PO.ID 064

Wind turbine drive train condition monitoring and fault classification based on improved BP neural network

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Abstract

Wind energy has attracted more and more interest due to its clean, non-pollution and renewable features. In order to reduce wind turbine operation and maintenance costs, this research introduces an improved Back Propagation (BP) neural network technique for wind turbine drive train condition monitoring, especially for fault classification.

In this approach, four types of fault signal, which are collected from main drive train components such as the main bearing, shaft, gearbox and generator, are used for fault classification. Firstly, in order to eliminate the effect of the difference of the orders of magnitudes, all the selected input signals are normalized. Secondly, to improve the BP neural network convergence efficiency and speed, improved learning algorithms are employed to train the proposed network. Thirdly, this paper introduces a new guideline to determine the hidden layer nodes.

The test results show that the proposed network has real potential for wind turbine condition monitoring and fault classification.

Objectives

The aim of this paper is to investigate the approach of signal fusion from different sensors, as well as feature extraction and fault classification from raw signals.

In the meantime, the structure design of the BP neural network with regard to the input layer nodes, hidden layer nodes and training method are also studied.

Moreover, by appropriate selection of the input features, the monitored wind turbine components' condition can be deduced in a timely manner.

Methods

A Back Propagation (BP) neural network is a multi-layered, feed forward network and is the most common neural network. Input signals propagate forwards through the network, and error signals propagate backwards. Weight adjustments are made to reduce error.

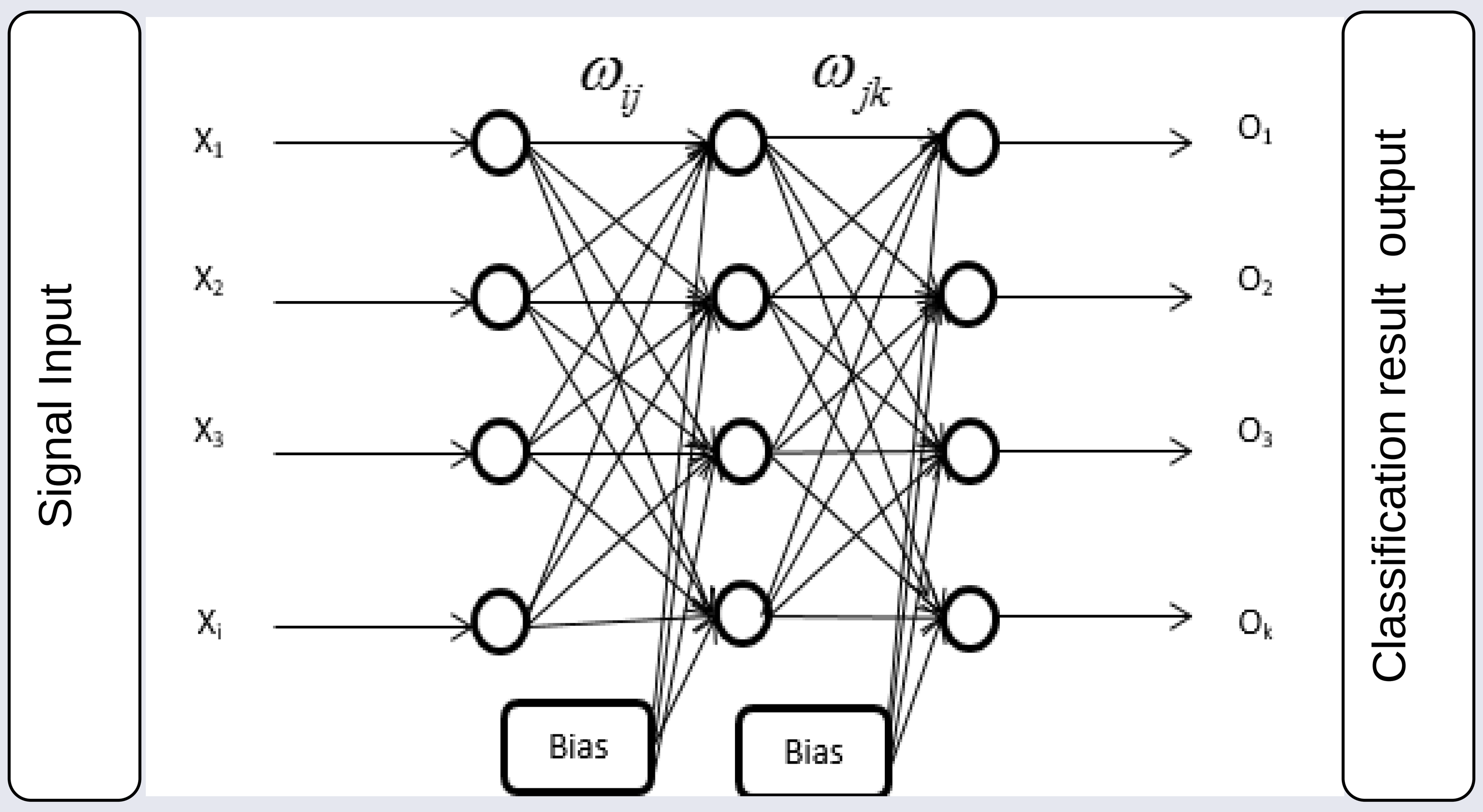

Figure 1: Back propagation neural network structure

Training the BP Network:

The BP neural network training process provides the BP neural network with an associative memory and predictive ability. The training process of the BP neural network is included in seven steps as follows (Figure 2):

Step 1: BP neural network initialization.

Step 2: Hidden layer output calculation.

Step 3: Output layer calculation.

Step 4: Error calculation.

Step 5: Connection weight update.

Step 6: Threshold value update.

Step 7: Has the iteration end condition been reached or not? If not, repeat from step 2.

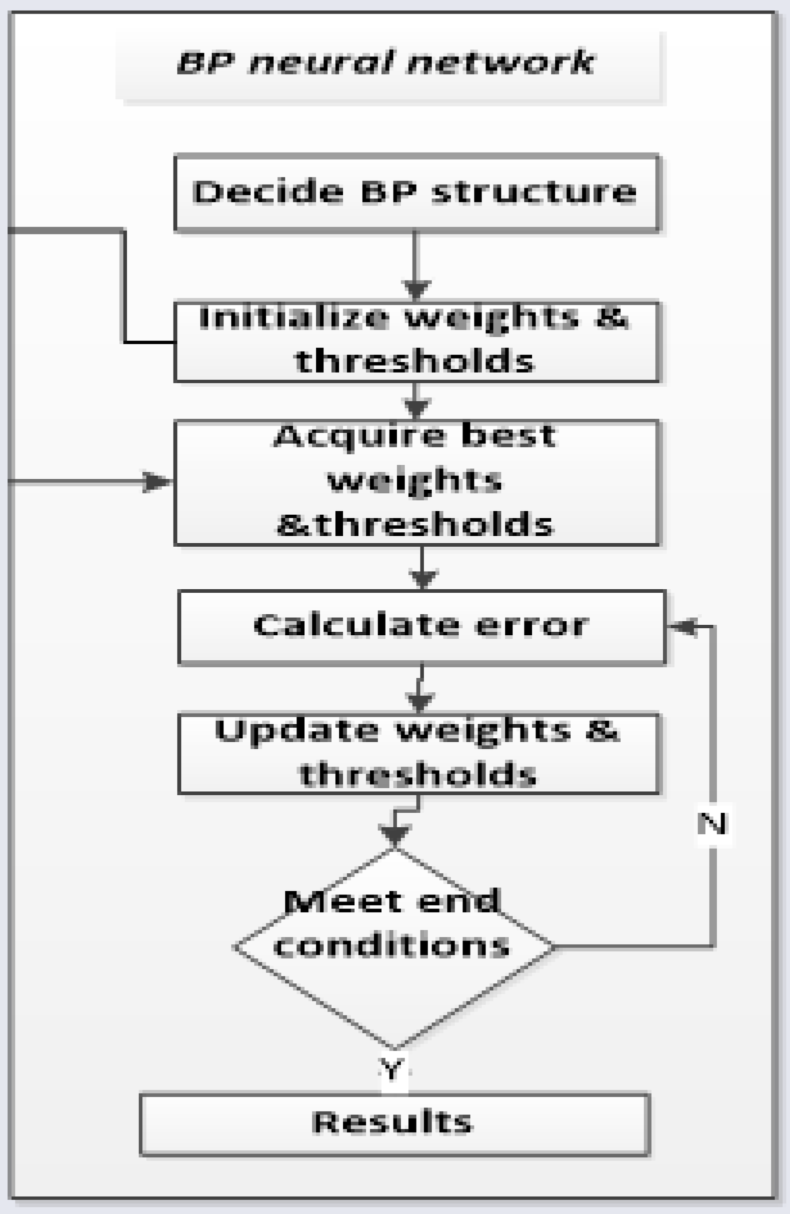

Figure 2: Flow chart of the BP training process

Results

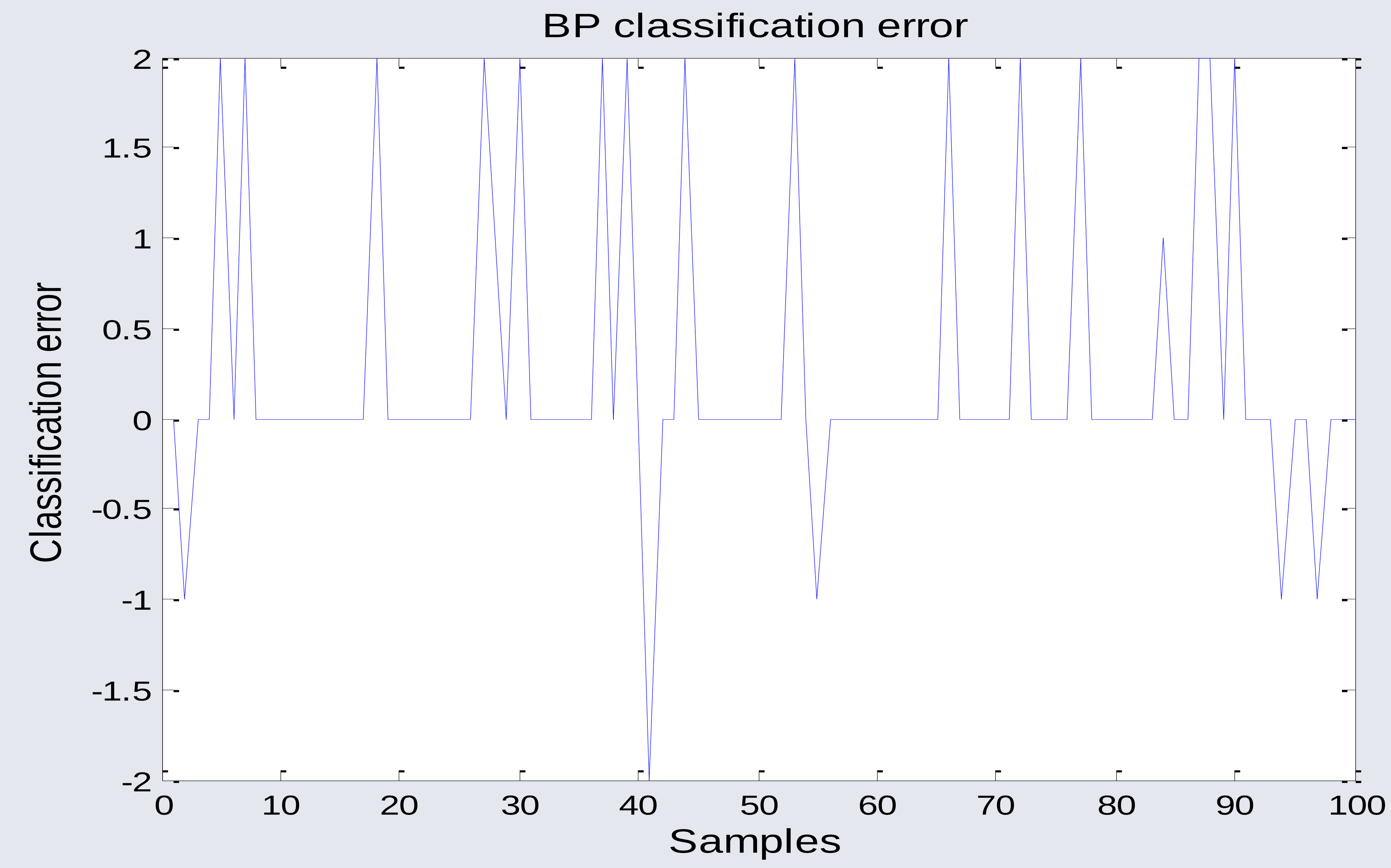

Figure 3: BP classification error result

Figure 3 presents the BP network classification error result. A total of 20 out of 100 test samples are wrongly classified by the BP network. This test result indicates that the BP neural network cannot be considered as an effective approach and improvement is needed.

