Bearing Health Condition Prediction Using Deep Belief Network

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ABSTRACT

Bearings play a critical role in maintaining safety and reliability of rotating machinery. Bearings health condition prediction aims to prevent unexpected failures and minimize overall maintenance costs since it provides decision making information for condition-based maintenance. This paper proposes a Deep Belief Network (DBN)-based data-driven health condition prediction method for bearings. In this prediction method, a DBN is used as the predictor, which includes stacked RBMs and regression output. Our main contributions include development of a deep leaning-based data-driven prognosis solution that does not rely on explicit model equations and prognostic expertise, and providing comprehensive prediction results on five representative run-to-failure bearings. The IEEE PHM 2012 challenge dataset is used to demonstrate the effectiveness of the proposed method, and the results are compared with two existing methods. The results show that the proposed method has promising performance in terms of short-term health condition prediction and remaining useful life prediction for bearings.

1. INTRODUCTION

Bearings are one of the most widely used components in rotating machinery. Not surprisingly, bearing failure is one of the major causes of breakdowns in rotating machinery (Sloukia et al., 2013). Bearing health condition prognosis predicts the future states of bearings based on current operating condition and maximizes the machine uptime to increase throughput and reduce maintenance costs. As a result, bearing prognosis has attracted extensive research efforts in recent years (Li et al., 2014).

The bearing condition prognosis methods can be roughly classified into data-driven and model-based methods (Liu et al., 2012). Model-based methods attempt to setup mathematical or physical models to describe degradation processes of machinery, and update model parameters using measured data (Lei et al., 2016), such as the Markov process model (Dui et al., 2015), the Winner process model (Si et al., 2013), the Gaussian mixture model (Yu et al., 2013), etc. However, accurate mathematical or physical models for bearings are always difficult to obtain. Data-driven approaches have recently become a popular method because of its flexibility and easy operation. The commonly used data-driven methods include artificial neural network (ANN) (Huang et al., 2007), relevance vector machine (RVM) (Miao et al., 2012), neuro-fuzzy system (Zhao et al., 2009) and so on.

Existing prognostics methods have made great achievements on bearing condition prediction. However, due to the diversity and complexity of bearings, existing methods show some limitations: (1) most model-based methods rely heavily on accurate physics-based model or complex signal processing techniques, which require extensive expert involvement; (2) In the age of Internet of Things and Industrial 4.0, massive real-time data are collected from various bearings and form a big data environment, which has the characteristics of large-volume, diversity, and high-velocity (Deutsch & He, 2016). Traditional data-driven methods are insufficient for feature extraction and health condition prediction. It is desirable to develop generic and system-independent prognostic algorithms to meet the needs of big data.

To address the above limitations, this paper proposes a Deep Belief Network (DBN)-based data-driven approach for bearing health condition prediction. In recent years, deep learning has attracted significant attention in fault diagnosis and prognosis because of its excellent performance on big data processing (Zhao et al., 2016). Although most of successes focus on fault diagnosis (Tamilselvan & Wang, 2013; Lei et al., 2016), deep learning has demonstrated potentials in prediction and prognosis, such as time series forecasting (Kuremoto et al., 2014) and RUL estimation (Deutsch & He, 2016; Babu et al., 2016). In (Deutsch & He, 2016) a deep learning based on a RBM is presented for bearing remaining useful life prediction. However, due to the RBM structure in existing works, the performance on prediction accuracy is not as good as traditional methods (Deutsch & He, 2016), which requires further research and advanced design.

To address the limitations of existing works, the paper develops a DBN-based approach for bearing prognosis. Compared with existing data-driven methods, our main contributions are two-fold: 1). Inspired by deep learning, a new data-driven method for bearing prognosis is developed, which consists of stacked RBMs and a regression output layer. One significant advantage of the proposed method is that it doesn't rely on explicit models or prognostic expertise, which greatly simplifies the design of prognosis and increases the flexibility. 2). Detailed analysis and experimental studies on five run-to-failure bearings are conducted to verify the proposed method. Performance of the proposed method in terms of short-term prediction and RUL prediction are discussed with experimental analysis. The results show that, the proposed method has promising performance on bearing health condition prediction.

