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A novel sensor fault diagnosis method based on Modified Ensemble Empirical Mode Decomposition and Probabilistic Neural Network

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ABSTRACT

A novel fault diagnosis method based on Modified Ensemble Empirical Mode Decomposition (MEEMD) and Probabilistic Neural Network (PNN) is presented in this paper. It aims to achieve more accurate and reliable sensor fault diagnosis in thermal power plant. To restrain the mode mixing problem in traditional EMD, an MEEMD is proposed based on signal reconstruction and pseudo component identification. The MEEMD is applied to decompose the original thermal parameter signals into a finite number of Intrinsic Mode Functions (IMFs) and a residual to extract the sensor fault feature. After analyzing the inherent physical meanings of each IMF and residual, the variances of them are extracted as feature eigenvectors to express the signal feature. Finally, PNN is used as the classifier for detection and identification of sensor faults. Based on the practical normal signals, which are collected from a main steam temperature sensor of a CLN600–24.2/566/566 steam turbine, three types of representative sensor fault signals are simulated to test the proposed method. By analyzing simulation and real signal, the analysis results indicate that the MEEMD can restrain the mode mixing problem in traditional EMD effectively, and the proposed fault diagnosis method had better performance than the other two fault diagnosis methods including basic PNN and EMD–PNN.

1. Introduction

The electric power industry in China has changed dramatically since the early 1990s to become the world's largest electricity producer and consumer, passing the United States in 2011 [1]. Most of the electricity in China is produced from fossil fuels. In particular, about 79% of annual electricity was produced with coal in China between 2004 and 2010 [2]. Scientists continue to search for methods to improve the efficiency of existing power generation systems and explore improved techniques to meet these ever increasing demands for efficiency and stability during power generation. A large amount of sensors had been installed in power plant for this reason. The intensive use of sensors is an important component in these power and energy improvement challenges. However, many sensors fail or fault frequently which impacts the safety for power generation. On the other hand, it is important to get the reliable and accurate data from sensors especially those operate in extreme conditions (e.g. high pressures and high temperatures). Therefore, sensor fault detection and identification is of extremely importance to improve safety and reliability of plant operations.

The process of sensor fault detection and identification is a process of pattern recognition essentially. In the pattern recognition problems, Probabilistic Neural Network (PNN)

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[3] has been widely used. Gorunescu et al. [4] explored a PNN-based approach to determine the diagnosis for hepatic cancer. Hsieh et al. [5] proposed an approach for locating partial discharge sources in the power cable and gas-insulated load break switches using PNN. Ford et al. [6] integrated a powerful multi-class PNN system with an autonomous electrochemical sensor to classify four species of organisms. Zeng and Zhou [7] presented a PNN-based hybrid algorithm to improve the ability of speaker recognition. The recognition effect of the PNN depends on the effectiveness of the extracted feature, so how to extract the fault features and identify the condition from the signals are the key steps in the fault diagnosis of sensor. A simple method to analyze any signal is Fourier Transform (FT) [8]. Fourier transform is a frequency domain technique that estimates the individual harmonic components and is suitable for stationary signals only. Windowed Fourier Transform (WFT) [9,10] can display a time signal on a joint time frequency plane, but once the window function is chosen, its size of the time frequency window would be fixed. Therefore the time and frequency resolution are same for all components that include different time scales. Short Time Fourier Transform (STFT) [11,12] can map a signal into a two dimensional function of time and frequency to extract time and frequency information. However, the disadvantage is that the window size is fixed for all frequencies. Wavelet Transform (WT) [13] is another technique suitable for analysis of non-stationary signals. The wavelet basis function must be chosen definitely before WT is used. So it cannot be changed adaptively according to the signals at different time. Moreover, an inappropriate wavelet will overwhelm the local feature of thermal parameters signal and lose some useful information of original signals.

Different from the methods mentioned above, Empirical Mode Decomposition (EMD) [14] is an automatic decomposition and fully data adaptive method, which provides an efficient analysis method for non-stationary and non-linear signals. EMD is a self-adaptive method which can decompose a complicated signal into a number of Intrinsic Mode Functions (IMFs) and a residual without energy diffusion or leakage. Therefore, EMD is valuable in engineering application for processing non-stationary and non-linear signals. Siwal et al. [15] carried out an investigation of EMD-based noise filtering algorithm on a mirror signal from a two fold germanium clover detector. Gan et al. [16] presented a novel EMD threshold de-noising method based on fractional Gaussian noise model for inertial sensors. Xie [17] studied the usage of EMD for manipulating the illumination issue on face images. Zhang et al. [18] demonstrated the feasibility and applicability of the EMD method in the analysis of engineering surfaces. Sonia et al. [19] explored the use of EMD to enhance the crackles information from basic respiratory sounds. Ambikairajah [20] used the EMD as an alternative method of extracting instantaneous frequency. Yang and Chang [21] demonstrated that bridge frequencies of higher modes can be successfully extracted with EMD method.

Although there are many advantages, traditional EMD has limitations such as the end-point effect and the mode mixing problem. End-point effect can be eliminated easily and effectively through end-points continuation [22,23]. Considering the fact that the length of the sampled thermal parameter signal is long enough, end-points continuation based on the practical storage data is applied to eliminate the end-point effect in this study. The mode mixing is the phenomenon that disparate frequencies exist in a single IMF. The occurrence of mode mixing is mostly caused by signal intermittency and may be interpreted incorrectly as different physical meaning. To overcome the mode mixing problem, the ensemble empirical mode decomposition (EEMD) was presented by Wu and Huang [24] recently based on their in-depth study on the properties of Gaussian white noise' influence on the decomposition result of EMD. EEMD has been widely applied in many areas. Guo and Tse [25] explored an EEMD-based signal compression method for bearing vibration signals. Breaker and Ruzmaikin [26] implemented EEMD in the examination of the 154-year record of monthly sea level at San Francisco. Mariyappa et al. [27] adopted EEMD to de-noise the magnetocardiography (MCG) signal. Wang et al. [28] combined EEMD with Tunable Q-factor wavelet transform in fault feature extraction of accelerated life test for rolling bearing's early weak fault. However, in practical applications of EEMD, some problems need to be solved, e.g., the reduction of the random noises embedded in original signal and the eliminating of the undesirable pseudo IMFs. Furthermore, due to the limitation of the filter condition and envelope calculation, potentially there is also mode mixing in the "single-frequency" components obtained through traditional EEMD (that is, there are still two or more frequencies exist in the "single-frequency" components). To solve the above-mentioned problems, a modified EEMD (MEEMD) is proposed based on signal reconstruction and pseudo component identification in this study.

A novel method for the sensor fault diagnosis based on MEEMD and PNN is presented here. The complete algorithm includes three principal steps: (1) the MEEMD is applied to decompose sensor signals into several IMFs and a residual; (2) the variance of the IMFs and residual are extracted as signal features; (3) the feature vectors composed by these features are input into the PNN for classification. The rest of the paper is structured as follows. In Section 2, the fundamental principles of the MEEMD and PNN will be illustrated. In Section 3, the feature extraction methods and the fault diagnosis steps for the proposed method will be explained in details. Section 4 will present the results and analysis of simulation experiment. Finally, the conclusion is drawn in Section 5.

2. Analyzing techniques

2.1. Modified Ensemble Empirical Mode Decomposition

EMD is a direct, posteriori, and self-adaptive method for signal decomposition first proposed by Huang et al. [14]. It is developed from the assumption that any signal consists of different simple intrinsic modes of oscillations. Any signal can be decomposed into a finite number of IMFs, each of which must satisfy the following definition: (1) In the