Estimating the remaining useful life of bearings using a neuro-local linear estimator-based method

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Abstract: Estimating the remaining useful life (RUL) of a bearing is required for maintenance scheduling. While the degradation behavior of a bearing changes during its lifetime, it is usually assumed to follow a single model. In this letter, bearing degradation is modeled by a monotonically increasing function that is globally non-linear and locally linearized. The model is generated using historical data that is smoothed with a local linear estimator. A neural network learns this model and then predicts future levels of vibration acceleration to estimate the RUL of a bearing. The proposed method yields reasonably accurate estimates of the RUL of a bearing at different points during its operational life.

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1. Introduction

Modern industries use preventive maintenance to achieve near-zero downtime. This largely involves the prognostics and health management of components such as bearings as they account for the majority of equipment failures, especially in induction motors (Thorsen and Dalva, 1999). Bearing prognostics involve detecting failure precursors and estimating the remaining useful life (RUL), given the current health assessment of the bearing and the expected conditions during future operations (Saxena *et al.*, 2008). The current state of a bearing is assessed using health indicators, which can be individual features of the vibration acceleration signal. This includes its root-mean-square (RMS) value (Li *et al.*, 2015); RMS of the acceleration frequencies (Lim and Mba, 2015); variance of the time-domain vibration acceleration signal and Renyi entropy of the Choi-Williams distribution (Singleton *et al.*, 2015); the RMS, mean, and average power values of the vibration acceleration signal (Soualhi *et al.*, 2014); or aggregation of these features in some form, such as the Pearson correlation coefficient calculated for the vibration acceleration values of normal and faulty bearings (Medjaher *et al.*, 2013). The RUL of a bearing is estimated by extrapolating the health indicator to the future assuming constant operating conditions and determining the point in time where the value crosses the failure threshold. The failure threshold for a health indicator is determined using historical run-to-failure data. The health indicator is extrapolated by assuming some parametric model, which is mostly constructed using historical data. Bearing degradation is a highly non-linear process and may change during the lifetime of a bearing (Lim and Mba, 2015). Most of the existing work assumes a single degradation model throughout the lifetime of a bearing, i.e., the exponential model (Medjaher *et al.*, 2013; Li *et al.*, 2015; Singleton *et al.*, 2015). This model may not always be a fair approximation of the degradation behavior, except when a bearing is very close to its end-of-life (EOL). In order to make reasonably accurate estimates of the RUL of a bearing throughout its operational life, it is important to learn the true degradation behavior of a bearing from historical run-to-failure test data.

In this letter, an approach based on a neuro-local linear estimator (NLLE) is proposed to estimate the RUL of a bearing. The proposed approach, which is discussed in detail in Sec. 3, models bearing degradation as a monotonically increasing function that is globally non-linear and locally linearized. The RMS value of the vibration acceleration signal is used as the health indicator for a bearing, which generally increases with increasing deterioration. The model is generated using historical run-to-failure test data, which is locally linearized through a non-parametric local linear estimator with a normal kernel function. Given their ability to model complex

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non-linear functions, a neural network is used to learn this model and then predict future values of the health indicator to estimate the RUL of the bearing. The method is tested using the run-to-failure test data of the Center for Intelligent Maintenance Systems (Qiu *et al.*, 2006; Lee *et al.*, 2007), yielding satisfactory results as discussed in Sec. 4.

2. Run-to-failure test data

The run-to-failure test data used in this study was generated by the Center for Intelligent Maintenance Systems using a test rig with four bearings installed on a single shaft. The shaft is coupled with an AC motor through rub belts and is rotated at a constant speed of 2000 revolutions per minute. A radial load of 6000 lbs is applied on the bearings and the shaft using a spring mechanism. The vibration acceleration is measured using high sensitivity integrated circuit piezoelectric accelerometers, which are installed on the housing of each bearing. The vibration acceleration signal is sampled at 20 kHz and is recorded for 1 s every 10 min using National Instruments data acquisition card 6062E (National Instruments Corporation, Austin, TX). A total of three run-to-failure tests were conducted, each of which used a set of four new Rexnord ZA-2115 double row bearings (Rexnord LLC, PT Components Inc., West Milwaukee, WI). In this study, data from the second run-to-failure test, which runs for approximately 7 days, is used to validate the proposed method (Qiu *et al.*, 2006; Lee *et al.*, 2007).