The rest of this paper is organized as follows: Section 2 briefly introduces the basic principle of DBN. Section 3 describes the proposed bearing health condition prediction method based on DBN. In Section 4, IEEE PHM 2012 challenge dataset is used to demonstrate the effectiveness of the proposed method. Conclusions are drawn in Section 5.

2. PRINCIPLE OF DBN

DBN is a generative model composed of stacked Restricted Boltzmann Machine (RBM) and a classifier or a regression (Hinton & Salakhutdinov, 2006). In this study, a logistic regression layer is used as the last layer to make the L-step ahead prediction for prognosis. Figure 1 shows an example of 3-layer DBN structure as a predictor, which consists of two stacked RBMs (Kuremoto et al., 2014). RBM is able to provide a learning model for unknown data distributions. Each RBM contains a visible layer and a hidden layer. The units in the same layer are not connected. The units in two adjoining layers have directed symmetrical connections. Note that the hidden layer in RBM1 works as the visible layer in RBM2. When the high dimension data are input to the visible layer of RBM1, the units of hidden layer of RBM1 extract features from input data according to the connection weights. The hidden layer of RBM2 gets "the feature of features (the outputs of RMB1)". In this study, the input data for DBN is taken from the root mean square (RMS) degradation curve of bearings using a sliding window strategy. The output $\bar{x}(t)$ denotes the predicted RMS value with DBN, i.e. using the data of the previous d time instants to predict the next data, and the instances of training are $\{[x(t-d), x(t-d+1), \dots, x(t-1),] \to x(t)\}$.

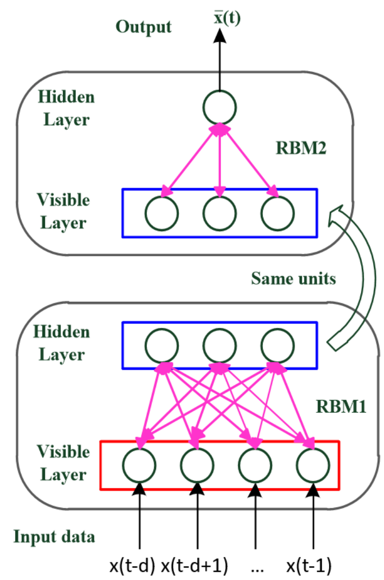

Figure 1. An example of 3-layer DBN structure

The training process of DBN includes an unsupervised layer-by-layer pre-training stage of stacked RBMs and a global fine-tuning stage by back propagation algorithm (Hinton et al., 2006). The pre-training stage aims to fully extract features from low-level to high-level and, at the same time, avoid local optimum. The fine-tuning stage of network parameters is to further optimize the network capability. When both pre-training and fine-tuning stages are completed, the DBN model can be used for practical predictions.

3. DBN-BASED HEALTH CONDITION PREDICTION METHOD FOR BEARINGS

This study proposes a bearing health condition prediction method based on DBN. The proposed method doesn't require explicit model equations and is suitable for big data applications. Figure 2 illustrates the overview of bearing prognostic procedure using DBN, which consists of the following steps:

Step1: For a system under test, define the prognosis problem and identify the fault feature and health indicator. This paper considers a bearing and RMS of vibration signals is used as the health indicator to determine the bearing's degradation over time. The RMS values serve as the input to the DBN. The RMS at each time interval (denoted as $x(t)$) is calculated as follows:

$$x(t) = \sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{N} f_{ti}^2} \tag{1}$$

where f_{ti} represents the *i-th* raw vibration data point at time interval t and N is the length of the signal. N is equal to 2560 in this paper. Using Eq. (1), the time series of RMS for bearings can be obtained. Formally, for the L-step ahead prediction, the input of DBN can be denoted as:

$$[x(t-d), x(t-d+1), \dots, x(t-2), x(t-1)] \tag{2}$$

and the predicted output as:

$$[x(t+L-1), x(t+L), \dots, x(n)] \tag{3}$$

where d represents the embedding dimension and determines the number of units of the visible layer in the first RBM.

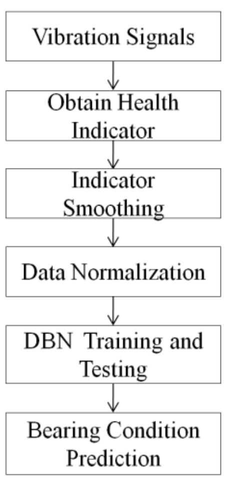

Figure 2. Overview of DBN-based bearing prognosis.

