Performance Prediction of Marine Diesel Engine Based on Long Short-Term Memory Network

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Abstract. Performance prediction is one of the core technologies for the health management of the marine diesel engine. To predict the overall performance of diesel engine, a prediction method combining Mahalanobis Distance (MD) and Long Short-Term Memory (LSTM) neural network is put forward. The MD is used to measure the degree of performance degradation of the diesel engine. The Performance Index (PI) is proposed to normalize the MDs at different time into PI sequence that describe the performance degradation process of diesel engine. The three-layer LSTM network is established. The one-step method and the multi-step method are used to predict the PI sequence respectively so as to achieve the trend prediction of the overall performance of the diesel engine. The method is verified by the performance data of the MAN B&W 6S35ME-B9 marine diesel engine. The results show that this method can be used for short-term fluctuation prediction and long-term trend prediction of diesel engine performance.

1. Introduction
The intelligent ship has put more requirements on the health management for the marine diesel engine, from monitoring the current state to predicting the future state, and from passive reactive maintenance to condition-based maintenance [1, 2]. It is essential for the health management of marine diesel engine to predict the performance trend. By predicting the performance of marine diesel engine, it is probable to prevent the occurrence of diesel engine failures, reduce downtime, save shipping costs, and ensure the continuous and stable navigation of ships.

Because of its simple and efficient characteristics, the intelligent prediction method is widely used in prediction problems [3]. The most typical representative is artificial neural network. Yusuf et al. [4] established a three-layer back-propagation network to predict fuel consumption rate, effective power, exhaust temperature and average effective pressure. By comparing with the experimental data, it was confirmed that the neural network model can be used to predict the performance of engine. Farag et al. [5] proposed a combined model that employed Artificial Neural Network and Multi-regression model to predict the ship’s fuel consumption at sea and validated its ability in real-time ship environment. However, traditional neural networks have certain limitations in dealing with long-term prediction.

The performance degradation of diesel engine is a long-term gradual process with a cumulative effect of time. Long Short-term Memory (LSTM) network is a kind of deep learning neural network. Due to its special design of gating unit and memory module, LSTM network has the function of long-term memory, by which the long-term dependence of traditional neural network is solved and “gradient disappearance” and “gradient explosion” phenomena during training is avoided [6, 7]. The
Mahalanobis Distance (MD) is used to measure the degree of performance degradation deviating from its shop test performance. The Performance Index (PI) is proposed to normalize the degree of performance degradation at different time. A three-layer LSTM network is established to predict the PI sequence.

2. Mahalanobis Distance and Performance Index

The performance of the diesel is observed by many parameters monitored in real time. The performance difference among different time points has to be measured by a certain method. Mahalanobis distance (MD) is a covariance distance proposed by Mahalanobis, an Indian statistician [8]. It is independent of data dimension and is often used to measure the similarity of different samples.

2.1. Mahalanobis Distance

The MD from observation sample y to the sample set X in Ref. [9] is calculated by equation (1).

\[ MD = \sqrt{(y - \bar{x})\Sigma^{-1}(y - \bar{x})^T} \]  

where, \(\bar{x}\) and \(\Sigma\) are the mean value and covariance matrix of X.

The observation sample consists of a set of performance parameters at a certain time. The shop test data of the diesel engine were used as its initial performance sample point. The degree of performance degradation of the diesel engine is measured by calculating MD between the observation sample at different times and its initial performance sample. The larger the MD is, the more severe the performance degradation of the diesel engine is.

2.2. Performance Index

In order to clearly show the performance degradation process of the diesel engine, the PI is proposed in conjunction with the hyperbolic tangent function, which normalizes the MD to the range of (0,1]. The definition of PI is as follows.

\[ PI = 1 - \alpha \tanh (MD) \]  

where, tanh is the hyperbolic tangent function while the value range is (-1, 1); \(\alpha\) is an adjustment factor.

Since MD\(\geq0\), 0\(\leq\tanh (MD)\)<1, then 0\(<PI\)<1. It’s assumed that the PI is equal to 1 when the diesel engine is first put into use in the factory. The performance at different time points is represented by the corresponding PI, and the performance trend of diesel engine is converted into the PI sequence prediction.

3. LSTM Network Model

The text of your paper should be formatted as follows: The LSTM network is a special RNN proposed by Hochreiter [10]. The LSTM neurons are specially designed to store and transfer long-term and short-term memories. So, the long-term dependence of traditional RNN is overcome. The LSTM neuron contains one or more memory cells and three gate units: forget gate, input gate and output gate. LSTM overcomes the disadvantage of traditional RNN and is more suitable for long-term sequence prediction.

