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Original Article

SEMISUPERVISED CLASSIFICATION FOR FAULT DIAGNOSIS IN NUCLEAR POWER PLANTS

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ABSTRACT

Pattern classifications have become important tools for fault diagnosis in nuclear power plants (NPP). However, it is often difficult to obtain training data under fault conditions to train a supervised classification model. By contrast, normal plant operating data can be easily made available through increased deployment of supervisory, control, and data acquisition systems. Such data can also be used to train classification models to improve the performance of fault diagnosis scheme.

In this paper, a fault diagnosis scheme based on semisupervised classification (SSC) scheme is developed. In this scheme, new measurements collected from the plant are integrated with data observed under fault conditions to train the SSC models. The trained models are subsequently applied to new measurements for fault diagnosis. In comparison with supervised classifiers, the proposed scheme requires significantly fewer data collected under fault conditions to train the classifier.

The developed scheme has been validated using different fault scenarios on a desktop NPP simulator as well as on a physical NPP simulator using a graph-based SSC algorithm. All the considered faults have been successfully diagnosed.

The results have demonstrated that SSC is a promising tool for fault diagnosis in NPPs.

1. Introduction

Safety and availability of a nuclear power plant (NPP) can be adversely affected by various component faults. It is important to diagnose potential faults early enough so that a minor fault may not develop into potentially disastrous consequences. Pattern classification has become an important tool for early fault diagnosis in NPPs and other industries [1–11]. The processes in a NPP are governed by physical laws such as balances of mass, energy, and momentum. When process

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faults have happened, these balances are altered. For different types of faults, the system reacts differently. As a result, different patterns of system behaviors can be observed. Therefore, with *a priori* knowledge of the system behaviors under specific fault, and with a proper selection of a set of measurements, the faults could be uniquely identified through pattern classification means.

In case of NPP applications, one of the problems is the lack of adequate training data to match faults and their corresponding symptoms. This makes pattern based fault classification particularly difficult in NPPs [12,13]. The majority of pattern classification based fault diagnosis applications use so-called supervised pattern classification models, where training data with known fault classes are used to train a classifier first. The classifier subsequently processes new measurements to diagnose potential faults by matching the patterns against the measurement data. However, reliable data under a specific fault condition are rare in NPP to train a classifier. One of the reasons is that one cannot simply inject real faults into an NPP system for the purpose of collecting training data. Another reason is that most of the critical system components in a NPP have gone through rigorous qualification process, inspection, and they are often of high quality and extremely reliable. Although there are some databases to describe fault conditions of some components, they may not coincide exactly with the fault classes considered by the diagnostic classifier. Use of an NPP simulator can be another way to generate training data, but there are inevitably differences between the simulator responses and the real plant responses due to modeling errors. Scarcity of reliable data under fault conditions can skew boundaries of a classifier, and subsequently lead to false classification. Therefore, there is a need to develop a fault diagnosis scheme, which relies less on the known fault patterns. A fault diagnosis scheme based on semisupervised classification (SSC) is developed in this paper to address the above issue.

In the terminology of classification, the data set under specific conditions are known as labeled data, whereas the data set with unknown conditions are referred to as unlabeled data. The objective of a classifier is to uncover specific conditions (i.e., faults) based on these unlabeled data (i.e., new measurements), and assign appropriate labels (i.e., fault types) to them accordingly. In the proposed scheme, both labeled and unlabeled data are used to train the classifier. Hence, it is called SSC. Once trained, the classifier can then be used to process the new measurements and perform fault diagnosis. There are two principles that most SSCs are based on: (1) *clustering assumption*, which states that nearby data points probably belong to the same class; and (2) *manifold assumption*, which says that data points on the same manifold structure are likely to be in the same class [14,15]. An SSC model can achieve superior performance because the classifier can be designed to avoid cutting through the high-density regions or the manifolds when processing the unlabeled data. In addition, a higher degree of uncertainties in the labeled data can be tolerated. In the case of physical systems in an NPP, correlations often exist among different measurements due to their physical and functional couplings. Therefore, data collected under the same fault condition tend to fall in the same high-density region or on the same manifold structure. For these reasons, SSC has become a promising fault diagnosis tool for applications in NPPs.

In the proposed fault diagnosis scheme, type of faults considered by the diagnostic system has to be defined first. Sensors that can be used to collect data for diagnostic purpose are also selected. Labeled data under these fault conditions are then generated through various means, such as by simulation, experiments on scaled physical mock-ups, or experience on the cause–effects associated with system components. If a fault is detected, measurements are collected and treated as unlabeled data. These data are then integrated with the available labeled data samples to train an SSC model. Once the model is trained, it will subsequently be used to classify/assign the most appropriate labels for the unlabeled inputs. In other words, they diagnose the underlying fault conditions embedded in the collected data; hence, the fault diagnosis task can be accomplished. The scheme has been validated using a desktop simulator of a Canada deuterium uranium (CANDU) NPP and a physical simulator of an NPP known as a NPP control test facility (NPCTF) that is essentially a simplified physical component based NPP simulator for instrumentation and control purposes. Three types of faults are considered in the CANDU simulator and six types of faults are on the NPCTF. Classification results have shown that all faults can be successfully diagnosed, even though the labeled data used contain a considerable amount of uncertainties, and the size of the labeled data is significantly smaller than typically required in a supervised classification scheme.

2. Materials and methods

2.1. *Pattern classification for fault diagnosis*

Suppose k faults can occur in a system and m sensors are used for data collection to diagnose them. The sensor outputs sampled at a time point t are organized into a vector $x_t \in R^{1\times m}$. Denote the hypothesis for the i-th fault as Hi, and hence, the fault is represented by a class label $y = i$. Normal operation is denoted as $H0$ and the class label is assigned as $y = 0$. In addition, it is assumed that a set of training data are available and denoted as $D^l = (X^l, Y^l) = [(x_i^l, y_i)]_{i=1,\ldots,nl}$, where nl is the total number of labeled data, X^l contains all the inputs and Y^l contains the class labels associated with X^l. The training data are selected to capture the uniqueness in sensor responses under different faults. When a fault is detected, a set of measurements $X^u = (x_i^u)_{i=1,\ldots,nu}$ is acquired, where nu is the number of unlabeled new measurements. The objective of a fault diagnosis system is to determine which fault has occurred by identifying the closest match of the underlying patterns between the new measurements and the training data model. This is essentially a pattern classification problem of assigning discrete labels to prove or disapprove the fault hypotheses, i.e., $y \in (0, 1, 2, \ldots, k)$ based on a set of new data X^u, given a set of training data D^l. In this paper, X^l and X^u are known as the labeled and the unlabeled data sets, respectively.

To implement a pattern classification system, a classification function $g_i(y = i|x)$ has to be defined for each class, which characterizes the match of the inputs x to the class $y = i$. The classification process can be expressed as: