# Prediction of the Remaining useful Life of the Rolling Element Bearings using Recurrent Neural Network

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*In this paper, the temperature feature was employed to track down the degradation trend of rolling element bearings. The remaining useful life(RUL) of the rolling element bearing was predicted by assuming root mean square growth (RMS) of the acceleration signal to exponential function form and extraction of two other features. Then, the performance of these features was investigated in the prediction using a recurrent neural network(RNN). The experimental data of the accelerated life test on the rolling element bearing have been extracted from the prognostic. Contrary to the previous works, this paper considers the temperature feature instead of the time feature and also assuming the RMS of the acceleration signal to the exponential function form and using a RNN which causes a new model more applicable than previous models.*

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## 1 Introduction

Prediction of the RUL of the rolling element bearings is an important issue for increasing reliability and reducing maintenance costs [1, 2]. As a result, many researchers have predicted the useful life of the rolling element bearing [3]. In recent years, the remarkable development of computers and measurement devices has led to the development of the data-driven method. One of the most common and effective procedures in the data-driven method is condition monitoring using vibration analysis for rotary machines [4]. In the data-driven method, a feature of the collected data required to detect the bearing degradation and also the RUL. The feature should have necessary and enough information about the machine health or the considered element. Therefore, to follow the failure trend and estimate the RUL, a feature needs to gradually show the health status of the considered element over time.

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In general, data-driven methods are classified into two groups of Statistical methods and Artificial intelligence methods [5]. Several research has been done on the prediction of the RUL. One of the most up-to-date and comprehensive studies in this field is Lei et al's [6] article in (2018). They showed the importance of this field by presenting the growing trend in the number of articles published in the last twenty years so that the articles of the last 5 years cover 60% of the articles of the last two decades. This paper focuses on artificial intelligence methods and the use of the neural network. In some studies, the focus has been on the use of different algorithms and the type of neural network. In (2001), Wang et al. [7] used the dynamic wavelet neural networks to estimate the RUL and compared it with the AutoRegression model. In another study, Cui et al. [8] in (2017), using a RNN, modeled the growth dynamics of failure and more efficiently predicted the degradation and RUL process. Another group of researchers has focused on the proper selection of neural network inputs. One of the first studies to be conducted in this field, we can refer to the article by Gebraeel et al. [9] in (2004). In this study, the Feed Forward Neural Network(FFNN) has been used to estimate the RUL. In this model, the amplitude of vibration in the failure frequency and its harmonics as the input of the network and RUL as the output are considered. Also, in (2012), Tian [10] fitted the Weibull function to the characteristics to prevent the impact of noise and disturbances on the training pattern and considered the result as the input of the neural network. In another study in (2010), Saon et al. [11] used the time feature to simulate the health phase and the RMS and Kurtosis features for the failure phase in their model. In (2013), Chen et al. [12] provided relative features for solving the problem of insufficient data of condition monitoring. Zhang et al. [13] used the Self Organising Neural Network to evaluate the trend of several variables and estimated the RUL of a rolling bearing system. Wang et al. [14] compared the results of using the RNN with neural-fuzzy systems in estimating fault damage. In another study, Behzad et al. [15-16] used high-frequency vibration amplitude in the frequency spectrum as a feature to predict the RUL using a feedforward neural network and showed that the use of this feature, compared to using the vibrations level as the input of the model, will improve the accuracy of predicting the RUL. Also, Gebraeel et al. [17] estimated the RUL of rolling bearings assuming the growth of the RMS acceleration signal in the form of an exponential function and using a neural network. In this paper, predicting the RUL of rolling bearings using RNN and assuming the RMS growth of acceleration signal in the form of an exponential function and extracting two statistical parameters from it has been studied. It has been shown that the use of these two features and the RNN increase the accuracy of predicting the RUL.

## 2 Experimental data

An experimental platform was performed by the FEMTO Laboratory to do accelerated life test on the rolling element bearing, which was presented in (2012) at the IEEE PHM international conference on the prediction of failure and health management of equipment to develop methods of failure prediction in bearings. Then, 17 accelerated life tests on the rolling element bearing were performed on this platform and the test data included vibration measurement in the horizontal and vertical directions throughout the bearing life period, named Prognostia, were available to the researchers [18]. In this test, an electric motor with a power of 250W and a speed of 2830rpm was used as a shaft rotation supplier. The engine speed was reduced by a gearbox to less than 2000 rpm. Two accelerometer sensors were used to measure vibrations in horizontal and vertical directions with a 90-degree angle relative to each other on the bearing shell. In experiments, reaching the vibration amplitude to 20g is considered as the threshold of rolling element bearing failure and test stop criterion. Characteristics of the working conditions and the number of tests are given in Table (1). In Figure (1), the test image and its different sections are shown.

