84	0.84	0.83	0.83
0.83	0.83	0.83	0.84	0.84	0.85	0.84	0.84	0.83	0.82	0.81	0.82	0.83	0.83	0.82	0.82
0.83	0.83	0.83	0.84	0.84	0.84	0.84	0.83	0.83	0.82	0.81	0.82	0.82	0.82	0.82	0.81
0.82	0.82	0.82	0.83	0.83	0.84	0.83	0.83	0.82	0.81	0.80	0.81	0.81	0.81	0.81	0.81
0.82	0.82	0.82	0.82	0.83	0.83	0.83	0.82	0.82	0.81	0.80	0.80	0.81	0.81	0.81	0.80

t=360	t=370	t=380	t=390	t=400	t=410	t=420	t=430	t=440	t=450	t=460	t=470	t=480	t=490	t=500	t=510
0.82	0.81	0.81	0.81	0.80	0.81	0.80	0.80	0.79	0.79	0.76	0.73	0.70	0.67	0.64	0.63
0.81	0.81	0.81	0.80	0.80	0.79	0.79	0.78	0.77	0.75	0.71	0.67	0.64	0.62	0.61	0.60
0.81	0.80	0.80	0.80	0.80	0.80	0.79	0.78	0.77	0.75	0.71	0.67	0.63	0.60	0.59	0.59
0.81	0.80	0.80	0.80	0.79	0.79	0.78	0.76	0.75	0.74	0.70	0.66	0.62	0.58	0.57	0.55
0.80	0.80	0.80	0.80	0.79	0.78	0.78	0.76	0.75	0.73	0.69	0.64	0.59	0.55	0.54	0.52

t=520	t=530	t=540	t=550	t=560	t=570	t=580	t=590	
0.62	0.61	0.60	0.57	0.54	0.54	0.49	0.49	failed at t=600
0.57	0.54	0.53	0.51	0.44	0.44	0.44	0.42	
0.56	0.51	0.51	0.43	0.34	0.28	0.27	0.25	
0.51	0.50	0.42	0.40	0.25	0.22	0.24	0.26	
0.50	0.42	0.35	0.29	0.09	0.09	0.17	0.23	

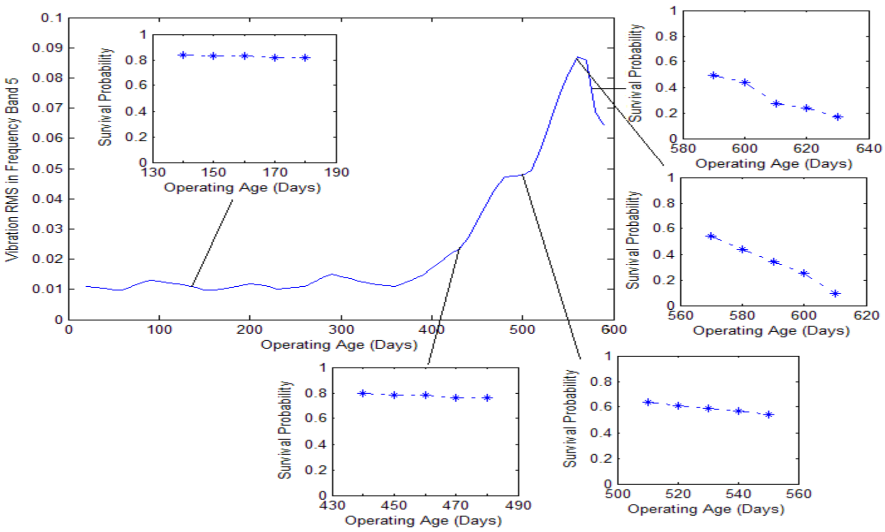

Figure 6. Graphical representation of the prediction output of the proposed model.

3.2 Model A

This model has similar FFNN structure and training function, but trained with the false assumption that suspension times were failure times. As expected, Model A underestimated the failure times even more than the proposed model. The predicted survival probability was lower than that estimated by the proposed model since the start of the bearing operation. The probability value falls below 0.5 as early as around t = 490 days in the 5th row in Table 2, meaning that the monitored bearing was expected to fail within the following 50 days. However, the actual failure only occurred 110 days later.

