A neural network based method for sensitive frequency component analysis of cavitation fault

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Abstract. In General, the frequency feature of cavitation was obtained by comparing it with normal signal. However, when there were a large number of samples, it was difficult to analyse the sensitive features of cavitation fault effectively. So, a neural network based method for sensitive frequency component analysis of cavitation fault was proposed, and Empirical Mode Decomposition(EMD) method, Fourier Transform and neural network were used. Firstly, the raw vibration signal was decomposed to 5 Intrinsic Mode Function(IMF) components and the frequency spectrum of each component were computed. So, the dataset of raw signal was divided into 5 datasets which contained different frequency components. And a neural network was built, trained and tested by the different datasets. By comparing the diagnosis accuracy of the neural network, the sensitivity of different IMF was analysed. And it is verified that the method can effectively analyse the sensitive frequency components of cavitation faults, reduce the size of the neural network.

1. Introduction
Cavitation failure was commonly found in blade machine such as centrifugal pumps and hydraulic turbines. The erosion of cavitation could cause pitting or crack of impeller, more seriously, may break the vane, which led to increased vibration of equipment and sharp decline in operating efficiency. So, it is significant to diagnose the cavitation fault based on vibration in the state of operating. Luo Bing[1] et al. artificially divided the frequency spectrum of cavitation failure into different frequency bands, and analysed the change in each bands by comparing the data of different working conditions. But only a small number of samples were analysed in each condition, which will affect the reliability of the conclusions. Dong Shaojiang[2] et al. proposed a method for bearing fault diagnosis based on EMD and Support Vector Machine(SVM), and all the IMF components were used in diagnosis, which led to large model size and high computing resource consumption. In terms of the problem of large amount of samples, it was difficult to artificially compare the samples of different working conditions one by one, so a neural network based method was proposed to automatically analyse the sensitivity of different IMF components, and the accuracy of network diagnosis reflects the importance of the components. And the size of the neural network can be effectively reduced by eliminating redundant frequency components.

2. Method for Sensitive Frequency Component Analysis
The basic idea of this method was that the diagnosis accuracy of neural network trained by different frequency component is positively related to the sensitivity of the corresponding component. The higher the diagnosis accuracy, the more fault features are in the component, which is worth studying in depth.
Firstly, EMD method was used to decompose the raw signal of normal condition and cavitation fault. EMD is developed to decompose a signal into IMF components which were used to extract features, and these IMFs include different frequency components. Then, the each IMF data was transform to frequency spectrum by fourier transform. Finally, the dataset of frequency spectrum of different IMF was used to train the same neural network one by one. And the sensitivity of different frequency component can be found out. In the further, we can do more research on the most sensitive component and use this component to diagnose cavitation fault. The procedure was shown in Figure 1.

![Figure 1. Procedure for sensitive frequency component analysis](image)

### 3. Case study

#### 3.1. Simulation bench introduction
Experiments were performed on the water supply system fault simulation bench, the system adjusted the opening of the inlet butterfly valve to change the resistance of the suction pipeline, thereby changing the effective cavitation margin and causing cavitation in the centrifugal pump. The shaft rotating speed was obtained by an eddy current sensor, as shown in Figure 2.

#### 3.2. Dataset setup
The data was collected with a sampling frequency of 65536 Hz for 120 second in normal and cavitation condition. Each signal was split into 1920 samples, and the sample consists of 4096 data points. Finally, a dataset consisting of 3940 samples was obtained.

The vibration signal and its EMD decomposition were shown in Figure 3. All the 3940 samples were decomposed by EMD, and the signal consists of 5 IMF components and one residue. And the frequency spectrum of raw signal and 5 IMF components were calculated, the frequency range was 0–11200Hz, as shown in Figure 4. It can be seen that the 5 IMF components represent the characteristics in different frequency and time scales, and highlights the local features of the signal.
3.3. Empirical study and discussion

With the 5 datasets were prepared, the artificial neural network model can be trained and tested by each datasets. The input dimension of the model was equal to the dimension of sample. The two hidden layers in the networks have 10 and 10 neurons, respectively, and the output dimension is 2, which equals the number of conditions. And the loss function was defined by crossentropy.

The size of the mini-batch used in the training process was 32. In the SGD optimizer, the learning rate was 0.01, and the momentum was 0.2. The train loss and accuracy of each dataset were shown in Figure 5, Figure 6, Figure 7 and Figure 8. In which, the loss was mean value of all the samples loss, the accuracy was computed by the method Sparse Categorical Accuracy. The model was trained for 10 epochs.
In terms of train dataset, it can be seen that dataset of IMF3, IMF4 and IMF5 performed well in the process of training. And the IMF5 had the highest recognition rate, the accuracy of IMF3 and IMF4 were almost the same. And in the test, the IMF5 was still the best dataset for recognition. However, the IMF3 performed better than IMF4, which was different from the result of train dataset.

To verify the effectiveness of the diagnosis based on sensitive IMF components, the model trained by raw dataset was used for comparison with the model train by IMF5 dataset. The test loss and accuracy of the two model were shown in Figure 9 and Figure 10, which showed that the stable accuracy of diagnosis was almost the same, around 89%. But the raw dataset converged faster than IMF5.
In the training of the neural network, the higher accuracy, the better the model fitted the train data. In the testing, the higher accuracy, the better generalization capacity of the model. So, the model trained by IMF5 fitted the data best and had a relatively better generalization capacity. Finally, by comparing the test accuracy of raw dataset and IMF dataset in Figure 10, it showed that information in the IMF5 component is enough to provide sufficient effective features for the diagnosis of cavitation faults.

4. Conclusion
The signal of cavitation was analysed based on the method of EMD and neural network, the following conclusions were reached:

(1). In the condition of the bench, the fifth layer of IMF components after the decomposition based on EMD were more sensitive to cavitation faults, which can effectively diagnose cavitation faults. And the neural network model trained by IMF5 had the best generalization capacity.

(2). Through the comparison of recognition accuracy of the raw signal and sensitive component, it was verified that the proposed method can effectively analyse the sensitive frequency component of cavitation fault.

In the next step, the proposed method will be applied to the sensitive frequency component analysis of other faults, and further verify the effectiveness of the method.

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References
[1] Luo B., Liu D.X., Chen J. (2015) Study on Cavitation Vibration Characteristics of Centrifugal Pump. Hydropower and New Energy, 06: 36-40+44.
[2] Dong S.J., Sun D.H., Tang B.P. (2014) A Fault Diagnosis Method for Rotating Machinery Based on PCA and Morlet Kernel SVM. Mathematical Problems in Engineering, 2014: 1-8.
[3] Ding Y., Ma L., Ma J., Wang C., Lu C. (2019) A Generative Adversarial Network-Based Intelligent Fault Diagnosis Method for Rotating Machinery Under Small Sample Size Conditions. IEEE Access, 99.
[4] Jiang L.L., Yin H.K., Li X.J., Tang S.W. (2014) Fault Diagnosis of Rotating Machinery Based on Multisensor Information Fusion Using SVM and Time-Domain Features. Shock and Vibration, 2014: 1-8.
[5] Yuan J., Liu X.M. (2013) Semi-supervised learning and condition fusion for fault diagnosis. Mechanical Systems and Signal Processing, 38: 615-627.
[6] Dong S.J., Tang B.P., Zhang Y. (2012) A repeated single-channel mechanical signal blind separation method based on morphological filtering and singular value decomposition. Measurement, 45: 2052–2063.