Step2: Construct the health indicator using the RMS feature, and obtain the degradation curves from vibration signals of learning and testing bearings.

Step3: Smooth the raw RMS curves. Although the overall tendency of RMS curves is monotonous, their local values are oscillating. Therefore, a smoothing process is introduced to reduce the influence of noise. This paper employs a moving average algorithm to smooth RMS curves.

Step4: Normalize the dataset to [0, 1] by $x^* = (x - x_{min})/(x_{max} - x_{min})$, where x^* is the normalized data, x is the raw RMS values for a bearing, x_{max} and x_{min} are the maximum and minimum of x, respectively. Then the normalized dataset is divided into training set and testing set.

Step5: Construct a DBN model and use the training set to train this DBN model. In this step, parameters of DBN, such as the number of hidden layers, the number of units for each layer, the pre-training iterations, and the fine-tuning iterations, etc. need to be determined. After the training process of DBN, the predicted value is compared with the ground truth value. If the performance is acceptable, the trained DBN model is ready to be used for applications. Otherwise, Step5 is repeated to adjust the DBN parameters.

Step6: Use the trained DBN model to predict the future condition of bearings. From the starting point of prediction, the trained DBN model is used to obtain predicted RMS step-by-step recursively until the RMS predicted from DBN reaches the failure threshold.

4. EXPERIMENTS AND RESULTS

In this section, the proposed method is verified and demonstrated by short-term and long-term condition predictions for bearings. For the short-term condition prediction, two prediction horizons of L=1 and 10 are used to predict 10 seconds and 100 seconds respectively into the future for bearings1_3 and 1_7. The long-term condition prediction performance is verified by RUL prediction.

4.1. Experimental system and vibration data

Experimental data comes from IEEE PHM 2012 prognostic challenge (Nectoux et al. 2012). This problem has multiple challenges including limited training samples, unknown failure modes, no fixed failure threshold, and a wide range of failure times (Sutrisno et al. 2012). The experimental system named PRONOSTIA is designed to test and validate methods for fault detection, diagnostic and prognostic of bearings. This experimental system is able to conduct accelerated degradation tests on bearing in a few hours.

Three different operation conditions are provided in the challenge data. In this paper, bearings 1_1 and 1_2 under the first condition are used as training set, bearings 1_3 to 1_7 under the first condition are used as testing set. The first condition is as follows: 1800 rpm and 4000 N. The sampling frequency is 25.6 kHz. Each sample contains 2560 points, i.e., 0.1 s, and sampling is repeated every 10 s. Figure 3 shows the vibration signals of bearing1_1 during its whole life cycle. It can be seen that the amplitude of the vibration signals increases over time.

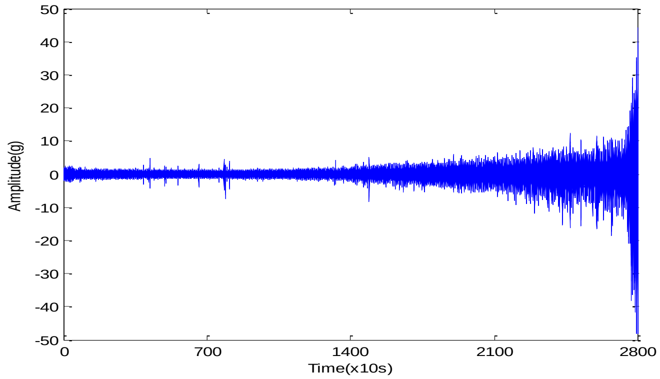

Figure 3. Vibration raw signals of bearing1_1.

4.2. Evaluation criterion

Three evaluation criteria are used to measure the performance of the proposed method.

1) *RMSE: Root Mean Square Error*

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x(i)-\bar{x}(i)\right)^2} \tag{4}$$

where $x(i)$ is the *i-th* actual bearing RMS value, and $\bar{x}(i)$ is the *i-th* predicted RMS value.

