Sensors and Actuators A 201 (2013) 421–427

Contents lists available at ScienceDirect

Sensors and Actuators A: Physical

journal homepage: www.elsevier.com/locate/sna

Stratified analysis of the magnetic Barkhausen noise signal based on wavelet decomposition and back propagation neural network

Ping Wang[a,*], Xiaoli Ji[a], Lei Zhu[a], Guiyun Tian[a,b], Entao Yao[a]

[a] *College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China*
[b] *School of Electrical and Electronic Engineering, Newcastle University, Newcastle upon Tyne, England, United Kingdom*

ARTICLE INFO

Article history:
Received 23 January 2013
Received in revised form 30 July 2013
Accepted 30 July 2013
Available online 7 August 2013

Keywords:
Magnetic Barkhausen noise
Wavelet decomposition
Back propagation neural network
Compressive stress
Temperature

ABSTRACT

Because the wavelet transform has the characteristic of multi-scale analysis and it can characterize local feature of signals, this article uses the wavelet decomposition method to investigate the sensitivity of different time-frequency components of the magnetic Barkhausen noise (MBN) signal with changes in temperature and stress. After using the db5 wavelet with six layers to decompose the MBN signal and reconstructing low-frequency signal at each layer, the mean and RMS value are extracted and followed by a discussion on the relationship between features and the variation of the applied temperature and stress. It is found that within the elastic range of the sample, both of the mean and RMS values of the low-frequency reconstructed signal at each layer have inverse relationship with as compressive stress. The mean and RMS value of the low-frequency reconstructed signals decrease at the first to fourth layer, remain constant at the fifth layer and increase at the sixth layer as temperature increases, respectively. A new neural network model is built by taking the temperature, the mean and RMS values of MBN signals and the decomposition coefficients as the input and the stress as the output. It is shown that the proposed neural network model for stress measurement has higher accuracy than the former BP neural network models in which the wavelet decomposition is not used.

1. Introduction

The operation practice of railways shows that the seamless rail line is the development trend in the future. The most prominent feature of the seamless line is that there are enormous temperature forces within the rail which determines the strength and stability of the seamless line. The rail temperature can change greatly due to changes in ambient temperature, especially in the summer, where the ambient temperature is up to 40 °C, and the rail temperature is usually 20 °C higher than the ambient temperature. The thermal expansion and cold contraction will only be seen at both ends of the rail, and the rest of the rail will not expand or contract with the changes in rail temperature. So it will store corresponding temperature stress (thermal stress) throughout the rail. When the rail temperature reaches a certain level, the rail will release the energy in the area of small fastener resistance and poor roadbed condition. When the energy is large enough, the rail track will deform, and it will cause serious traffic accident [1]. So some preventive measures must be made to prevent the above situation, however, so far we have not found a suitable method to detect the thermal stress.

Several non-destructive testing techniques can be applied for material evaluation [2–5], such as X-ray, blind hole drilling, eddy current, BN [6,7] and so on. Among them, both X-ray method and blind hole drilling method will have damage on the specimens in detection progress. At the same time, the detection speed of these two methods is also slow. Eddy current testing can provide a quick method to detect the existing defects with no contact and no coupling agent, but it cannot discover or predict the defects which will happen. Thus, eddy current testing cannot solve the sudden destruction problem of equipments. BN can overcome the drawbacks of other methods [8], and the most important is that it offers exceptional material and stress characterization capabilities. Magnetic materials consist of a patchwork of magnetic domains where all the magnetic moments in a particular domain point in the same direction, usually on the axis of the crystal. When a changing magnetic field is applied, the walls separating the domains move so that domains aligned close to the field direction grow at the expense of those that are less aligned. The movement occurs in a series of sudden jumps as the domain walls break away from pinning sites such as dislocations, precipitates and grain boundaries. This leads to corresponding jumps in the magnetization of the material, known as magnetic Barkhausen noise (MBN) [9].

There will be magnetization in the ferromagnetic material under the effect of an external magnetic field. When the saturation

---

* Corresponding author. Tel.: +86 13815863471.
E-mail address: JXL_1880@126.com (P. Wang).