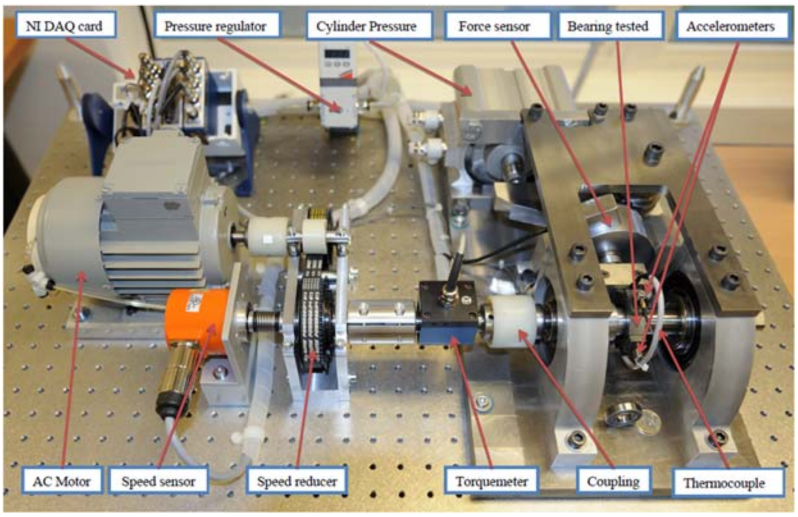


**Figure 1** Overview of PRONOSTIA[18]

**Table 1** Characteristics of Pronostia test[18]

| Number of tests | Load(N) | Speed (rpm) | Working condition |
|---|---|---|---|
| 7 | 4000 | 1800 | 1 |
| 7 | 4200 | 1650 | 2 |
| 3 | 5000 | 1500 | 3 |

Used data in this article is from the PRONOSTIA test. In this paper, only four bearing data is used which is in the first working condition as shown in Table (1). The sampling frequency of the accelerometer sensor was 25.6 kHz. The defects in rolling element bearings generally do not occur in a short time and usually begin to grow during a random time. This process can be observed with the help of changes that occur in the vibration signal. To estimate the life of the rolling element bearing, a feature needs that can accurately reflect the defect occurrence process until the bearing degradation condition. Time is an ascending feature, but it is not a function of bearing degradation. The temperature and RMS of the signal are important and common features in the data-driven method in the time domain, which also indicate bearing defect. In many cases, these features are appropriate tools for tracking the degradation trend. In this paper, the data of the four bearings published in the Progenostia experiment have been used.
Figure (2) and Figure (3) show the RMS and temperature of these four bearings, respectively.

## 3 Algorithm for extraction of two statistical parameters from RMS acceleration signal

As shown in Figure (2), the RMS of the acceleration signal features charts has two parts, the first part of the charts is a straight and approximately fixed value that is related to the time that there isn’t any defect in rolling element bearing, in the second part RMS is rising and almost an exponential function that is related to the time that there is a defect in rolling element bearing and growing. This is shown in Figure (4). Also in Figure (3), temperature variations from the start of testing to the failure time of rolling element bearing, are shown. In the first step, the first part of the chart, which is a constant value, is filtered, and in the second step, on the second part of the chart, from the moment of the start of growth of the graph to every prediction moment, an exponential function is fitted. An example of that at $t_k$ time is shown in Figure (5).

