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Fault detection and diagnosis of an industrial steam turbine using a distributed configuration of adaptive neuro-fuzzy inference systems

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ABSTRACT

The issue of fault detection and diagnosis (FDD) has gained widespread industrial interest in process condition monitoring applications. An innovative data-driven FDD methodology has been presented in this paper on the basis of a distributed configuration of three adaptive neuro-fuzzy inference system (ANFIS) classifiers for an industrial 440 MW power plant steam turbine with once-through Benson type boiler. Each ANFIS classifier has been developed for a dedicated category of four steam turbine faults. A preliminary set of conceptual and experimental studies has been conducted to realize such fault categorization scheme. A proper selection of four measured variables has been configured to feed each ANFIS classifier with the most influential diagnostic information. This consequently leads to a simple distributed FDD system, facilitating the training and testing phases and yet prevents operational deficiency due to possible cross-correlated measured data effects. A diverse set of test scenarios has been carried out to illustrate the successful diagnostic performances of the proposed FDD system against 12 major faults under challenging noise corrupted measurements and data deformation corresponding to a specific fault time history pattern.

1. Introduction

Different diagnostic procedures are usually recommended by equipment manufacturers on the basis of specific periodic time schedules. Thus, the recommended procedures are emphasized to be carried out routinely as maintenance tasks to prevent major fault occurrences. However, this might include dismantling the equipments, increasing the subsequent risk of other potential problems such as vibration and leakage [1].

Automated fault detection and diagnosis prevents regular and costly equipment maintenances by continuously detecting performance problems and bringing them to the attention of operators. Fault detection implies the conception of any relevant symptom from the fault indicators and the consequent evaluation of the time of fault occurrence. Fault diagnosis refers to fault-root discrimination which can be done on the basis of an analytical system model, representing the normal system behavior in the absence of any fault [2]. This is by no means an easy task to be carried out, especially in non-linear dynamic systems [3], model imprecision often leads to difficulties in making a clear distinction between deviations made by model uncertainty and those imposed by a fault affecting the system or unknown disturbances. For this reason, a trade-off is usually necessitated to be considered between false alarm rate and missed detection rate. Following a proper fault diagnosis, recovery procedures can be accommodated, resulting in fault tolerant control system [4]. However, obtaining a sufficiently precise

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Nomenclature

Subscripts

ANFIS	adaptive neuro-fuzzy inference system
FDD	fault detection and diagnosis
SOM	self-organizing map
MLP	multi-layered-perceptron
ANN	artificial neural network
FL	fuzzy logic
NNs	neural networks
FKB	fuzzy knowledge base
W	weight vector
A_i, B_i	linguistic labels
$p1$, $p2$, $q1$, $q2$, $r1$, $r2$	design parameters
$\mu_{A_i}(x), \mu_{B_i}(y)$	membership functions
OLi	ith output layer of ANFIS
x,y	inputs

analytical model for complex processes is by no means an easy task to be done and hence other diagnostic approaches must be utilized [5]. Signal processing offers a candidate approach when an analytical model is not a priori available [6].

Signal characteristics can be investigated either with time domain methods (e.g., correlation and mean-change), frequency domain methods (e.g., spectral analysis), or with time–frequency or wavelet analysis [7]. However, the difficulty relates to the way a change in some quantity (e.g., the signal mean, the spectrum, etc.) is correlated with the characteristic of a particular fault. Classification or pattern recognition approach presents a third way to deal with diagnostic objectives. This is mainly based on historical process data or expert knowledge about the system and its corresponding misbehaviors. Relevant symptoms are hence identified to be representative of each type of failure. The relationships between symptoms and faults are then correlated by an appropriate supervised learning when faults are known a priori, for instance by an expert [8].

Steam turbines are widely utilized in power plants as the main energy generating sources. These turbines generally have a complex dynamic structure, consisting of multistage steam expansion. Therefore, providing on-line monitoring of their performances is critically important to maintain normal operations. Their most common faults are often due to produced damages and failures in the components of the sensor steam extractions, feed water heaters, and the related actuators. These faults can endanger their operation, jeopardizing the consistency of its reliable power generation. Therefore, proper monitoring of the affective components can be highly cost effective in minimizing maintenance downtime by providing advanced warning in order to prepare the appropriate corrective actions upon an adequate fault diagnosis.

Different approaches have been considered for fault detection and diagnosis in steam turbines. They include methods of determining steam turbine condition by thermodynamic calculations to disclose turbine efficiency and leakage condition [9], and evaluation of the turbine steam path component deterioration by means of exergoeconomics [10]. These approaches, however, require a priori knowledge of complex thermodynamic equations. Self-organizing map (SOM) presents another method for fault diagnosis [11]. However, its classification is not precise and hence can lead to an increase rate of miss-alarm. A modified fuzzy min–max neural network with rule extraction capability has been introduced for fault detection and classification purposes [12] in which a small number of large hyper boxes are formed in the network. A detection fault scheme, based on the multi-layered-perceptron (MLP) artificial neural network (ANN), has been presented to interactively isolate faults by Bayesian [13]. Since NNs are treated as black box systems, therefore they are sensitive to learning data. Other machine learning approaches have been proposed in the literature. For example, fault diagnosis with support vector machine [14], and fault diagnosis methods, based on neural network and fuzzy logic schemes, are attracted many research works in recent years [15–24].

The work presented in this paper focuses on fault diagnosis of an industrial steam turbine by an adaptive neuro-fuzzy inference system (ANFIS) methodology as a powerful data-driven scheme. The main motivation is due to the inherent adaptive learning scheme, incorporated in ANFIS structure, enabling it to appropriately perform the fault diagnostic task.

Neural networks (NNs) and fuzzy logic (FL) systems are known as the most powerful algorithms for monitoring data pattern classification in diagnostic tasks. NNs have, in fact, inspired by the function of the nerve cells in the brain, which can provide an efficient way to model and forecast non-linear systems. They can learn to perform a desired non-linear mapping through training on many different examples of the input/output mapping of interest. The obtained results, however, are difficult to interpret physically and thus the underlying model remains cryptic. On the other hand, FL modeling is designed to handle imprecise linguistic concepts such as ‘small’, ‘big’, ‘young’ and ‘low’ [25]. Thus, FL models scheme exhibit an inherent flexibility which has proven to be successful in a variety of industrial control and pattern recognition tasks [26–28]. FL modeling compared with other schemes which deal with imprecise data fuzzy knowledge base (FKB) in a rule format, making it easy to examine and understand. This rule format consequently makes it easy to update the resulting FKB. The main