Assembly Quality Diagnosis of Planetary Gear Sets

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ABSTRACT

Product quality is one of the most important factors to be considered in manufacturing industries. Autonomous production line rapidly increases its productivity; however, quality check becomes a difficult problem and a smart system for quality assurance is indispensable in the modern production line

In this study, we developed a transmission error based machine learning algorithm to check the quality of planetary gear assemblies and identify the defective parts in the planetary gear sets.

1. INTRODUCTION

In the modern era, most of manufacturing processes rely on automated systems. These systems have successfully increased the production speed and satisfied customers' demand. However, as production technology evolves, customers' requirements are also rapidly increased. One of the most important requirements is the quality of product. However, manually checking the quality of every manufactured product is time consuming and the accuracy is not always good. Therefore, a fast and accurate automatic diagnosis system is necessary to satisfy customers' and manufacturers' requirement.

In this study, we focus on the quality of planetary gear assembly of which faults results in noise or vibration and reducing product reliability. It was difficult to identify defective parts using traditional noise and vibration analyses. Moreover, it was virtually impossible to disassemble the planetary gear sets to identify those at the end of the manufacturing line. In this reason, we developed a diagnosis system of assembly quality of a planetary gear sets by checking transmission error of the gear sets and machine learning processes for the in situ diagnosis.

2. THEORY

2.1. Artificial Neural Network

The artificial neural network (ANN) is the one of the most popular method which has been a useful tool in classification (Dreiseitl, & Ohno-Machado, 2002) and regression problems (Wimarshana, Ryu, & Choi, 2014). This is an algorithm based on the human nervous system and brings it to mathematical model. It is an algorithm that learns many experiments or simulation data through feedback and adjusts the weights to derive nonlinear and complex correlations that are difficult for human to construct as shown in Figure 1 (Han, Seo, & Choi, 2015). In the back-propagation process, weight changes continuously to reduce error which is difference of real output and output of the previous function.

Because of the activation function in hidden layer, the complex interaction in data can be formulated and this helps the algorithm effectively handle massive data.

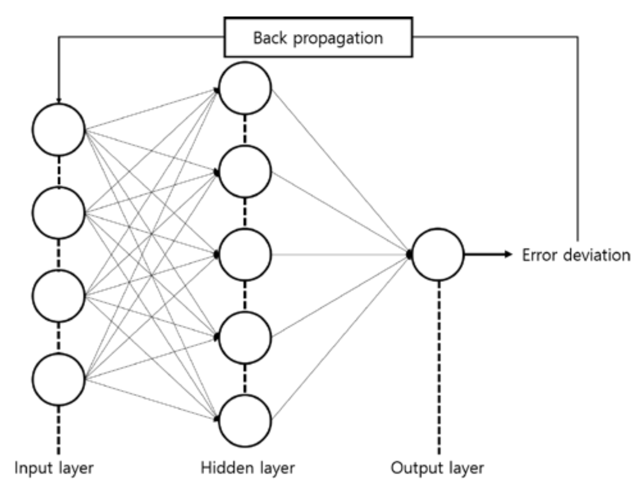

Figure 1. Structure of artificial neural network.

3. ANN TRAINING PROCEDURE

3.1. Factor Screening

Transmission error (TE) is delay between angular velocity of input and output of a gear set (Tamminana, Kahraman, and Vijayakar, 2007). In this research, TE is used to distinguish faulty products. In this process, we identify a few dominant factors from the TE signals using *t*-test among hundreds signal factors achieved from a gear sets.

3.2. Finding Optimum Structure

Setting a model structure is very important due to its influence on the accuracy of the model. In this research, the number of hidden layers is set to 1. Although there are several existing methods to select the number of hidden neurons (Sheela and Deepa, 2013), we developed an algorithm that determines the optimum number of neurons.

The *t*-test based screened factor combination is also decided with this algorithm. An optimum ANN structure was selected based on its prediction accuracy and robustness.

4. RESULTS AND DISCUSSION

For the verification of the algorithm, we divided the data into training and test sets. As a result, 97% of good assemblies were judged as good; however, 73% of defective ones were judged as defective. The reason for inaccuracy in the diagnosis of defective assemblies may be due to the limited number of defective samples. As the defective sample size increases, we expect more accurate diagnosis will be achieved by the machine learning process.

5. CONCLUSION

Quality inspection is essential in modern manufacturing industry. Especially, fast and accurately diagnosing the health of a product is the top priority of the quality inspection.

In this study, quality inspection was carried out by a TE method other than the vibration measurement method. This approach overcomes the limitations of the existing method and shows reasonable accuracy to establish a useful database.

We utilize ANN capable of predicting the property of interest from a great amount of complex data to build the quality inspection model with statistical factor screening process. This model is used as a mean of accurate fault diagnosis tool of planetary gear sets.

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REFERENCES

Tamminana, V. K., Kahraman, A., & Vijayakar, S. (2007). A study of the relationship between the dynamic factors and the dynamic transmission error of spur gear pairs. Journal of Mechanical Design, vol. 129(1), pp. 75-84.

Han, S., Seo, S., & Choi, H. J. (2015). A study on modeling customer preferences for conceptual design. Journal of Mechanical Science and Technology, vol. 29(12), pp. 5083-5091

Wimarshana, B., Ryu, J., & Choi, H. J. (2014). Neural network based material models with Bayesian framework for integrated materials and product design. International journal of precision engineering and manufacturing, vol. 15(1), pp. 75-81.

Dreiseitl, S., & Ohno-Machado, L. (2002). Logistic regression and artificial neural network classification models: a methodology review. Journal of biomedical informatics, vol. 35(5), pp. 352-359.

Sheela, K. G., & Deepa, S. N. (2013). Review on Methods to fix number of hidden neurons in neural networks. Mathematical problems in engineering 2013, pp. 1-11.

BIOGRAPHIES

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