Table 2. Predicted survival probabilities produced by Model A.

	t=110	t=120	t=130	t=140	t=150	t=160	t=170	t=180	t=190
Survival Probability in1st following interval, $\hat{S}(t+\Delta)$ →	0.89	0.89	0.89	0.89	0.90	0.89	0.89	0.89	0.88
… 2nd following interval, $\hat{S}(t+2\Delta)$ →	0.88	0.88	0.87	0.88	0.89	0.91	0.91	0.91	0.91
… 3rd following interval, $\hat{S}(t+3\Delta)$ →	0.87	0.86	0.86	0.86	0.88	0.90	0.91	0.92	0.91
… 4th following interval, $\hat{S}(t+4\Delta)$ →	0.86	0.85	0.85	0.86	0.88	0.90	0.92	0.92	0.91
… 5th following interval, $\hat{S}(t+5\Delta)$ →	0.85	0.85	0.84	0.84	0.87	0.89	0.91	0.90	0.90

t=200	t=210	t=220	t=230	t=240	t=250	t=260	t=270	t=280	t=290	t=300	t=310	t=320	t=330	t=340	t=350
0.89	0.89	0.89	0.89	0.89	0.90	0.90	0.89	0.89	0.88	0.88	0.88	0.89	0.89	0.89	0.89
0.90	0.89	0.89	0.88	0.89	0.90	0.90	0.91	0.91	0.89	0.87	0.86	0.86	0.87	0.87	0.88
0.91	0.89	0.88	0.87	0.88	0.89	0.89	0.90	0.90	0.89	0.86	0.84	0.84	0.84	0.85	0.87
0.90	0.88	0.87	0.86	0.87	0.89	0.90	0.91	0.90	0.88	0.85	0.82	0.83	0.84	0.85	0.88
0.89	0.88	0.86	0.86	0.86	0.87	0.88	0.89	0.89	0.87	0.84	0.82	0.82	0.83	0.84	0.86

t=360	t=370	t=380	t=390	t=400	t=410	t=420	t=430	t=440	t=450	t=460	t=470	t=480	t=490	t=500	t=510
0.89	0.88	0.88	0.87	0.87	0.87	0.87	0.87	0.86	0.86	0.84	0.82	0.80	0.79	0.79	0.79
0.90	0.91	0.90	0.89	0.88	0.86	0.84	0.82	0.80	0.78	0.74	0.70	0.67	0.66	0.68	0.71
0.89	0.92	0.91	0.90	0.89	0.86	0.83	0.79	0.76	0.74	0.70	0.65	0.61	0.59	0.62	0.65
0.90	0.93	0.91	0.89	0.88	0.84	0.81	0.77	0.73	0.71	0.66	0.61	0.56	0.54	0.57	0.62
0.88	0.91	0.90	0.89	0.87	0.83	0.79	0.75	0.71	0.69	0.63	0.56	0.51	0.50	0.53	0.58

t=520	t=530	t=540	t=550	t=560	t=570	t=580	t=590	
0.78	0.76	0.69	0.64	0.59	0.57	0.48	0.50	failed
0.74	0.71	0.61	0.56	0.52	0.49	0.41	0.39	at
0.69	0.66	0.54	0.43	0.29	0.21	0.16	0.22	t=600
0.67	0.65	0.49	0.33	0.15	0.08	0.08	0.22	
0.62	0.49	0.34	0.11	0.00	0.00	0.00	0.24	

Table 3. Predicted survival probabilities produced by Model B

	t=110	t=120	t=130	t=140	t=150	t=160	t=170	t=180	t=190
Survival Probability in1st following interval, $\hat{S}(t+\Delta)$ →	0.84	0.84	0.84	0.84	0.85	0.84	0.84	0.83	0.83
… 2nd following interval, $\hat{S}(t+2\Delta)$ →	0.83	0.83	0.83	0.83	0.84	0.84	0.83	0.82	0.82
… 3rd following interval, $\hat{S}(t+3\Delta)$ →	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.82	0.83
… 4th following interval, $\hat{S}(t+4\Delta)$ →	0.82	0.82	0.82	0.82	0.83	0.83	0.82	0.82	0.82
… 5th following interval, $\hat{S}(t+5\Delta)$ →	0.82	0.82	0.82	0.82	0.82	0.82	0.82	0.81	0.82

