

Developing the CNN-LSTM model for reliability prediction of repairable systems

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Abstract

The machines used by humans are becoming more and more complex and intelligent, and the environments in which machines are used are more diverse. Reliability prediction has become a very challenging research topic, attracting more and more interested researchers. Many products are repairable systems, such as vehicles, boats, and aircraft. Deep learning is the latest artificial intelligence technology. Long short-term memory (LSTM) and CNN-LSTM models among neural network models can be used to predict temporal data. Based above, this study proposes the LSTM and CNN-LSTM models for reliability prediction of repairable products. Both academia and industry can benefit from this research.

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Introduction

Products can be classified into two fundamental types: non-repairable systems and repairable systems [1]. For non-repairable systems, if the product fails during operation, the entire product must be replaced during repair to restore product performance. For repairable systems, if the product fails to perform its function properly while in operation, repair can restore the product's performance without replacing the whole

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product. Product reliability is an important topic in diverse fields of industrial engineering and management as it is associated with quality and allocation cost of products. The purpose of this study is to discuss the issue of reliability for repairable systems. Generally, a repairable system is deteriorating if the time between failures get shorter with advancing time. Conversely, the system is improving if the time between failures get longer. The reliability in a system may be influenced by numerous factors such as improvement or deterioration of the environment, strategy and resources. In fact, the reliability would change over time.

Recently, many studies have discussed the problems of repairable systems, such as [2].

Reliability prediction models for repairable products can be categorized into two means. The preceding means is to choose an appropriate mathematical or statistical reliability prediction model ahead of time for predicting future reliability.

Time series analysis is the second method. Time series analysis is suitable for analyzing the reliability of repairable systems [1]. The method can be used to build a model that characterizes the change of faults over time, and then analyze the failure data of repairable systems. Among deep learning models, the long short-term memory (LSTM) model [3] can be used for reliability prediction because it can handle time series data. LSTM belongs to a relatively new class of recurrent neural networks (RNN). LSTM can be employed to solve the learning model of RNN, which makes it generate favorable results in miscellaneous tasks such as forecasting and constructing language models [4].

The CNN-LSTM model integrates the CNN model with the LSTM model and can solve many problems, such as demonstrating exceptional classification accuracy [5] and obtaining more accurate predictions in many studies, such as [4].

Based above, this paper proposes the LSTM and CNN-LSTM models to construct a reliability prediction model of repairable systems.

Literature overview

The literature on repairable systems mainly focuses on failure time modeling, where point process theory is the main tool. Non-homogeneous poisson process (NHPP), homogeneous poisson process (HPP) and renewal process (RP) are frequently employed models of failure processes for repairable systems [6]. Among three processes, NHPP is

used most frequently and widely because NHPP does not assume that the time between repairs follows independent, identically distributed.

Traditional time series analysis includes regression, exponential smoothing, moving average, time series decomposition and ARIMA methods. Some of them, such as exponential smoothing [7], moving average [8], time series decomposition [9] and ARIMA methods [10], have been employed for repairable systems.

In addition, artificial intelligence neural networks can be employed for reliability prediction [11] because they can be used for time series prediction. Neural networks are non-parameter models. The advantages of neural networks are capable of analyzing complex variables, have high tolerance for uncertainty, and instantaneously offering predicted variable patterns. The disadvantage of neural networks is that to obtain good data quality, a large amount of data is required, but this data is not easy to obtain at an affordable cost, and some are even very expensive [11].

Following the advancement of artificial neural networks, researchers discover that deep learning methods, especially Among many types of neural networks, RNNs are more suitable for processing complex time series than feedforward neural networks. However, RNNs have the disadvantage of gradient vanishing during training. LSTM networks [12] solve this weakness of traditional RNNs.

LSTM uses gating modules and loop mechanisms to process message sequences. Based on the above architecture, LSTM detects and learns complex sequence dynamics and produces lower prediction errors.

