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Research and design of distributed fault diagnosis system in nuclear power plant

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ABSTRACT

Nuclear power plant (NPP) is a complex system with abundant operation data and various fault types. Moreover, in most cases, change of system parameters and prompt of the alarm system can not necessarily tell us directly what types the fault belongs to or where it lies in. When multiple faults occur, there is no one-to-one relationship between the fault symptom and the fault itself. Furthermore, the degree and response rate of the fault are different, so some faults are gradual and some are sudden. It is thus clear that for different faults, we need to conduct combined diagnosis with a variety of diagnostic methods to ensure accuracy and instantaneity in NPP fault diagnosis. According to the characteristic of the distributed function of equipment and the digital instrument and control (I&C) system, we studied and designed the distributed condition monitoring and fault diagnosis system in NPP. Based on the "disassemble-synthesizing" diagnostic idea, this paper proposed an intelligent diagnosis method which applied the fuzzy neural network (FNN) in doing local diagnosis and multi-source information fusion technology in global diagnosis. The simulation result showed that this method can quickly and accurately complete the tasks of diagnosing different levels of the single fault and different types of multiple faults.

1. Introduction

Since the discovery of natural radioactivity in 1896, artificial radioactivity in 1934 and nuclear fission in 1938, nuclear science has been developing with an amazing speed and has made extraordinary achievements. Nuclear energy has made great contribution to the development of our society and the progress of economy. It is the worldwide human's goal to make use of nuclear energy in a safe and peaceful way, however, the nuclear accident or will go against the human's good wishes, destroy the ecological environment on the earth and even threaten people's life and health. As for the Three Mile Island nuclear accident took place in the U.S. in 1979 and the Chernobyl nuclear disaster in Soviet Union in 1986, many people got scared at mere mention of radioactivity for a long time. On Mar. 11, 2011, affected by earthquake and tsunami in Japan, radioactive substances leaked out from the Fukushima NPP, causing a worldwide nuclear panic and drawing people's overwhelming attention to NPP safety once more. So how to ensure the safety of NPP has become a major problem awaiting for immediate solution (Bevelacqua, 2012; Bowyer et al., 2011). In view of this, the International Atomic Energy Agency (IAEA), the World Association of Nuclear Operation (WANO), the US Nuclear Regulatory Commission (NRC) and other nuclear organizations put forward the importance of developing the computer based Operator Support System (OSS). The OSS provide operational support for NPP operators, including the operational instructor under normal running condition, the fault diagnosis technology during accident progression, the safety analysis and control instructor and so on (Zhang, 1997).

Fault detection and diagnosis (FDD) technology during the accident progression has always been given high attention in the NPP(Li and Upadhyaya, 2011; Li et al., 2012). Appling the effect method of fault diagnosis, such as artificial neural networks (ANN), fuzzy logic (FL), data fusion and etc. or hybrid intelligent diagnosis method of these method integrated, this could provide real-time help on line for the operators of NPP, and help them distinguish the fault progression state quickly and accurately, and adopt the correct operating method to suspend the fault process or alleviate the consequences of the accident. As shown in Table 1, fault

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Table 1
Classification of FDD methods.

Model-based methods	Model-free methods	
	Data-driven methods	Signal-based methods
Parity equations	Artificial neural networks (ANN)	Spectrum analysis
Diagnostic observers	Fuzzy logic (FL) Multivariate state estimate technique (MSET)	Time-frequency analysis (TFA)
Kalman filters	Principal component analysis (PCA)	Wavelet transform (WT)
Parameter estimation	Partial least squares (PLS) Autoassociative kernel regression (AAKR) Expert system (ES)	Autoregressive (AR) signal model Control charts

diagnosis methods can be classified into model-based methods and model-free methods. The latter can be further classified into data-driven methods (multivariate) and signal-based methods (univariate). Over the past four decades, various fault diagnosis methods, especially model-based methods and data-driven methods, have been applied to NPPs (Hashemian, 2011; Uhrig, and Hines, 2005). Examples of model-based condition monitoring can be found in Zhao and Upadhyaya (2006) and Gross et al. (1997). Among data-driven tools, ANN and Principal Component Analysis (PCA)-based tools (Upadhyaya et al., 2003; Lu and Upadhyaya, 2005) are most popular. While model-based techniques have their advantages in terms of physical understanding, their reliability and computational efficiency for fault detection often are less attractive when the systems become more complex. Alternatively, despite increased system complexity if the goal is to monitor the input–output information from a collection of (appropriately calibrated) sensors while considering the whole system as a black box, data-driven techniques are expected to remain reliable and efficient. However, unless the collection of acquired information is handled properly, data-driven techniques may become computationally intensive and the performance of fault detection may deteriorate due to sensor degradation. Furthermore, data-driven techniques would require high volume of training data.