3. Proposed approach for RUL estimation

The proposed approach based on a NLLE for the health prognosis of a bearing is illustrated in Fig. 1. This approach works in two phases: a *training phase*, in which degradation behavior of a bearing is learned using historical run-to-failure data, and a *prognosis phase*, in which the RUL of a bearing is estimated at a given point in time, and a probable future trajectory is generated for the health indicator. The degradation behavior of a bearing is learned by investigating how the health indicator evolves during operation. The RMS of the vibration acceleration signal is used as an indicator of bearing health, as it is positively correlated with bearing degradation, i.e., as a bearing degrades it results in more powerful vibrations and hence, higher RMS values of the vibration acceleration. The health indicator h is the RMS of the vibration acceleration signal and is calculated using Eq. (1)

$$h = x_{\mathrm{RMS}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}, \tag{1}$$

where x_i is the instantaneous value of the vibration acceleration and N is the total number of samples in a vibration acceleration signal. The health indicator is calculated for each of the 984 one-second snapshots of the vibration acceleration signal, each of which includes 20 480 samples ($N = 20\,480$). Thus, a time series such as the one given in Eq. (2) is obtained which shows the evolution of the health indicator and hence the bearing degradation behavior during a run-to-failure test.

$$H = \{h_t : t \in T\}. \tag{2}$$

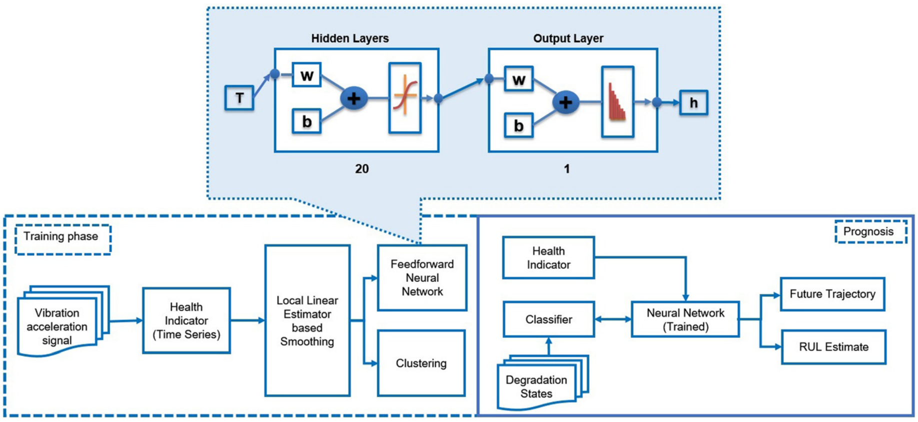

Fig. 1. (Color online) The proposed scheme for the health prognosis and RUL estimation for a bearing using neural networks and local linear estimation-based smoothing.