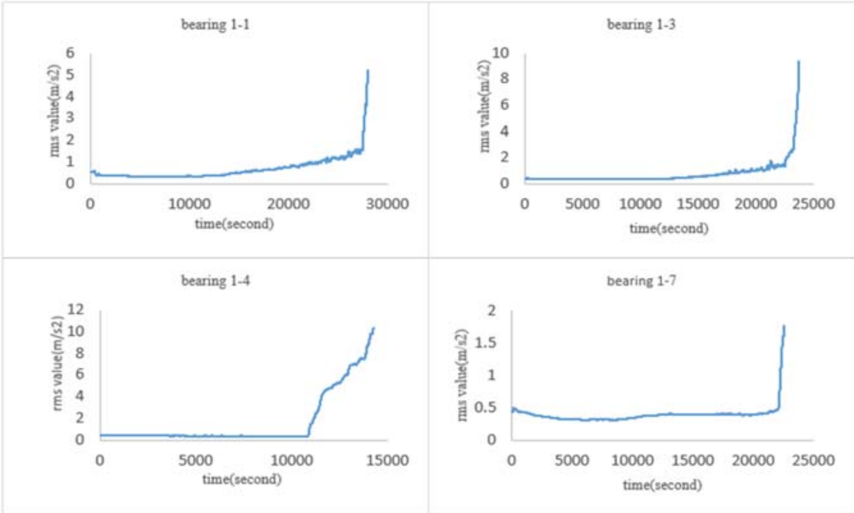


**Figure 2** RMS of the acceleration signal for four bearings in the first working condition[18]

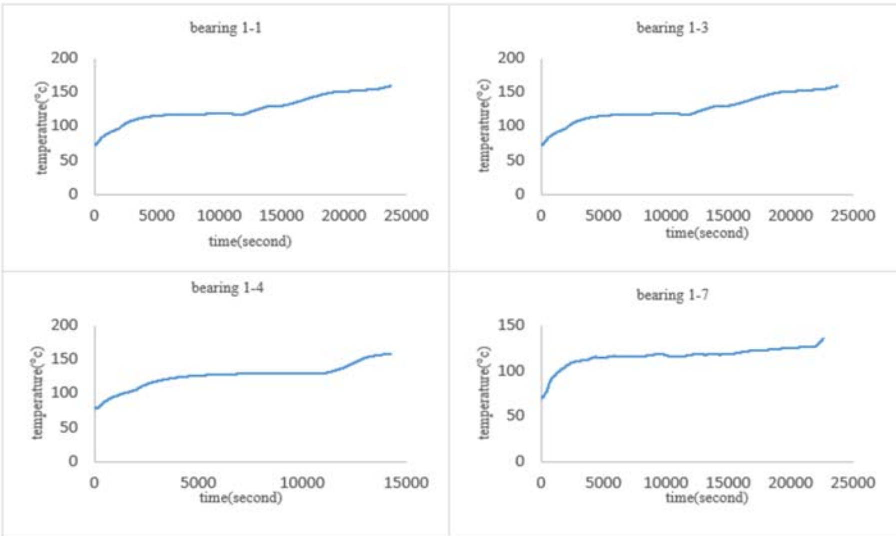


**Figure 3** Temperature of four bearings in the first working condition[18]

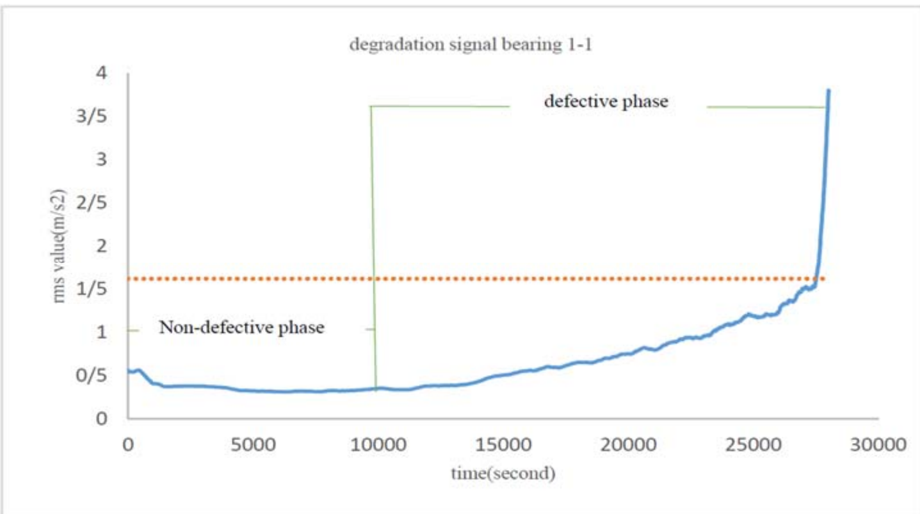


**Figure 4** Division of the RMS of the acceleration signal area for the first bearing[18]

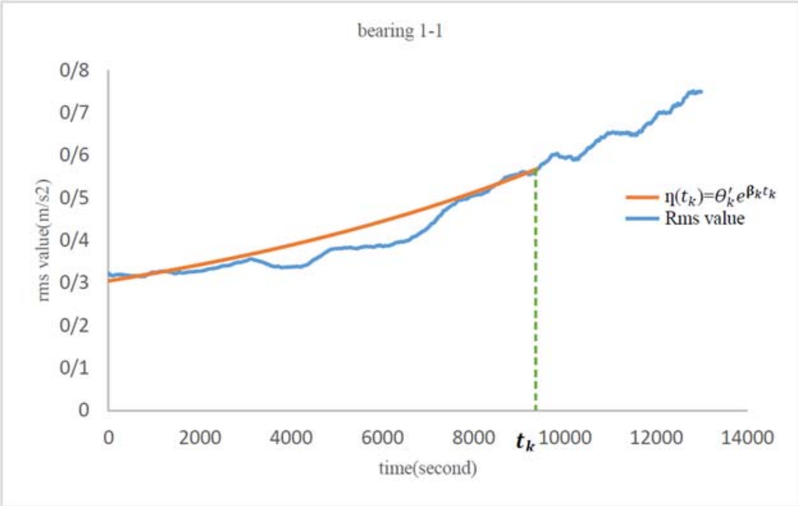


**Figure 5** Fitting an exponential function on RMS of the acceleration signal at prediction moment

In the third part, the logarithm is taken from exponential function and it is converted into a linear function according to Equation (1). As it was seen, the two statistical parameters θ and β have been extracted as a feature for following the degradation trend of rolling element bearings. In Figure (6), the values of the θ and β are displayed after the signal filtering for a bearing sample. In Figure (7), also the value of the temperature and ln(RMS) features are displayed after filtering the signal for a bearing sample.

$$\ln(\eta(t_k)) = \ln(\theta'_k) + \ln(e^{\beta_k t_k}) = \theta_k + \beta_k t_k \tag{1}$$

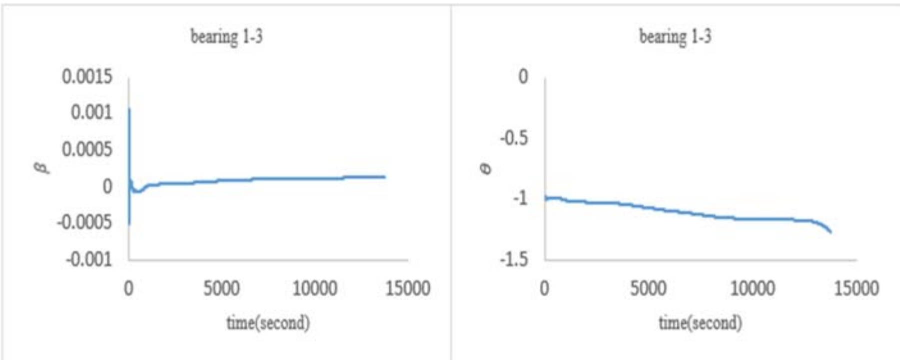


**Figure 6** Display of θ and β for third bearing

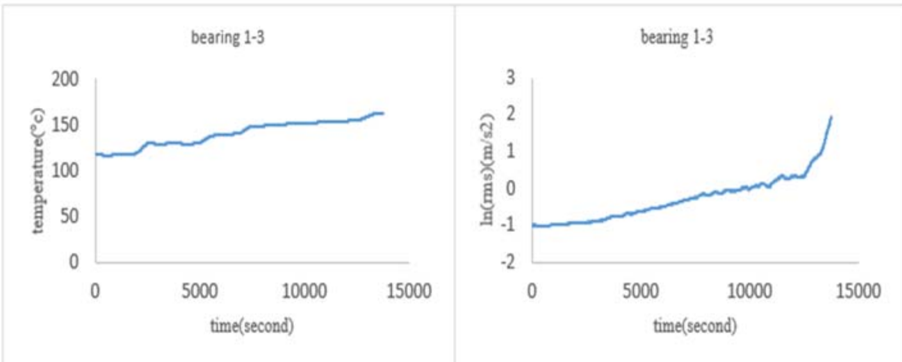


**Figure 7** Display the temperature and ln(RMS) features for third bearing after filtering the first part

## 4 Prediction by Neural Network

The neural network method is a structure inspired by the nervous system and the function of neurons in the nervous system of living organisms that can learn the connection between inputs and outputs and can model complex connections between inputs and outputs of a system. The neural network used in this paper is a RNN. A neural network may consist of several layers and in each layer, some neurons and bias. The neural network considered in this paper consists of one layer and six neurons. Also, the output of the last layer uses a nonlinear function(for example, a Sigmoid Function). After being multiplied by the weight coefficients, the inputs are applied to all the neurons of the first layer, and the output of each neuron in the first layer is inserted to the neurons of the next layer by applying the weight coefficients. In the neural network training process, the main purpose is to determine the weight coefficients of the neurons and the bias values of each layer, so that the connection between output and input is well established in the data used in the training. More layers and neurons in each layer make the neural network more complex. However, it should be noted that the structure of the neural network should be selected according to the desired problem, and complicating the structure of the neural network will not necessarily lead to better performance of the neural network.