The sequence prediction method mainly includes one-step method and multi-step method. One-step method has the characteristics of high prediction accuracy, which is conducive to the observation of short-term performance fluctuations. Multi-step method is more advantageous in predicting the long-term change trend of performance, so it has high practical value in early warning and decision-making.
Assuming that the $PI$ at time $t$ is $P_{I_{t}}$ and the trained LSTM network is represented by $f_{\text{lstm}}$. So, the LSTM prediction model is expressed as follows:

$$\bar{P}_{I_{t+h}} = \begin{cases} 
    f_{\text{lstm}}(P_{I_{t}}, P_{I_{t-1}}, \cdots, P_{I_{t-m+1}}), & h = 1 \\
    f_{\text{lstm}}(\bar{P}_{I_{t+h-1}}, \cdots, \bar{P}_{I_{t+1}}, P_{I_{t}}, \cdots, P_{I_{t-m+1}}), & 2 \leq h \leq m \\
    f_{\text{lstm}}(\bar{P}_{I_{t+h-1}}, \bar{P}_{I_{t+h-2}}, \cdots, \bar{P}_{I_{t+h-m}}), & h > m 
\end{cases} \quad (5)$$

where, $h$ is the predicted time step; $m$ is the historical time step.

When the one-step method is used to predict the $PI$ sequence ($h = 1$), the performance indicators of $m$ historical time steps ($P_{I_{t}}, P_{I_{t-1}}, \cdots, P_{I_{t-m+1}}$) are used as the input of the LSTM network, and the output of network is the predicted value of the next time step ($\bar{P}_{I_{t+1}}$). When the multi-step method is used to predict the $PI$ sequence ($2 \leq h \leq m$ or $h > m$), the predicted value of the next $h$ steps ($\bar{P}_{I_{t+1}}, \bar{P}_{I_{t+2}}, \cdots, \bar{P}_{I_{t+h}}$) is predicted through $h$ iterations.

4. Case Study

4.1. Data Source

The data comes from the MAN B&W 6S35ME-B9 marine two-stroke diesel engine. The sampling interval is 1 min and the total number of samples is 1047. The main technical parameters of the diesel engine are shown in table 1.

| Technical parameters | Parameter values |
|----------------------|------------------|
| Number of cylinders  | 6                |
| Stroke (m)           | 1.5              |
| Bore (m)             | 0.35             |
| Rated power (kW)     | 3570             |
| Rated speed (r/min)  | 142              |
| Maximum combustion pressure (MPa) | 18              |

4.2. Process of Performance Prediction

The performance prediction process of diesel engine is shown in figure 1. At first, 20 parameters are chosen to describe the overall performance of the diesel engine, including engine speed, engine power, exhaust temperature of 6 cylinders, jacket cooling water temperature of 6 cylinders, exhaust manifold temperature, scavenging air pressure, scavenging air temperature, lubricating oil outlet temperature, lubricating oil inlet temperature, and non-uniformity of exhaust temperature of 6 cylinders.

Because of the limitation of the test bench, tests are only made at 50% rated load of the engine. The cropped 1009 samples constitute the sample set $X_{s}$. The 100 sets of the shop test data under the 50% rated power are used as the initial performance sample space. The 1009 samples in the sample set $X_{s}$ with the same time interval are used as observation samples. Then, the $MD$ between the observation sample at different times and the initial performance space could be calculated by equation (1). As can be seen from figure 2, with the increase of operation time, the $MD$ gradually increases and shows an overall upward trend. When the sample number is 0, the $MD$ is $5.29 \times 10^{5}$, which shows that the performance of the diesel engine has deviated from the initial performance at this time. After working for a period of time, the overall performance of the diesel engine gradually deviates from the initial performance.

According to the initial space, it is determined that the $\alpha$ value is equal to 1.2, and the $MD$ at different times is normalized to $PI$ by equation (2). It can be seen from figure 3 that the longer the running time of the diesel engine is, the closer the $PI$ value to 0, and the overall trend is a gradual downward trend that conforms to the general performance degradation law of diesel engine.
Therefore, the PI calculated based on the 20 parameters can intuitively reflect the performance degradation of the diesel engine.

**Figure 1.** Performance prediction process of diesel engine.

- Determine performance parameters
- Data preprocessing
- Calculate the MDs
- Calculate the PIs
- Build LSTM network model
- Predict the performance of diesel

**Figure 2.** MD curve.

**Figure 3.** PI curve.

A three-layer LSTM network is built by using MATLAB’s Deep Learning Box. The input of network is a series of sequences, the number of hidden layer neurons is 50, and the output of the network is a sequence with one-dimension. The default loss function is the mean square error.