t=200	t=210	t=220	t=230	t=240	t=250	t=260	t=270	t=280	t=290	t=300	t=310	t=320	t=330	t=340	t=350
0.83	0.83	0.84	0.84	0.85	0.85	0.85	0.84	0.84	0.83	0.82	0.83	0.84	0.84	0.83	0.83
0.83	0.83	0.83	0.84	0.84	0.85	0.84	0.84	0.83	0.82	0.81	0.82	0.83	0.83	0.82	0.82
0.83	0.83	0.83	0.84	0.84	0.84	0.84	0.83	0.83	0.82	0.81	0.82	0.82	0.82	0.82	0.81
0.82	0.82	0.82	0.83	0.83	0.84	0.83	0.83	0.82	0.81	0.80	0.81	0.81	0.81	0.81	0.81
0.82	0.82	0.82	0.82	0.83	0.83	0.83	0.82	0.82	0.81	0.80	0.80	0.81	0.81	0.81	0.80

t=360	t=370	t=380	t=390	t=400	t=410	t=420	t=430	t=440	t=450	t=460	t=470	t=480	t=490	t=500	t=510
0.82	0.81	0.81	0.81	0.80	0.81	0.80	0.80	0.79	0.79	0.76	0.73	0.70	0.67	0.64	0.63
0.81	0.81	0.81	0.80	0.80	0.79	0.79	0.78	0.77	0.75	0.71	0.67	0.64	0.62	0.61	0.60
0.81	0.80	0.80	0.80	0.80	0.80	0.79	0.78	0.77	0.75	0.71	0.67	0.63	0.60	0.59	0.59
0.81	0.80	0.80	0.80	0.79	0.79	0.78	0.76	0.75	0.74	0.70	0.66	0.62	0.58	0.57	0.55
0.80	0.80	0.80	0.80	0.79	0.78	0.78	0.76	0.75	0.73	0.69	0.64	0.59	0.55	0.54	0.52

t=520	t=530	t=540	t=550	t=560	t=570	t=580	t=590	
0.62	0.61	0.60	0.57	0.54	0.54	0.49	0.49	failed
0.57	0.54	0.53	0.51	0.44	0.44	0.44	0.42	at
0.56	0.51	0.51	0.43	0.34	0.28	0.27	0.25	t=600
0.51	0.50	0.42	0.40	0.25	0.22	0.24	0.26	
0.50	0.42	0.35	0.29	0.09	0.09	0.17	0.23	

3.3 Model B

This model has similar FFNN structure and training function, but trained using only complete failure histories. Table 3 shows the failure time estimated by this model was closer to the actual failure time compared to the other models. The predicted survival probability value first dropped to below 0.5 in column t = 530 in the 5th row, meaning that the monitored bearing was forecasted to fail around day 580, which was 20 days before the actual failure. The reasonable prediction accuracy might be due to the relatively large number of failure histories available for training in this assessment. If the 6 failure histories were sufficient for training the network to recognise failure patterns, the network would be able to predict well although it did not utilise the suspended histories for training. Although Model B produced quite accurate results, it appears to be inconsistent as the estimated probability for the other two test-sets were not monotonously decreasing. This deficiency greatly reduced the reliability of the model.

3.4 Overall model comparison for all assessments

For model comparison, we define a penalty function which considers the mean prediction accuracy and the prediction horizon of a prognostic model:

$$p(y) = \frac{1}{c}\sum_{j=1}^{c}\left[p_G(y_j)\right] + p_H(y) \quad (9)$$

where c is the number of test-sets, P_G is the prediction accuracy function and P_H is the prediction horizon function [2]. The penalty points of the proposed model and Models A and B are presented in Table 4. The comparison suggests that the proposed model provides more accurate outputs than those of the other control models in all assessments. Model A was greatly penalised as it underestimated the time to failures. The performance of Model B dropped substantially when there were only a limited number of complete histories (which is often the case in practice). If there are only suspended data available for training, Model B will be totally incapable of performing prediction.

Table 4. Penalty for the three models in each assessment.

Assessment\Model	Proposed	A (models suspensions as failures)	B (excludes suspensions from training)
I	0.868	1.568	1.101
II	1.035	1.901	1.035
III	0.785	2.001	8.168

4. Conclusions

The case study results verified that the proposed model which includes suspended condition data in the prognostics model performs better than models that do not include suspended data and population characteristics in prognostic modelling. This work presented a compelling concept for longer-range fault prognosis utilising available information more fully and accurately. Future work includes applying the proposed model to other types of asset degradation, such as tool wear, structure corrosion and electronics failures.

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