Annals of Nuclear Energy 122 (2018) 297–308

Contents lists available at ScienceDirect

Annals of Nuclear Energy

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

Framework for fault diagnosis with multi-source sensor nodes in nuclear power plants based on a Bayesian network

Guohua Wu [a,b,c], Jiejuan Tong [a,b,c], Liguo Zhang [a,b,c,*], Yunfei Zhao [d], Zhiyong Duan [e]

[a] Institute of Nuclear and New Energy Technology, Tsinghua University, Beijing 100084, China
[b] Collaborative Innovation Center of Advanced Nuclear Energy Technology, Tsinghua University, Beijing 100084, China
[c] The Key Laboratory of Advanced Reactor Engineering and Safety of Ministry of Education, Beijing 100084, China
[d] Department of Mechanical and Aerospace Engineering, The Ohio State University, Columbus, OH 43210, USA
[e] Nuclear Power Institute of China, Chengdu 610000, China

ARTICLE INFO

Article history:
Received 21 November 2017
Received in revised form 27 August 2018
Accepted 31 August 2018

Keywords:
Nuclear power plant
Fault detection and diagnosis
Bayesian network
Multi-source sensor node
Principal component analysis
Data fusion

ABSTRACT

Fault detection and diagnosis (FDD) provides safety alarms and diagnostic functions for a nuclear power plant (NPP), which comprises large and complex systems. Here, a technical framework based on a Bayesian network (BN) for FDD is introduced because of its advantages of easy visualization, expression of parameter uncertainties, and ability to perform diagnosis with incomplete data. However, a BN raises a new problem when it is applied to NPPs; i.e., how to cope with parameter or node information from multiple sensors. Sensor data must be consolidated because creating a single node for each sensor in the network would lead to information overload. This paper proposes a possible solution to this issue and then constructs an FDD system framework with a BN as the backbone. Within this framework, principal component analysis is used to remove information from malfunctioning sensors, and fuzzy theory and data fusion are combined to further improve data accuracy and combine data from multiple sensors into one node. On this basis, a BN inference junction tree algorithm is used in FDD because it can deal with incomplete data. A BN model for a pressurized water reactor is created to validate the method framework. Simulation experiments indicate the suitability of the proposed method for online FDD in NPPs using multi-sensor information. It is thus concluded that the proposed method is a feasible scheme for the FDD of NPPs.

1. Introduction

A nuclear power plant (NPP) is a modern industrial plant comprising large and complex systems. A typical NPP control room is equipped with about 2000 alarms (Mo et al., 2007). A fault occurring in an NPP may therefore trigger numerous alarm signals, making it difficult for operators to determine the current state of the NPP (Zhao et al., 2015). Current research focuses on how to improve the reliability of operation in complex industrial systems, such as NPPs (Liu and Peng et al., 2013), chemical refineries (Peng et al., 2014), chiller plants (Wang et al., 2017), and other systems (Chung and Bien, 1994). Fault detection and diagnosis (FDD) is one technology that may promote reliability because it provides safety alarms and diagnostic functions for NPPs and thus helps operators rapidly discover the causes of accidents and gives operators real-time operation guidance (Ma and Jiang, 2015). In this way, FDD can prevent further deterioration during an accident and improve the reliability, safety, and economics of an NPP.