2) *Er_n: Percent Error of Prediction Result for the bearing with index n*

$$Er_n = \frac{ActRUL_n - RUL_n}{ActRUL_n} \times 100\% \tag{5}$$

where $ActRUL_n$ is the actual RUL value for the bearing with index *n*, RUL_n is the predicted RUL value for the bearing with index *n*. In order to get the predicted RUL value, EOP (End of Point) and SP (Starting Point of prediction) need to be determined. EOP is defined as the time instant when the predicted curve of bearing condition reaches the failure threshold, the remaining useful life is given by RUL_n=EOPn-SPn.

3) *Score:* The *Score* is used to comprehensively evaluate the performance of the prediction method

$$Score = \frac{1}{N}\sum_{n=1}^{N} A_n \tag{6}$$

where

$$A_n = \begin{cases} \exp(-\ln(0.5)\cdot(Er_n/5)) & if\ Er_n \le 0 \\ \exp(+\ln(0.5)\cdot(Er_n/20)) & if\ Er_n > 0 \end{cases} \tag{7}$$

4.3. Experiments results

The method proposed in Section 3 is used to process the vibration signals. Note that the bearing data are truncated at the time when the vibration amplitude exceeds 20 g. Firstly, RMS curves are obtained from the raw vibration signals using Eq. (1). Figure 4 shows an example of the raw RMS curve for bearing1_3, it is clear that the raw RMS curve has big noise and their local values are oscillating. Therefore, the 15-point moving average algorithm is used to reduce the influence of noise. The smoothed RMS curves are then normalized in the range of [0, 1]. The RMS curves after smoothing and normalizing are shown in Figure 5.

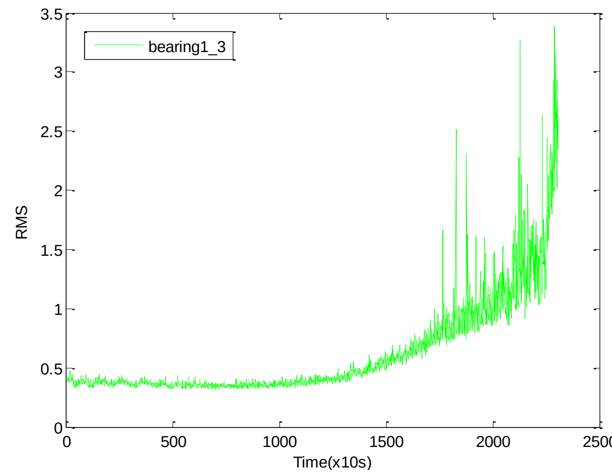

Figure 4. Raw RMS curve for bearing1_3

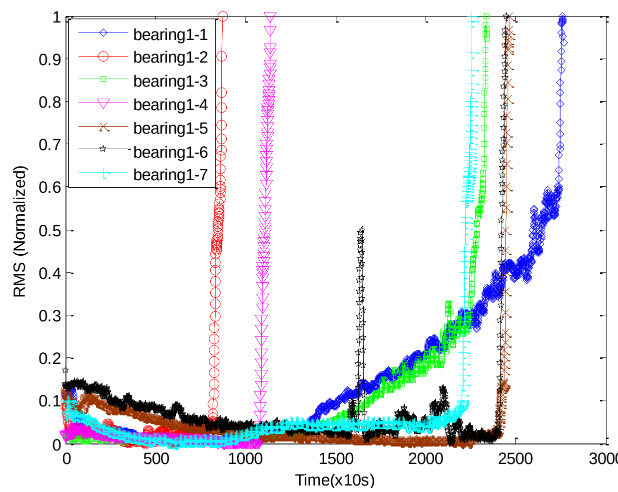

Figure 5. RMS curves after smoothing and normalizing.

Bearing health condition prediction experiments show that the number of DBN layers and the embedding dimension are critical to the performance of prognosis. Table 1 shows the impacts of the number of DBN layers on RMSE for 1-step ahead prediction. Note that the RMSE values shown in this table are the averaged value from 10 experiments on the same data. In Table 1, 3-layer DNB has structure of 10-20-1, which means the input layer has 10 units, the hidden layer has 20 units, and the output layer has one unit. Same representation is employed for 4-layer and 5-layer DBN structure. These three models are used to conduct 1-step ahead prediction. From Table 1, it can be seen that the 4-layer DBN is the best structure for this case. Table 2 summarizes the best embedding dimension for *L*-step ahead prediction. In this experiment, a 4-layer DBN structure *d*-20-20-1 and the evaluation criteria *RMSE* are used to find the best embedding dimension using a grid search. DBN structure *d*-20-20-1 means the input layer has *d* units, the two hidden layers have 20 units, and the output layer has one unit. From Table 2, it is clear that the number of embedding dimension should increase with the increase of prediction horizon given by *L*. In addition, it also indicates that it is difficult to find the best unified embedding dimension for all bearings.