In the neural network training phase, the training data are divided into three groups, which include training data, validation data, and test data. Dividing the data into these three groups was also done randomly. Training data is used to calculate the output and correct weights.

However, validation data is used only to evaluate the quality of training at each stage, and the criterion for stopping the training algorithm is based on network performance error on validation data at each stage of weight correction. Test data plays no role in the training process, and test data is used to observe the quality of the final network only after the training has been completed and the training algorithm has been stopped. Usually, in the classification of data, the portion of training data is more, but it should be noted that the validation and test data should be sufficient. To train this neural network, the Levenberg-Marquardt algorithm was used, which is based on correcting the weight coefficients after the output calculation step and comparing the output error to the desired output. The neural network used in this paper is a RNN, that the inputs of the system are temperature and statistical parameters $\theta$ and $\beta$, and the output of the system is the RMS of the acceleration signal. Seven nodes and one layer are used in this RNN. Also, given that the temperature value is a function of time, rpm and load, the temperature function approximately obtained. To estimate the life, first, the network is trained with three bearing data, and then for the test bearings, this is done in this way that after a while from the start of the bearing work, the values of $\theta$ and $\beta$ are given to the network as constant values.

The temperature of the test bearing obtained from its function, which is increasing over time. These inputs are given to the network until the RMS of acceleration signal reaches the failure threshold value, and then the network is stopped, and with the help of this stop criterion, the RUL of the bearing is obtained. The model of the RNN used in the paper is shown in Figure (8). According to Lei et al. [6] in (2018), which categorized several articles published in the last twenty years, they reported a 20 to 50 percent error in all of these articles. Due to the random dynamics of the process of failure of bearing bearings, they have considered this amount of error appropriate. Also, although the error in the prediction made by the model may seem high, it should be noted that the performance of the model is much better than a feedforward neural network model and using only the RMS feature, and this model has been able to express prediction values more logically. It is important to note that prediction using the proposed method does not necessarily lead to a life prediction of more or less than the actual value, and this depends more on the data used in the training and prediction. It should be noted that the only error criterion should not be considered as a suitable prediction and acceptable prediction of the model, Rather, the prediction behavior of the model should be justified based on the similarity of behavior between the training data and the test. For example, the prediction of the first bearing by the other three bearings when the model has the maximum error value is shown in Figure (9). As shown in Figure (9), the proposed neural network has been able to predict the RMS of the acceleration signal, with some error and with the help of that, the RUL of rolling element bearing is estimated. Error values for all test bearings are given in Table (1). The error is calculated according to Equation (2). Since the neural network-based model has uncertainty due to the random initial selection of weight coefficients and twice training with the same conditions and data will never lead to a specific model, in this article the training and prediction process are repeated ten times. Table (2) shows the maximum and minimum error values for different bearings.