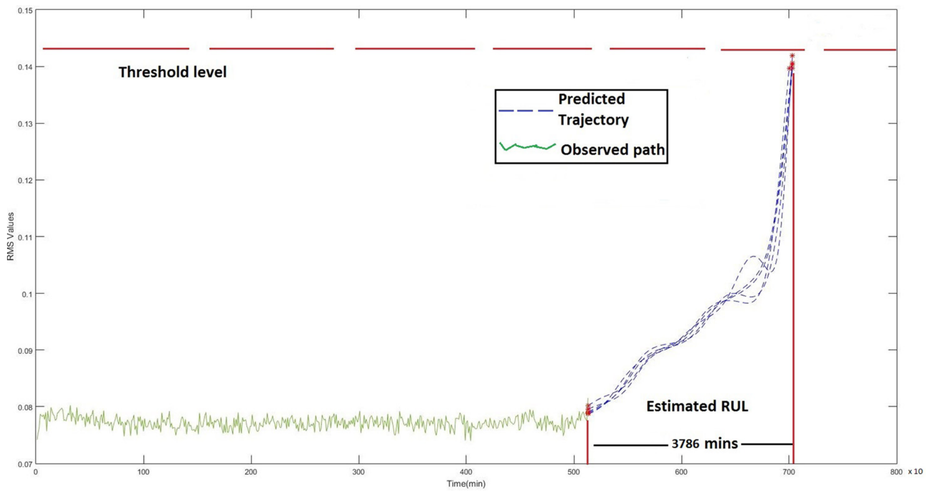

Fig. 2. (Color online) The probable future trajectories of the health indicator generated by the proposed method at a given time index.

Here, T is the set of time indices, where the last value indicates the EOL of the bearing. The RUL of a bearing can be estimated with reasonable accuracy if the time series in Eq. (2) is accurately modeled. Given the excellent ability of neural networks to model complex non-linear functions, this letter proposes the use of feedforward neural networks to model the degradation behavior of a bearing. The neural networks are trained using the time series in Eq. (2), which is obtained for one of the four bearings used in the test. However, before using it to train the neural network, this time-series is first smoothed using a non-parametric, local linear estimator with a normal kernel function. The local linear estimator is a non-parametric regression tool, which can be used to model data with intrinsic nonlinearities. It assumes the following model for the health indicator (Bowman and Azzalini, 1997):

$$h = m(t) + \varepsilon, \tag{3}$$

where t is the time index, ε is an independent error term with zero mean and variance σ^2, and $m(t)$ is the smoothed version of the health indicator, which is estimated using the local linear estimator in Eq. (4).

$$\tilde{m}(t) = \frac{1}{N}\sum_{i=1}^{N} \frac{\{s_2(t;b) - s_1(t;b)(t_i - t)\}w(t_i - t;b)h_i}{s_2(t;b)s_0(t;b) - s_1(t;b)^2}. \tag{4}$$

Here, $s_r(t;b) = \{\sum(t_i - t)^r w(t_i - t;b)\}/n$, b is the smoothing parameter that controls the width of the kernel function and hence the amount of smoothing applied to the data, and $w(t_i - t;b)$ is the normal or Gaussian kernel function that assigns weight to the values of the health indicator close to the time index t. Smoothing removes spurious local fluctuations and nonlinearities in the health indicator and improves the predictive performance of the neural network. Moreover, in order to model bearing degradation as a monotonically increasing function, the estimated values of the health indicator, from Eq. (4), are subject to the following condition:

$$\tilde{m}(t+1) \geq \tilde{m}(t) \qquad \forall t. \tag{5}$$

Hence, if the value of the health indicator at time $t+1$ is less than its value at t, then at $t+1$, the value of the health indicator is assumed to be the same as its value at t. The smoothed values of the health indicator are also grouped into two clusters using the k-means clustering algorithm. These two clusters are used as two representative states of bearing health: *safe-to-operate* or *unsafe-to-operate*. A bearing that is either normal or with initial signs of degradation is considered to be in the *safe-to-operate* state, whereas a bearing in a severe state of degradation is considered in the *unsafe-to-operate* state. In the proposed scheme, the RUL of a bearing is estimated only when it is in the *safe-to-operate* state. When a bearing enters a severe state of degradation, it is assumed to have reached the end of its useful life, at which point the actual run-to-failure tests were terminated as it was unsafe to continue the test any further.

Table 1. The actual and estimated RUL values of the bearing at different points during its useful life.