Table 1. RMSE results under different number of DBN layers.

Testing bearing	*RMSE*($\times 10^{-3}$)		
	3-layer	4-layer	5-layer
DBN structure	10-20-1	10-20-20-1	10-20-20-20-1
Bearing1_3	7.9620	4.798	11.917
Bearing1_4	10.013	9.032	15.954
Bearing1_5	10.637	6.201	13.615
Bearing1_6	3.6400	2.251	9.6530
Bearing1_7	5.2080	2.249	7.4070

Table 2. Best embedding dimension for L-step ahead prediction for 4-layer DBN *d*-20-20-1.

Testing bearing	Best embedding dimension (*d*)		
	L=1	*L*=5	*L*=10
Bearing1_3	10	100	200
Bearing1_4	5	45	100
Bearing1_5	10	50	150
Bearing1_6	3	15	45
Bearing1_7	10	100	150

Due to limited space, bearing1_3 and bearing1_7 are taken as examples to illustrate the RMS predictions. Figures 6 and 7 show the comparison of DBN predicted RMS curve vs. actual RMS curve for bearing1_3 and bearing1_7 with *L*=1, respectively. Figures 8 and 9 show the same comparison with *L*=10, respectively. For 1-step ahead prognosis, the DBN structure is set as 10-20-20-1. The pre-training iterations of each RBM is 200, and the fine-tuning iterations is 200. For 10-step ahead condition prediction, the DBN structure is set as 150-20-20-1. The pre-training iterations of each RBM is 200, and the fine-tuning iterations is 200. Note that these parameters are selected based on trial-and-error.

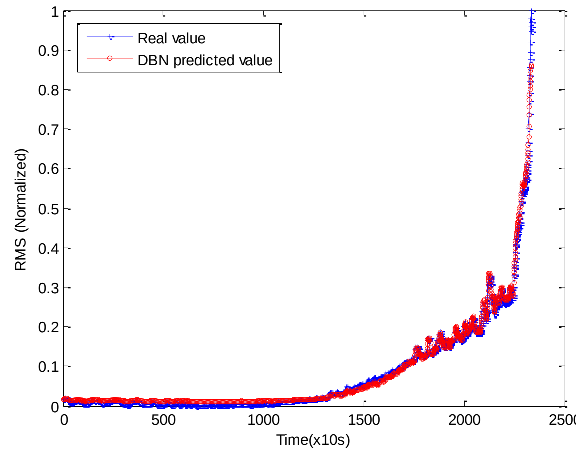

Figure 6. Performance of DBN 1-step ahead prognosis (*L*=1) for bearing1_3.

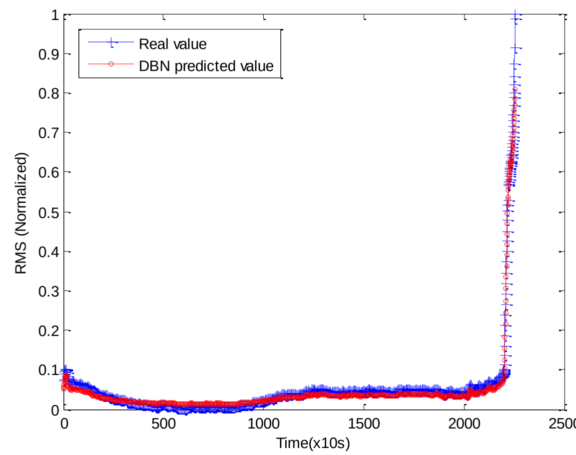

Figure 7. Performance of DBN 1-step ahead prognosis (*L*=1) for bearing1_7.