0924-4247/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.sna.2013.07.040

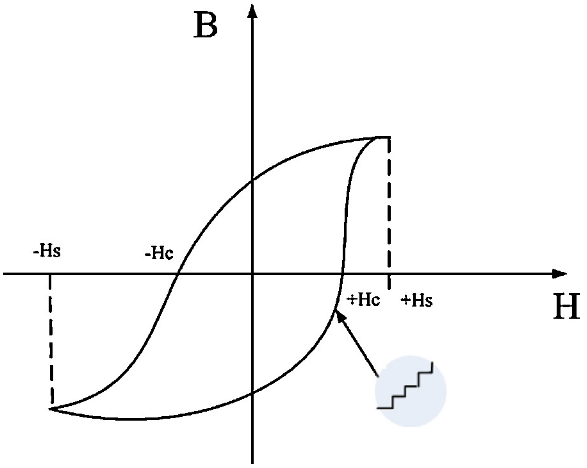

Fig. 1. Barkhausen noise generated diagram.

occurs in the ferromagnetic material, the magnetization state is not restored to its original state after removing the magnetic field. When the magnetic field changes back and forth (positive and negative), the magnetization of the media is in a cycle, thus forming a hysteresis loop. Observing the hysteresis loop of the ferromagnetic material, we can find that the curve displays a step-jitter state (see Fig. 1) in the irreversible magnetization phase, rather than a smooth and continuous curve [10]. A pick up coil placed on the surface of the specimen produces a noise pulse in the form of voltage allowing the measurement of Barkhausen noise. This indicates that the magnetization process of the ferromagnetic material is not continuous.

Studies [11] have shown that not only the thermal stress which is produced by the temperature can affect the MBN signal, but temperature itself has an impact on the MBN signal [12]. So it is necessary to develop a relationship between the MBN signal, temperature and stress, and to implement temperature compensation when using MBN to detect the rmal stress. The studies found in the literature typically use only one or a few features. Usual features are the RMS-value of the signal, the so called BN energy and peak height, width and position [13]. In order to improve the processing method of the MBN signal, researches [14] use wavelet transform to analyze the MBN signal, so that the sensitivity on the stress had been improved. However, they did not research the relationship between decomposition coefficients at each layer and stress and temperature. As wavelet decomposition has the characteristics to separate high and low frequency of signal [15], we use it to analyze whether high frequency component or low frequency component can be more sensitive to the changes of stress and temperature. We are also able to obtain much more effective and refined characteristic information of MBN signal through different layers. It was found in practical testing and the result analysis that the data processing method of neural networks could be used well on stress testing based on MBN [16]. Because the exact equation between MBN and stress is not achieved [17], neural networks could provide a bridge, which connects the MBN and the stress. After wavelet decomposition the mean and RMS values of decomposition coefficients at each layer as the input parameters of the neural network make input parameters refined, so we use a combination of wavelet decomposition and neural network on stress testing.

2. Wavelet decomposition and spectrum analysis of the MBN signal

2.1. Wavelet decomposition of the MBN signal

Wavelet transformation of a given signal is expanding the signal with a wavelet function. It means that the signal is expressed as a linear combination of the wavelet function of a series of different scales and time shifting. Each of the coefficients called wavelet coefficients and the linear combination of the wavelet function of different time shifting in the same scale called the wavelet component of the signal in this scale.

A discrete MBN signal is decomposed using the ‘wavedec’ function in Matlab which performs a multilevel 1-D wavelet analysis using either a specific wavelet or a specific set of wavelet decomposition filters. Fig. 2 is a typical structure of three-layer decomposition. As can be seen from the figure, after being decomposed once the data is halved and the wavelet coefficients in all scales coupled with the remainder coefficient of the maximum scale is equal to the length of the original sequence. After the sequence is projected onto the wavelet domain and each component of them will assemble again according to different frequency,

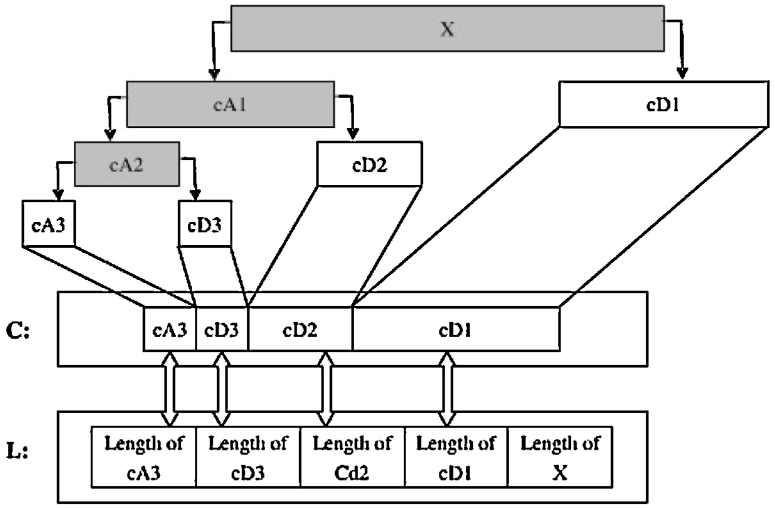

Fig. 2. A typical structure of three-layer decomposition.