Data-driven modeling based on using ANN in NPP is quite diversified and it ranges from single component fault diagnosis (Zhao and Upadhyaya, 2006) to recent works related to fault diagnosis in the whole nuclear steams supply system (NSSS) (Xin et al., 2010). Majority of the works (Upadhyaya et al., 2003; Lu and Upadhyaya, 2005; Xin et al., 2010; Santosh et al., 2009) have explored Multilayer ANN with back propagation training, as this type of ANNs has an excellent capacity of approximation and generalization. In addition to the above-mentioned ANN, other intelligent information processing techniques, such as FL and data fusion, have been employed in recent years in FDD and structural damage detection, largely due to their inherent capabilities in extracting and attaining precise, reliable, consistent and intelligible information from imprecise, unreliable, inconsistent and uncertain data (Gao, 2004; Pedrycz, 1997).

The ANN technique alone, capable of auto-association, self-organization, self-learning and non-linear modeling, gradually began to be utilized for FDD. The ANN can provide high training precision with generalization for continuous function mapping of the underlying process models and has applications for specific output rules. The FL technique acts to model human knowledge in the form

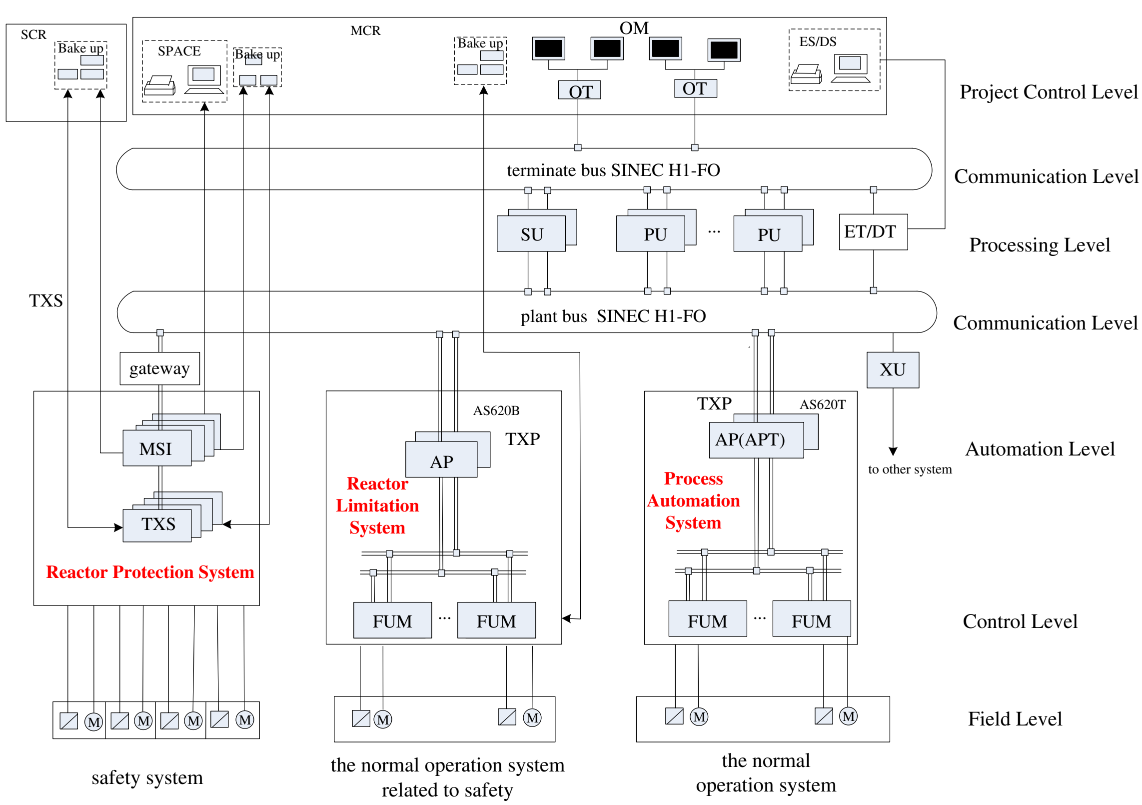

Fig. 1. The structure of Siemens's TELEPERM XP + XS system. PU-Process Unit; SU-Sever Unit; AP-Automatic Processor; APT-Automation Processor of Turbine; XU-External Unit; OM-Operation and Monitoring System; ES-Engineering System; DS-Diagnosis System; OT-Operating Terminal; ET-Engineering Terminal; DT-Diagnosis Terminal; SINEC-SIMATIC NET; FUM-Function Module; MSI-Monitoring and Service Interface; TXS-Teleperm XS; TXP-Teleperm XP; MCR-Main Control Room; SCR-Standby Control Room; SPACE-Specification And Coding Environment.