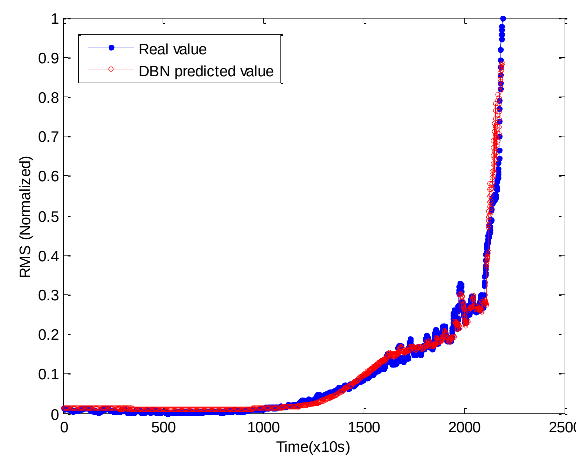

Figure 8. Performance of DBN 10-step ahead prognosis (*L*=10) for bearing1_3.

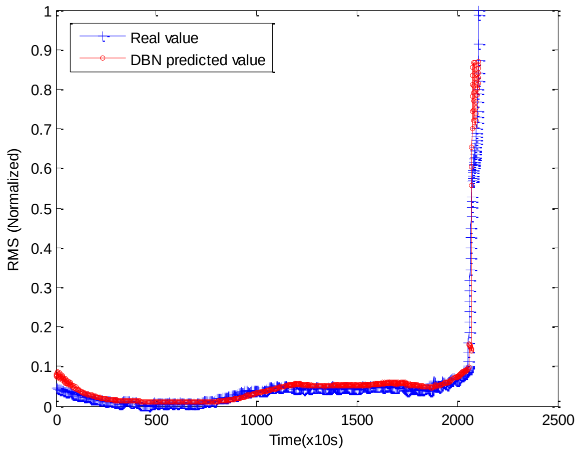

Figure 9. Performance of DBN 10-step ahead prognosis (L=10) for bearing1_7.

Inspection of Figures 6-9 indicates that DBN predicted RMS values are very close to actual RMS values during their whole life cycle, which indicates that the DBN model is able to describe the fault dynamics and is very effective in short-term condition prognosis.

To further evaluate the long-term prognosis performance, DBNs are used to estimate the bearing RUL. In this experiment, the DBN structure is set as 250-110-20-1. Based on the observation of health indicator, the failure threshold of bearings is set to 0.7. According to the PHM 2012 challenge, the starting point of prediction (SP) for bearing1_3 and bearing1_7 is set as 18010 s and 15010 s, respectively. Figures 10 and 11 show the predicted curves for bearing1_3 and bearing1_7, respectively. The RMS prediction include two phases: Before the starting point of prediction, the trained DBN model is used to obtain "DBN fitted value" with 1-step ahead prediction. After the starting point of prediction, the trained DBN model is used to obtain "DBN predictive value" step-by-step recursively until the RMS predicted from DBN reaches the failure threshold. The EOPD is the intersection point of failure threshold line with DBN predicted curve, the EOL is the intersection point of failure threshold line with real RMS curve. In Figure 10, EOPD is very close to EOL, which indicates DBN predicted RMS values are very close to actual RMS values during long-term prediction. From Figures 10 and 11, it is obvious that DBN can predict the bearing degradation and estimate the remaining useful life. The predicted RUL for bearing1_3 and bearing1_7 is 5170 s and 5960 s, which are 560 s and 1610 s away from the ground truth RUL, respectively.

Table 3 shows the RUL prediction results of the proposed method, and the results are summarized and compared with those of two existing studies (Lei et al., 2016; Sutrisno et al., 2012) based on the same dataset. In Lei et al. (2016), a fusion health indicator called weighted minimum quantization error (WMQE) was constructed, and RUL was predicted using a particle filtering-based algorithm with model parameters initialized using the maximum likelihood estimation algorithm. Its prediction performance is one of the best in the existing works using the same dataset. The second one is the winner of the IEEE PHM 2012 prognostic challenge. It proposes a data-driven bearing condition prediction method based on anomaly detection, degradation feature extrapolation, and survival time ratio. From Table 3, it is obvious that most of the bearing RUL prediction results using the proposed method are promising, bearing1_4 is an exception.