In LSTM model, for time $t=1, \dots, T$, input data, hidden layer units, and output data are separately represented by $X = (x_1, x_2, \dots, x_T)$, $H = (h_1, h_2, \dots, h_T)$, and $Y = (y_1, y_2, \dots, y_T)$:

$$h_t = H(W_{hy}x_t + W_{hh}h_{t-1} + b_h), \quad (1)$$

$$y_t = W_{hy}h_t + b_y, \quad (2)$$

For time $t = 1, \dots, T$, $f_t, \sigma_g, \sigma_c, \sigma_h$ activation function, t, f, o, c separately represents the activation vector of input gate, forget gate, output gate, memory cell, W weight matrix :

$$i_t = \sigma_g(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i), \quad (3)$$

$$f_t = \sigma_g(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f), \quad (4)$$

$$c_t = f_t * c_{t-1} + i_t * \sigma_c(W_{xc}x_t + W_{hc}h_{t-1} + b_c), \quad (5)$$

$$o_t = \sigma_g(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_{t-1} + b_o), \quad (6)$$

$$h_t = o_t * \sigma_h(c_t), \quad (7)$$

Figure 1 illustrates LSTM.

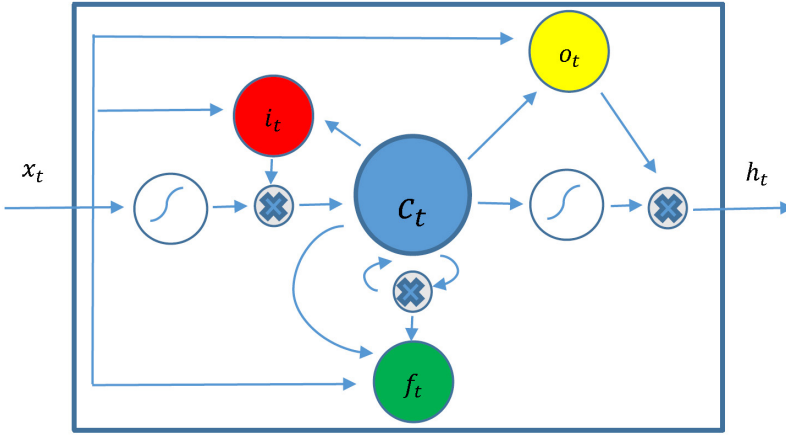


Figure 1
LSTM

Lecun *et al.* [13] proposed the CNN model. CNN is a feed-forward neural network in which neurons can make a response to adjacent units in a partial coverage region. CNN has good performance in speech recognition and image processing, and is gradually expanding its application to other fields. The inspiration of the convolutional neural network comes from the neural connection mode of the visual cortex of animals. A single neuron only responds to stimuli in a limited area, and the perception areas of different neurons overlap to cover the entire field of vision. CNN consists of convolutional layers and pooling layers, and each convolutional layer contains multiple convolution kernels. After the convolution operation, the convolution layer extracts the characteristics of the data, but the feature dimension after extraction is still very high. Therefore, in order to overcome this problem, a pooling layer is added after the convolution to reduce the feature dimension, thereby reducing the cost of training the network.

The CNN-LSTM model combines the features of CNN and LSTM. The CNN network can extract useful knowledge and learn the features of time series data, while the LSTM network can make effective predictions. The CNN-LSTM mainly consists of two parts: the first part consists of convolutional layers and pooling layers, which are used to establish the features of the input data; the second part uses LSTM to make predictions. It is worth noting that since the pooling layer will reduce the data size too quickly, the current trend in the study is to adopt smaller pooling filters or even no pooling layers [14]. Figure 2 illustrates CNN-LSTM.