No.	Bearing age (Minutes)	Actual RUL (minutes)	Estimated RUL (mean value in minutes)
1	5550	3450	3382
2	5880	3120	3058
3	6120	2880	2816
4	6570	2430	2362
5	6820	2180	2112
6	7190	1810	1746
7	7580	1420	1338
8	7700	1300	1236
9	7800	1200	1134
10	7880	1120	1052

In the prognosis phase, at a given time index, the RUL of a bearing and the probable future trajectory of the health indicator are determined, provided the bearing has not entered the *unsafe-to-operate* state. First, the current state of a bearing is determined using a simple distance-based classifier that categorizes a given value of the health indicator using the distance from the boundary for each cluster. The boundary around each cluster represents the average distance of all the samples in the cluster from the cluster mean. If the bearing is determined to be in the *safe-to-operate* state, then the neural network is used to predict the next value of the health indicator. Every time the neural network predicts the next value of the health indicator, the state of the bearing is determined using the predicted value of the health indicator. The neural network is used to predict the future values of the health indicator and thus generate its possible trajectory until the bearing enters the *unsafe-to-operate* state. At any given time index t_i, the RUL $\hat{r}(t_i)$ of a bearing can be estimated as follows:

$$\hat{r}(t_i) = n \cdot \Delta T, \tag{6}$$

where n is the number of time indices in the projected trajectory of the health indicator before the bearing enters the *unsafe-to-operate* state and ΔT is the sampling period for the health indicator or the time interval between two consecutive time indices. The time interval between two consecutive time indices is approximately 10 min for this dataset.

4. Results and discussion

The proposed method for bearing health prognosis and RUL estimation is applied to the run-to-failure test data discussed in Sec. 2. A feedforward neural network is used to learn the mapping between time index values, which are received as inputs, and the values of the health indicator, which are produced as outputs. It employs 20 hidden layers of neurons as illustrated in Fig. 1, each of which uses a sigmoid activation function, whereas the output layer employs a linear activation function. The feedforward

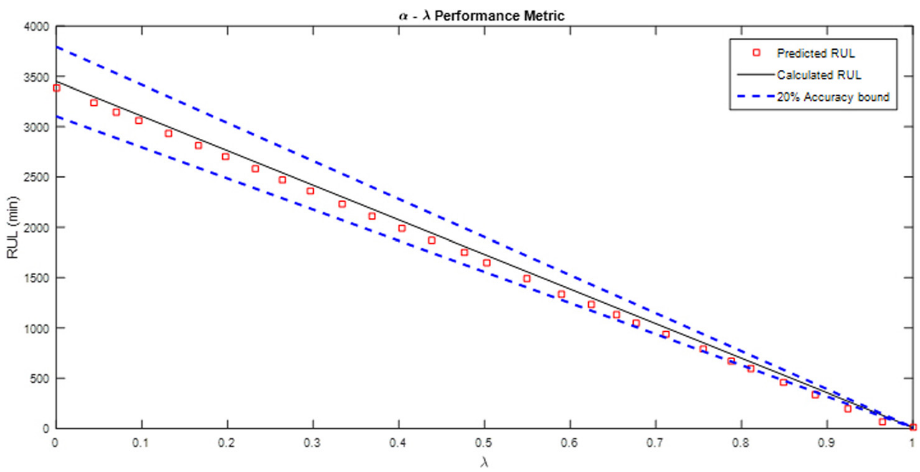

Fig. 3. (Color online) Prognostic performance of the proposed method using the $\alpha - \lambda$ metric with $\alpha = 20\%$.