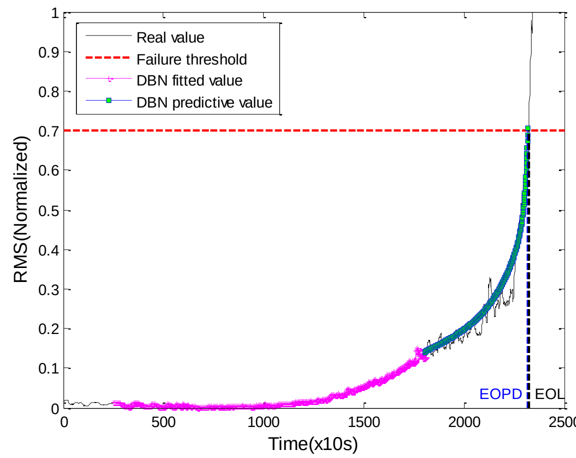

Figure 10. Prognosis of RUL prediction for bearing1_3.

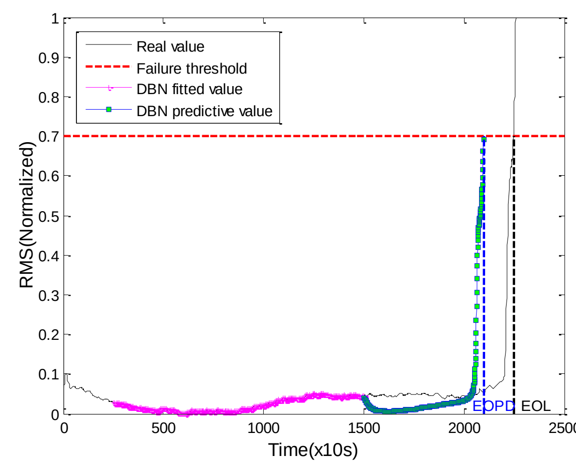

Figure 11. Prognosis of RUL prediction for bearing1_7.

The percent error and score of the three methods are calculated and displayed in Table 4. According to Eq. (7), Underestimates and overestimates of RUL will not be considered in the same manner: good performance of estimates relates to early predictions of RUL (i.e. cases where $Er > 0$), with deduction to early removal, and more severe deductions for RUL estimates that exceed actual component RUL (i.e. cases where $Er \leq 0$). The higher the score is, the better the performance of the prediction method.

Table 3. Comparison of RUL prediction results ($\times$10s).

Testing bearing index	Start point of prediction	Actual RUL	*RUL Prediction Results*		
			Proposed method	Lei et al. (2016)	Sutrisno et al. (2012)
1_3	1801	573	517	575	361
1_4	1138	34	66	32	7
1_5	2301	161	148	0	147
1_6	2301	146	115	105	153
1_7	1501	757	596	905	772

Table 4. Comparison of percent error and score.

Testing bearing	*Percent Error of Prediction Result (Er)*		
	Proposed method	Lei et al. (2016)	Sutrisno et al. (2012)
Bearing1_3	9.77%	-0.35%	36.99%
Bearing1_4	-94.12%	5.88%	79.41%
Bearing1_5	8.07%	100%	8.70%
Bearing1_6	21.23%	28.08%	-4.79%
Bearing1_7	21.27%	-19.55%	-1.98%
Score	0.4853	0.4488	0.4711

From Table 4, DBN achieves the highest score on the five testing bearings. Since there are 11 bearings for testing in IEEE PHM 2012 prognostic challenge, we can’t draw the conclusion that the proposed method outperforms the published works for all bearings. One of our future works will conduct the RUL prediction experiment on the other six bearings. Note that the proposed method does not require mathematical or physical model of the bearings, and the prediction performance may improve by using better health indictor. We can draw a conclusion that our proposed method is promising for long-term bearing RUL prognosis.

5. CONCLUSION

This paper proposes a data-driven method for bearing health condition prediction, which is based on Deep Belief Network. The design and implementation of the proposed method are discussed in detail. Experiments on the IEEE PHM 2012 prognostic challenge dataset are presented to demonstrate the effectiveness of the proposed method. The proposed method does not require mathematical or physical model of the bearings, and it has shown its promising ability for bearing health condition prediction with big data. Our future work will focus on RUL prediction experiment on more bearings and DBN parameters optimization.

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