In order to ensure that the predicted time step of the network is consistent with the actual time scale of the diesel engine, the PIs of consecutive same time intervals are formed into a PI sequence with a length of 1009 equal time steps. To facilitate the analysis of the prediction results, the first 80% of the
PI sequence is divided into 807 samples as the training set for model training and model parameter adjustment; the remaining 20% is made up of 202 samples as the model test set for model evaluation.

4.2.1. One-Step Prediction. The PI of the first 806 consecutive historical moments in the training set \((PI_{1}, PI_{2}, \ldots, PI_{806})\) are used as the input sequence of the LSTM network, and the one time step delayed PI sequence \((PI_{t-2}, PI_{t-3}, \ldots, PI_{t-807})\) as the target output sequence of the network. The network is trained 250 epochs. After 100 epochs, the MSE almost no longer reduces. After trained, the LSTM network was evaluated by the 202 samples from the test set. Each prediction uses the actual PI value of the previous time step as the network input to predict the PI value of the next time step. The one-step prediction curve is shown in figure 4. Comparing the error of the forecast and actual values, it is found that the one-step prediction accuracy of the LSTM network model is high. The error as a whole changed smoothly and stabilized within ±0.05, with RMSE=0.0166 and MAE=0.0128.

![Figure 4. One-step prediction of PI.](image)

4.2.2. Multi-step Prediction. The same network structure and training parameters as the one-step prediction are used to train the LSTM network and perform multi-step prediction. The PI prediction of 20, 40, 60, 80 and 100 steps are carried out through multiple iteration predictions respectively. Under the same prediction model, along with the number of time steps of iterative prediction increases, the prediction accuracy gradually decreases. When the number of consecutive prediction steps is less than 100 steps, both RMSE and MAE are within ±5%. Among them, the 60-step PI prediction curve is shown in figure 5. The fluctuation range of the error is from -0.08 to 0, and the overall trend of the forecast value and the actual value is consistent.

![Figure 5. 60-step prediction of PI.](image)
5. Conclusions
Footnotes should be avoided whenever possible. If required they should be used only for brief notes that do not fit conveniently into the text. Based on the monitoring data of the 20 parameters of the marine diesel engine, the MD between the performance at different time points and the initial performance is calculated. The PI is put forward by normalizing the MD. The three-layer LSTM network model is established to predict the performance of the diesel. And the one-step method and multi-steps method are applied to predict the PI sequence respectively. The results show that the prediction method can be used for short-term fluctuation prediction and long-term trend prediction of diesel engine performance. Moreover, it is found that the prediction error increases with the increase of prediction steps. When the predicted step is less than 100, the RMSE and MAE of the test set are within ±5%, and the predicted performance trend and the actual performance trend are basically the same.

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References
[1] Pagán Rubio J A, Vera-García F, Hernandez Grau J, Muñoz Cámara J and Albaladejo Hernandez D 2018 Marine diesel engine failure simulator based on thermodynamic model Appl. Therm. Eng. 144 982-995.
[2] Guan F, Cui W, Li L and Wu J 2020 Comprehensive evaluation method of sensor selection for PHM based on grey clustering Sensors 20 (6) 1710.
[3] Fink O, Wang Q, Svensén M, Dersin P, Lee W and Ducoffe M 2020 Potential, challenges and future directions for deep learning in prognostics and health management applications Eng. Appl. Artif. Intel. 92 103678.
[4] Çay Y, Çiček A, Kara F and Sağiroğlu S 2012 Prediction of engine performance for an alternative fuel using artificial neural network Appl. Therm. Eng. 37 217-225.
[5] Farag Y B A and Ölçer A I 2020 The development of a ship performance model in varying operating conditions based on ANN and regression techniques Ocean Eng. 198 106972.
[6] Schmidhuber J 2015 Deep learning in neural networks: An overview Neural Networks 61 85-117.
[7] Mirza A H, Kerpicci M and Kozat S S 2020 Efficient online learning with improved LSTM neural networks Digit. Signal Process. 102 102742.
[8] Shang J, Chen M and Zhang H 2018 Fault detection based on augmented kernel Mahalanobis distance for nonlinear dynamic processes Comput. Chem. Eng. 109 311-321.
[9] Pronzato L, Wynn H P and Zhigljavsky A A 2018 Simplicial variances, potentials and Mahalanobis distances J. Multivariate Anal. 168 276-289.
[10] Song X, Liu Y, Xue L, Wang J, Zhang J, Wang J, Jiang L and Cheng Z 2019 Time-series well performance prediction based on Long Short-Term Memory (LSTM) neural network model J. Petrol. Sci. Eng. 186 106682.