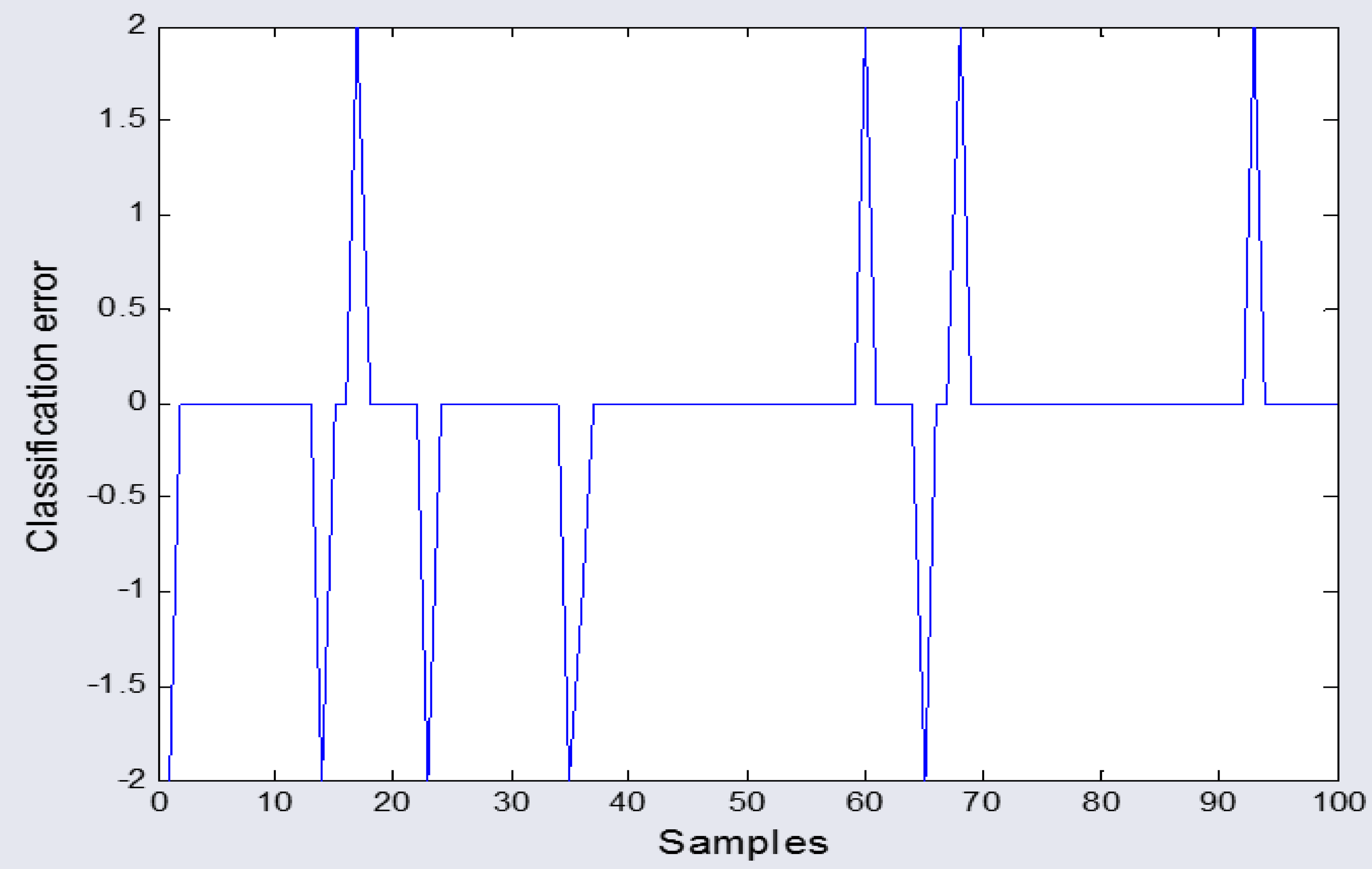

Figure 4: Improved BP network classification error

Figure 4 presents the improved BP network classification error result. Compared to Figure 3, 9 incorrect classification results out of 100 test samples can be seen. This is clearly a significant improvement.

Conclusions

It can be seen from the neural network classification results that the fault signal classification based on a normal BP neural network algorithm is able to identify the fault signal category with a certain level of accuracy. However, this classification result still falls short of the expected target and there are many aspects that need to be improved.

The proposed approach can significantly improve the performance of the BP neural network fault classification result.

References

1. O. Ondel, E. Boutleux and G. Clerc, A method to detect broken bars in induction machine using pattern recognition techniques, IEEE Transactions on Industry Applications, vol. 42, no. 4, pp. 916-923, 2006.
2. Yang Wenxian, Tavner PJ, Crabtree C, Feng Y, Qiu Y. Wind turbine condition monitoring: technical and commercial challenges. Wind Energy. 2012.
3. Yang Wenxian, Tavner PJ, Wilkinson M. Condition monitoring and fault diagnosis of a wind turbine synchronous generator drive train. IET Renewable Power Generation 2009;3(1) 1-11
4. Bearing data centre, http://csegroups.case.edu/bearingdatacenter/home. [accessed on 30.11.14].
5. Pu Shi, Zheng Chen, Yuriy Vagapov, Zoubir Zouaoui. A new diagnosis of broken rotor bar fault extent in three phase squirrel cage induction motor. Elsevier Mechanical Systems and Signal Processing, 2014;vol. 42, no.1-2, pp.388-403