Abbreviations: ACP, AC power; APPRCS, Average primary pressure in a reactor coolant system; BN, Bayesian network; CPTs, Conditional probability tables; DST, Dempster–Shafer theory; FCL (1), Flow of coolant in loop 1; FCL (2), Flow of coolant in loop 2; FCL (3), Flow of coolant in loop 3; FDD, Fault detection and diagnosis; JT, Junction tree; LOCA, Loss of coolant accident; LOFW, Loss of feed water; MSLB, Main steam line break; NPP, Nuclear power plant; PC, Pressure of the containment; PCA, Principal component analysis; PCL, Pressure of second-loop; PCLL (1), Pressure of cold leg in loop 1; PCLL (2), Pressure of cold leg in loop 2; PCLL (3), Pressure of cold leg in loop 3; PPZ, Pressure of pressurizer; PSG (1), Pressure in steam generator 1; PSG (2), Pressure in steam generator 2; PSG (3), Pressure in steam generator 3; PWL, Pit water level; RC, Radioactivity of the containment; RSG (1), Radioactivity in steam generator 1; RSG (2), Radioactivity in steam generator 2; RSG (3), Radioactivity in steam generator 3; SBO, Station blackout; SGTR, Steam generator tube rupture; SPC, Sub-cooling of primary coolant; SVI, Sensor validity index; TC, Temperature of the containment; TCLL (1), Temperature of the cold leg in loop 1; TCLL (2), Temperature of the cold leg in loop 2; TCLL (3), Temperature of the cold leg in loop 3; WLPZ, Water level in the pressurizer; WLSG (1), Water level in steam generator 1; WLSG (2), Water level in steam generator 2; WLSG (3), Water level in steam generator 3.

* Corresponding author at: Institute of Nuclear and New Energy Technology, Tsinghua University, Beijing 100084, China.

E-mail address: lgzhang@tsinghua.edu.cn (L. Zhang).

https://doi.org/10.1016/j.anucene.2018.08.050
0306-4549/

1.1. Sensor condition monitoring

The first step of FDD is to obtain multi-sensor data from the digital and control system of the NPP. To ensure the accuracy and reliability of data for FDD, most studies employ sensor condition monitoring for safety, economics, and accuracy. In terms of safety, sensor condition monitoring identifies malfunctioning sensors, which improves the reliability and safety of instruments and the control system. In terms of economics, the quick location of faulty sensors provides guidance for operators to shorten the maintenance cycle. In terms of accuracy, sensor condition monitoring improves the reliability of data that have a critical effect on the accuracy of FDD (Lu and Upadhyaya, 2005). It is therefore necessary to carry out sensor condition monitoring.

Data-driven methods that dig into data have been studied for the monitoring of the sensor condition (Li et al., 2017). Principal component analysis (PCA), which was proposed by Pearson (1901), transforms high-dimensional information into low-dimensional information. Elnokity et al. (2012) used an optimized neural network for sensor condition monitoring. A support vector machine was used to predict the critical heat flow (Cai, 2012) and monitor the status of an NPP to improve economics (Liu and Seraoui et al., 2013). Artificial immunity and distributed condition monitoring were proposed to monitor an NPP water supply system (Wang et al., 2016). Self-associative kernel regression was used for the calibration of sensors in an NPP (Hines and Garvey, 2007). Kim et al. (2015) used a Gaussian distribution to evaluate the state of a plant.

1.2. Fault diagnosis

As an artificial intelligence method, FDD obtains important signals from a large quantity of data and judges the current state of a system (Liu et al., 2014). FDD techniques can be divided into data-driven, signal-based, and model-based methods. These methods are schematically shown in Fig. 1 (Ma and Jiang, 2011). Data-driven FDD mainly relies on numerous data to establish relationships between parameters and faults taking various approaches, such as using a neural network (Amal et al., 2011; Mo et al., 2007), conducting PCA (Gajjar et al., 2017), conducting qualitative trend analysis (Maurya et al., 2005), and other approaches (Žarković and Stojković, 2017). Signal-based methods operate in the time domain and employ techniques such as wavelet analysis, time–frequency analysis, and spectral analysis (Ma and Jiang, 2011). There are two main approaches for model-based FDD. One is based on the use of expert knowledge; e.g., expert systems (Kramer and Palowitch, 1987). The other is based on graph theory; i.e., the model graphically displays relationships between the various parameters and faults, as in a Bayesian network (BN) (Kang and Golay, 1999), first-principle model (Pantelides and Renfro, 2013), signed directed graph (Liu et al., 2016), and dynamic uncertain causality graph (Zhou and Zhang, 2017).