neural network is trained using the smoothed values of the health indicator, which are calculated for bearing 1. The trained neural network is then used to generate potential trajectories of the health indicator for bearing 2 at different time indices before the bearing reaches its EOL. Example trajectories generated using the neural network at a given time index are shown in Fig. 2. At each time index, the process of generating future trajectories and RUL estimation is repeated multiple times. Table 1 lists the actual RUL value and the mean values of the estimated RUL at different time indices. The performance of the proposed method is measured using the $\alpha - \lambda$ metric for prognostic algorithms, which determines whether the proposed approach estimates the RUL within the specified error margins of the actual RUL at any time index of interest (Saxena *et al.*, 2008, 2009). The error margins are specified by the parameter α, which is set to 20% in this study, as shown in Fig. 3. The parameter α creates a converging cone of error bounds for the estimated RUL around the true RUL, i.e., $[(1-\alpha)r(t_i)] \le \hat{r}(t_i) \le [(1+\alpha)r(t_i)]$, where $r(t_i)$ is the true RUL at t_i. The parameter λ specifies the relative distance at a given time to the failure or EOL of a bearing. Here, $\lambda = 0$ corresponds to the time of first prediction, whereas $\lambda = 1$ corresponds to a bearing's EOL. $\lambda = 0.5$ would mean that we are half-way to failure after the first RUL estimate was made. As evident from Fig. 3, the proposed algorithm performs within the specified error bounds for almost all values of λ.

5. Conclusions

In this letter, a data-driven, NLLE-based method is proposed for the RUL estimation and health prognosis of bearings. Bearing degradation is a highly non-linear process that is difficult to model. The proposed method employs feedforward neural networks to model the degradation behavior of a bearing by learning how the health indicator of a bearing evolves during a run-to-failure test. The modeling accuracy of the neural networks is improved by first using local linear estimators to smooth the health indicator, which is extracted from historical run-to-failure test data. The trained neural network is then used to generate probable future trajectories for the health indicator and estimate the RUL at a given time index. The prognostic performance of the proposed method is determined using the $\alpha - \lambda$ metric. The proposed algorithm yields RUL estimates within the error bounds set by $\alpha = 20\%$ for almost all values of λ, which is an indication of the relative time to the EOL of a bearing.

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References and links

Bowman, A. W., and Azzalini, A. (**1997**). *Applied Smoothing Techniques for Data Analysis: The Kernel Approach with S-Plus Illustrations* (Oxford University Press, Oxford).

Lee, J., Qiu, H., Yu, G., Lin, J., and Rexnord Technical Services (**2007**). *Bearing Data Set*, edited by U. O. C. IMS [NASA Ames Research Center, Moffett Field, CA, NASA Ames Prognostics Data Repository, http://ti.arc.nasa.gov/project/prognostic-data-repository (Last viewed 22 August 2016)].

Li, N., Lei, Y., Lin, J., and Ding, S. X. (**2015**). "An improved exponential model for predicting remaining useful life of rolling element bearings," IEEE Trans. Ind. Electron. **62**, 7762–7773.

Lim, C. K. R., and Mba, D. (**2015**). "Switching Kalman filter for failure prognostic," Mech. Syst. Signal Process. **52**, 426–435.

Medjaher, K., Zerhouni, N., and Baklouti, J. (**2013**). "Data-driven prognostics based on health indicator construction: Application to PRONOSTIA's data," in *IEEE European Control Conference* (*ECC*), pp. 1451–1456.

Qiu, H., Lee, J., Lin, J., and Yu, G. (**2006**). "Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics," J. Sound Vib. **289**, 1066–1090.

Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., and Schwabacher, M. (**2008**). "Metrics for evaluating performance of prognostic techniques," in *Prognostics and Health Management*, IEEE International Conference, pp. 1–17.

Saxena, A., Celaya, J., Saha, B., Saha, S., and Goebel, K. (**2009**). "On applying the prognostic performance metrics," in *Annual Conference of the Prognostics and Health Management Society*.

Singleton, R. K., Strangas, E. G., and Aviyente, S. (**2015**). "Extended Kalman filtering for remaining-useful-life estimation of bearings," IEEE Trans. Ind. Electron. **62**, 1781–1790.

Soualhi, A., Razik, H., Clerc, G., and Doan, D. D. (**2014**). "Prognosis of bearing failures using hidden Markov models and the adaptive neuro-fuzzy inference system," IEEE Trans. Ind. Electron. **61**, 2864–2874.

Thorsen, O. V., and Dalva, M. (**1999**). "Failure identification and analysis for high-voltage induction motors in the petrochemical industry," IEEE Trans. Ind. Appl. **35**, 810–818.