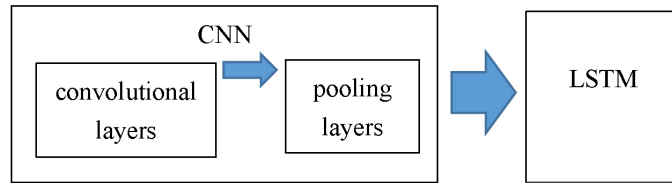


Figure 2
CNN-LSTM

Research Method

This work proposed the LSTM and CNN-LSTM approaches for reliability prediction of repairable systems. The following is a description of the analytical steps:

Step 1: Collect the data of repairable systems.
Collect the required on-site fault data.

Step 2: Using the LSTM and CNN-LSTM models for forecasting.

Two-thirds of the failure data are employed to train the proposed models, and the remaining one-third are employed for testing the proposed models. Analysis and prediction using the proposed models. MAE and RMSE forecast error evaluation indicators are used to evaluate the forecast performance.

Results

This study selected 36 months of electronic equipment failure data (including the number of test samples and repairs per month) provided by Chrysler Corporation suppliers in Wang's study [15] as the experiment data to verify the proposed model. Using the graphical method [16] to

calculate the mean number of repairs. Figure 3 illustrates the calculating results.

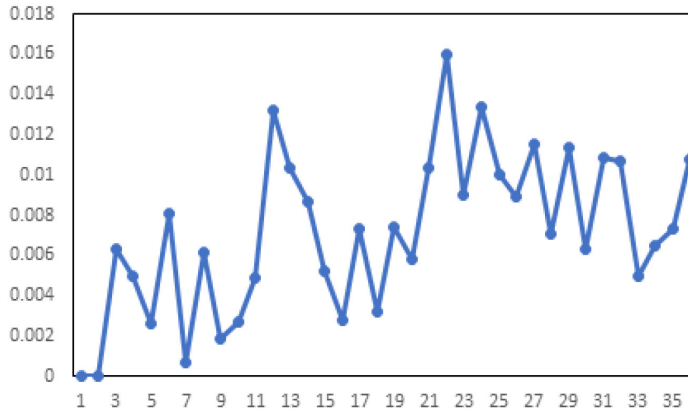


Figure 3

The calculating results.

This study completed the LSTM and CNN-LSTM model development and model evaluation under the Google Colab framework.

The first 24 months of the mean number of repairs T were selected for training, and the remaining 12 months for testing. Table 1 illustrates the results of the proposed models.

Table 1

Employ the proposed models for reliability prediction.

Month	LSTM	CNN-LSTM
25	0.00816634	0.00967104
26	0.00705403	0.00822655
27	0.00671171	0.00776392
28	0.00753480	0.00886112
29	0.00617066	0.00701182
30	0.00750226	0.00881868
31	0.00593795	0.00667952
32	0.00734058	0.00860678
33	0.00727641	0.00852215

Contd...

34	0.00557015	0.00614210
35	0.00599567	0.00676248
36	0.00622959	0.00709508
MAE	0.00272055	0.00231270
RMSE	0.00319464	0.00275669

This study also uses the prediction results of the regression method in traditional time series analysis methods to compare the prediction results of the methods proposed in this study. Table 2 lists the comparing results. The CNN-LSTM model outperforms the LSTM model and the regression method from the results. Table 2 lists the comparing results.

Table 2
The comparing results.

	LSTM	CNN-LSTM	regression
MAE	0.00272055	0.00231270	0.00483479
RMSE	0.00319464	0.00275669	0.00563524

Conclusions

In an era where machines are becoming more and more complex, reliability prediction has become a very challenging research field, and its research results have also attracted a lot of attention from the industry.

This study aims to evaluate the application of artificial intelligence deep learning technologies in the analysis and prediction of repairable system failure data, and to construct a reliability prediction model of repairable systems using the proposed models. The results are compared with the regression method and evaluated through the prediction error index. The results show that the CNN-LSTM model performed best among the three models. Adding the CNN model into the LSTM model can decrease the prediction error, which is of great significance for the adoption of deep learning in the field of reliability.

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