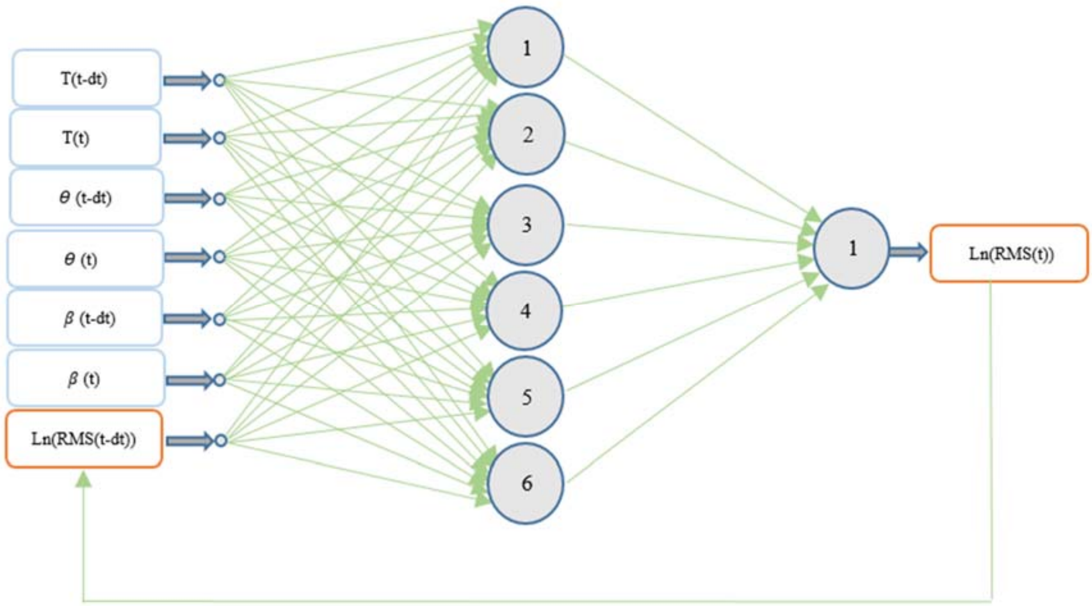


**Figure 8** Display of RNN model

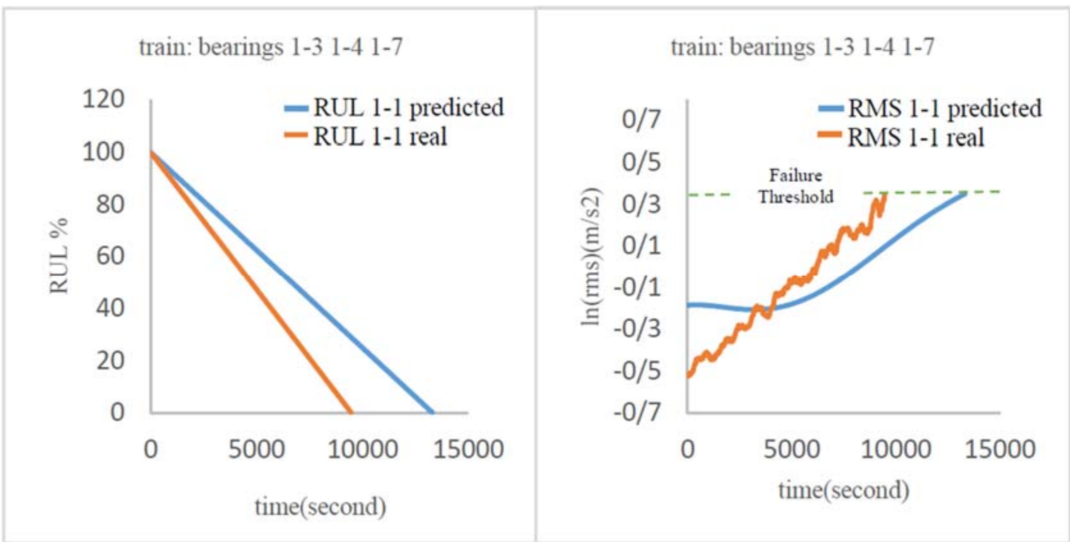


**Figure 9** Estimation of RMS of the acceleration signal and RUL of the first bearing

$$\mathrm{Error} = \frac{\mathrm{RUL}_{\mathrm{predicted}} - \mathrm{RUL}_{\mathrm{real}}}{\mathrm{RUL}_{\mathrm{real}}} \quad (2)$$

**Table 2** Error values of the experiments

| Minimum error value | Maximum error value | Training bearings | Test bearing number |
|---|---|---|---|
| 18.32 | 39.79 | 1-3 1-4 1-7 | 1 |
| 20.71 | 40.21 | 1-1 1-4 1-7 | 3 |
| 26.08 | 48.32 | 1-1 1-3 1-7 | 4 |
| 24.62 | 47.21 | 1-1 1-3 1-4 | 7 |
| 22.43 | 43.88 | Average of error(%) | |

## 5 Conclusion

In this paper, new features are introduced to determine the failure growth trend and with the help of the RNN, the RUL of rolling element bearings was predicted. The statistical parameters θ and β, as well as the temperature feature, show the growth of failure from the early stages, which also has uniform behavior. The results presented in the proposed method, with the consideration of the temperature feature instead of the time feature, as well as the assumption of the growth of the RMS of acceleration signal into the exponential function form, have made the intended model more applicable than previous models.

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