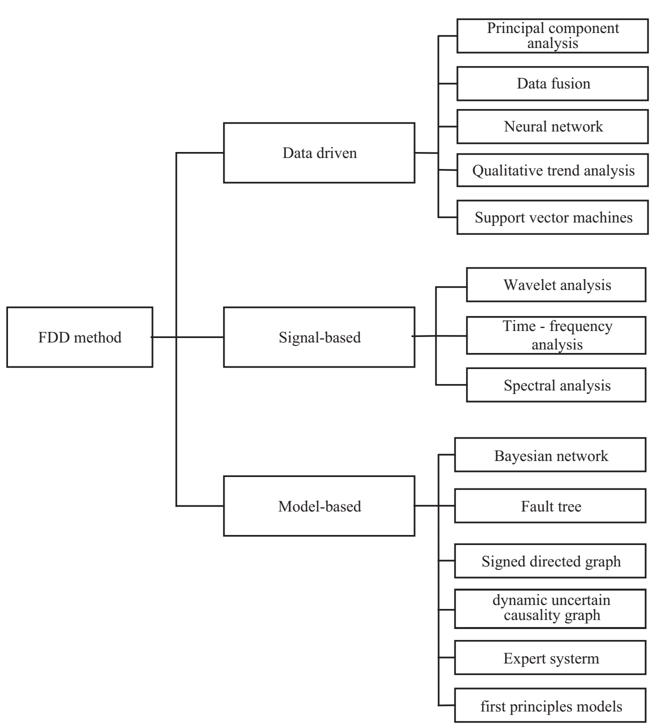

Fig. 1. Classification of common fault diagnosis methods.

Table 1
Comparison of fault diagnosis methods.

Characteristic	BN	Neural network	PCA	Signed directed graph	Expert system
Robustness	√	–	–	×	×
Explanation	√	×	×	√	√
Uncertainty information	√	√	√	–	–
Rapid diagnosis	√	√	√	√	√
Accuracy in general	√	√	√	√	√
Resolution	–	√	√	×	×

Table 1 compares fault diagnosis methods. In the table, "√" indicates that the method has the characteristic, "×" indicates that the method does not have the characteristic, and "—" indicates that the method does have the characteristic but there is room for improvement (Liu and Liu et al., 2013; Liu et al., 2018). It is seen from the comparison that the BN has advantages over most other methods.

1.3. Proposed hybrid intelligent framework for fault diagnosis

Although many FDD methods have been used for NPPs, only a few studies have focused on FDD using multi-source sensor nodes and incomplete data. These node and data characteristics introduce three critical problems: (1) in a real NPP, a parameter may be measured by multiple sensors, and it is therefore important for FDD to judge which sensor data are accurate; (2) the consideration of multi-source sensor nodes results in there being too many input nodes in the model, which can easily lead to information overload; and (3) in a real NPP, it is common for there to be incomplete data because of sensor hardware failure or data acquisition system malfunction (Liu et al., 2015). When there is a severe accident or a sensor malfunction in an NPP, the resulting incomplete data challenge the availability and effectiveness of FDD.

This paper proposes a hybrid artificial intelligence approach that addresses the three critical problems described above. In terms of the first problem, PCA has advantages in terms of feature extraction and data compression. In terms of the second problem, fuzzy logic and data fusion methods are proposed to consolidate the multi-source sensor data into one input node and thus avoid information overload. In terms of the third problem, a BN is used to realize FDD when data are incomplete.

The following architecture is proposed according to the approach described above. First, a PCA model is trained with multi-source sensor data and then used to eliminate data from malfunctioning sensors. Second, valid sensor data are processed with fuzzy theory equations, which transforms parameters into probably events. Third, the event probabilities are the input for data fusion, which converts multiple data points into one data point for each parameter. Fuzzy theory and data fusion are used