Progress in Nuclear Energy 53 (2011) 255–266

Contents lists available at ScienceDirect

Progress in Nuclear Energy

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

Applications of fault detection and diagnosis methods in nuclear power plants: A review

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ARTICLE INFO

Article history:
Received 3 June 2010
Accepted 3 December 2010

Keywords:
Fault detection
Fault diagnosis
Nuclear power plant

ABSTRACT

Nuclear power industries have increasing interest in using fault detection and diagnosis (FDD) methods to improve safety, reliability, and availability of nuclear power plants (NPP). A brief overview of FDD methods is presented in this paper. FDD methods are classified into model-based methods, data-driven methods, and signal-based methods. While practical applications of model-based methods are very limited, various data-driven methods and signal-based methods have been applied for monitoring key subsystems in NPPs. In this paper, six areas of such applications are considered. They are: instrument calibration monitoring, instrumentation channel dynamic performance monitoring, equipment monitoring, reactor core monitoring, loose part monitoring, and transient identification. The principles of using FDD methods in these applications are explained and recent studies of advanced FDD methods are examined. Popularity of FDD applications in NPPs will continuously increase as FDD theories advance and the safety and reliability requirement for NPP tightens

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1. Introduction

As a safety-critical system, safety is of prime importance for any nuclear power plant (NPP). In addition, there is an ever increasing demand to operate NPPs more cost-effectively with a high capacity factor. To improve safety and capacity factors, preventive actions are desirable to deal with potential issues in NPPs. A fault is an unpermitted deviation of one characteristic property from the desired condition for a system. A failure is a permanent interruption of a system's ability to perform a required function with specified performance requirements (Isermann and Balle, 1997). Various faults and failures can occur in instruments, equipment, and processes of an NPP, which can have a significant impact on plant performance. For example, drift in steam generator (SG) feedwater flow sensors can result in reactor power output reduction by as much as 3% (Chan and Ahluwalia, 1992). Six types of potential faults that can occur in an NPP are summarized in Table 1. Aged NPPs are more vulnerable to aging-related faults (IAEA-TECDOC-1147, 2000) (IAEA-TECDOC-1402, 2004). This becomes a major concern as existing NPPs on average are over 26 years old (Nuclear Power Plants Information, 2010).

Fault detection and diagnosis (FDD) is the process to detect, isolate, and identify faults in a system. Fault detection determines whether faults are present. Following fault detection, fault isolation determines the location of the fault. Fault identification determines the size and time-variant characteristics of the fault (Isermann and Balle, 1997). Fault diagnosis includes fault isolation and fault identification. FDD methods can be applied to monitor a system continuously during operation, which is often referred to as on-line monitoring (OLM). As shown in Table 2, FDD 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). In a model-based FDD, a mathematical model is used to represent the normal behavior of the system. Faults in the system are detected and diagnosed by checking consistency between the observed behavior and the predicted behavior through the model. Practical applications of model-based FDD methods are very limited due to the requirement of an accurate model that is always hard to obtain in practice. Data-driven FDD methods also rely on relationships between correlated measurements within a system. However, the relationships can be formulated in an implicit way by training an empirical model through analysis of fault-free training data obtained during normal operations. The empirical model is then used to estimate true values of new measurements, and faults are detected and diagnosed by evaluating the estimation residuals. Signal-based methods make FDD decisions by comparing features (e.g., spectrum) extracted from a signal with desired normal baseline

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0149-1970/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.pnucene.2010.12.001

Nomenclature

AAKR	Autoassociative kernel regression
AANN	Autoassociative neural network
AR	Autoregressive
AE	Acoustic emission
ANN	Artificial neural network
BWR	Boiling water reactor
CANDU	CANada Deuterium Uranium
DNBR	Departure from nucleate boiling ratio
FDD	Fault detection and diagnosis
FFT	Fast Fourier transform
I&C	Instrumentation and control
ICA	Independent component analysis
LER	Licensee event report
LPMS	Loose part monitoring system
MCC	Motor control center
MCSA	Motor current signature analysis
MSET	Multivariate state estimation technique
MTC	Moderator temperature coefficient
NR	Narrow range
NPP	Nuclear power plant
NRC	Nuclear regulatory commission
O&M	Operation and maintenance
OLM	On-line monitoring
PLS	Partial least squares
PCA	Principal component analysis
PEANO	Process evaluation and analysis by neural operators
PRZ	Pressurizer
PSD	Power spectral density
PWR	Pressurized water reactor
RCS	Reactor coolant system
RMS	Root mean square
SG	Steam generator
SPND	Self-powered neutron detector
TFA	Time-frequency analysis
VVER	A Russian type nuclear reactor
WR	Wide range
WT	Wavelet transform

values. Data-driven FDD methods and signal-based FDD methods have been extensively used in various industrials (Chiang et al., 2001) (Yue and Qin, 2001) (Venkatasubramanian et al., 2003) (Hines and Davis, 2005) (Zhang and Dudzic, 2006) (Peng and Chu, 2004) (Rehorn et al., 2006) (Sejdić et al., 2009).

Over the past four decades, various FDD methods, especially data-driven methods and signal-based methods, have been applied to NPPs (Hashemian and Feltus, 2006) (Uhrig and Hines, 2005). Applications of FDD methods to solve the problems presented in Table 1 are briefly summarized in Table 3. Those applications lead to benefits for safe and efficient plant operations. From the viewpoint of NPP safety, such benefits include, but are not limited to:

a. *Reduce radiation exposure to personnel*: FDD can lead to the optimal scheduling of maintenance and repair activities. