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Real-time fault diagnosis for gas turbine generator systems using extreme learning machine

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ABSTRACT

Real-time fault diagnostic system is very important to maintain the operation of the gas turbine generator system (GTGS) in power plants, where any abnormal situation will interrupt the electricity supply. The GTGS is complicated and has many types of component faults. To prevent from interruption of electricity supply, a reliable and quick response framework for real-time fault diagnosis of the GTGS is necessary. As the architecture and the learning algorithm of extreme learning machine (ELM) are simple and effective respectively, ELM can identify faults quickly and precisely as compared with traditional identification techniques such as support vector machines (SVM). This paper therefore proposes a new application of ELM for building a real-time fault diagnostic system in which data pre-processing techniques are integrated. In terms of data pre-processing, wavelet packet transform and time-domain statistical features are proposed for extraction of vibration signal features. Kernel principal component analysis is then applied to further reduce the redundant features in order to shorten the fault identification time and improve accuracy. To evaluate the system performance, a comparison between ELM and the prevailing SVM on the fault detection was conducted. Experimental results show that the proposed diagnostic framework can detect component faults much faster than SVM, while ELM is competitive with SVM in accuracy. This paper is also the first in the literature that explores the superiority of the fault identification time of ELM.

1. Introduction

The gas turbine generator system (GTGS) is commonly used in many power plants. The main components of a GTGS are: power turbine, gearbox, flywheel and asynchronous generator. In the first phase of the GTGS, the power turbine is driven by the exhaust gas, the output of the turbine then drives a gearbox that connects to the flywheel which keeps constant moment of inertia to protect the generator from sudden stop. Finally, the rotating flywheel drives the asynchronous generator to generate the electric power. The system is designed to run 24 h per day. Any abnormal situation of the GTGS will interrupt the electricity supply to cause enormous economic loss. The traditional manual inspection on the GTGS is difficult to accomplish the fault-monitoring task because the GTGS is complicated and also cannot be arbitrarily stopped. In order to ensure that the operation of the power plant can run smoothly, development of a suitable real-time fault monitoring system for the GTGS is necessary.

In recent years, researches on the development of intelligent real-time monitoring systems for the GTGS and rotating machinery have become very active. A real-time fault diagnostic system for steam turbine generator based on hierarchical artificial neural network was found in [1]. An online condition monitoring and diagnostic system for feed rolls was developed by [2]. This system measures the bearing vibration signals and judges the feed roll condition automatically according to the diagnostic rules stored in a computer. In the literature [3–5], expert systems and knowledge base systems for fault diagnosis of turbine generators were developed. In a nutshell, modern methods for fault diagnosis of GTGSs and rotating machinery usually rely on the procedures of (1) processing of the vibration signal and (2) fault identification/classification [1–9].

In terms of processing of the vibration signal, the signal contains high-dimensional data and is enclosed by a lot of irrelevant and redundant information, which cannot be easily fed into the real-time fault diagnostic system. The high-dimensional data will degenerate the accuracy and fault identification time of the diagnostic system too. Therefore, extracting the useful information from the vibration signal is desirable. Currently, there are several common feature extraction techniques, such as wavelet packet transform (WPT) [7,8,10], independent component analysis [11] and time-domain

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Nomenclature

b_i	threshold of the ith hidden node
C	regularization parameter of SVM
$D_{KPCA\text{-}TRAIN}$	feature set selected by KPCA
$D_{Proc\text{-}TRAIN}$	representative features of training data set after offline data pre-processing
D_{TRAIN}	training data set
$D_{WT\text{-}TRAIN}$	feature set extracted by WPT and TDSF
d	hyperparameter of polynomial kernel for KPCA
d'	hyperparameter of polynomial kernel for SVM
E_i	prediction error for the ith test case
ELM	extreme learning machine
GTGS	gas turbine generator system
h	number of hidden nodes of ELM
H	hidden layer output matrix
H^+	Moore–Penrose pseudo inverse of matrix H
j	number of classes for classification
KPCA	kernel principal component analysis
$K(.)$	kernel function of KPCA
L	level of WPT decomposition
L_{ELM}	level of WPT decomposition for ELM classifier
L_{SVM}	level of WPT decomposition for SVM classifier
P_{ELM}	hyperparameter of KPCA for ELM classifier
P_{SVM}	hyperparameter of KPCA for SVM classifier
q	number of test cases
R	radius of RBF kernel for KPCA
R'	radius of RBF kernel for SVM
SVM	support vector machine
TDSF	time-domain statistical features
$\boldsymbol{t}_n$	nth output pattern
$t_{n,j}$	jth binary output in the nth output pattern
$\boldsymbol{w}_i$	weight vector connecting the ith hidden node and input nodes
WPT	wavelet packet transform
x_i	ith raw signal data
$\boldsymbol{x}_{KPCA}$	feature set selected by KPCA for unseen real-time signal
x_{max}	upper limit of feature
x_{min}	lower limit of feature
$\boldsymbol{x}_n$	nth set of features in $D_{Proc\text{-}TRAIN}$
$\boldsymbol{x}_{new}$	unseen real-time signal
$\boldsymbol{x}_{Proc}$	representative features of unseen real-time signal after data pre-processing
$\boldsymbol{x}_{WT}$	feature set extracted by WPT and TDSF for unseen real-time signal
y	normalized feature
$z_r(x_{WT})$	transformed variables z_r for vector x_{WT}
$\alpha_{r,I}$	Ith element in eigenvector α corresponding to the rth largest eigenvalue
β_i	weight vector connecting the ith hidden node and output nodes
λ_r	rth eigenvalue of KPCA

statistical features (TDSF) [12,13]. The above literature reveals that WPT and TDSF are commonly used for rotating machinery so that both techniques are considered in this project. After performing feature extraction, there may be still some irrelevant and redundant information in the extracted features. In order to resolve this problem, a feature selection method should be employed to wipe off irrelevant and redundant information such that the amount of raw data can be reduced, resulting in improvement on diagnostic accuracy. The available feature selection approaches include compensation distance evaluation technique (CDET) [13], kernel principal component analysis (KPCA) [14] and the genetic algorithm (GA) based methods [15,16]. Although CDET and GA-based methods provide a good solution, the optimal threshold in CDET is difficult to set and the result of GA is unrepeatable. In other words, when a GA is run for two times, two different results will be obtained. In this way, KPCA is considered in this study.

Regarding identification/classification techniques, traditional neural networks, such as multi-layer perception (MLP), were commonly used for fault diagnosis of the steam turbine and rotating machinery [10,17,20]. However, MLP has many drawbacks, such as local minima, time-consuming for determination of optimal network structure, and risk of over-fitting.

To date, a number of researchers have already applied support vector machines (SVM) to diagnose rotating machine faults and other engineering diagnosis problems [8,9,11,18–21], and have shown that SVM is superior to traditional ANN [20,22–24]. The major advantages of SVM are global optimum and higher generalization capability [20,24]. Recently, an emerging machine learning method called extreme learning machine (ELM) has been developed [25,26], which has a simple structure and efficient learning algorithm. The learning speed of ELM is extremely fast while it has higher generalization than the gradient-descent based learning (e.g. the back-propagation method) [32]. In addition, the issues of local minima, improper learning rate and over-fitting suffered in traditional ANN are overcome [27]. A few studies have already demonstrated the use of ELM for many engineering applications. The approach based on wavelet transform and ELM for fault identification in a series compensated transmission line was presented in [28]. Reference [29] presented a multi-stage ELM for fault diagnosis on hydraulic tube testers. Nevertheless, the application of ELM to real-time fault diagnosis of rotating machinery is still very rare.

However, there are three major challenges in the development of real-time fault diagnostic systems for the GTGS. The first one is that there is a huge number of data collected from the real-time monitoring system, which are multivariate and nonlinear. It is believed that the existing data pre-processing techniques can help a lot. The second challenge is that there are many classes of faults in the GTGS. The final one is the demand of quick fault identification time. It is well-known that only a few seconds of power interruption may cause many kinds of losses, such as losses of money and computer data, for a modern city. Therefore, if any fault exits, the diagnostic system should be able to detect the fault immediately and then send an alarm signal to inform the control center to start a spare generator in order to avoid any power interruption.

Currently, SVM is the most popular classifier for diagnostic systems. However, recent studies showed that ELM tends to have better scalability and achieve much better generalization performance at much faster learning speed than traditional SVM [25,26]. Moreover, traditional SVM usually requests at least two hyperparameters to be specified by users, single parameter setting makes ELM be used easily and efficiently. Besides, ELM is a multi-input and multi-output structure, whereas SVM is a multi-input and single-output structure. So ELM is easier to be implemented for multi-class problem. With the aforesaid advantages of ELM, this paper proposes a new application of ELM for building a real-time fault diagnostic system for the GTGS.

This paper is organized as follows: Section 2 presents the proposed diagnostic framework and the techniques involved in the framework. Experimental setup and sample data acquisition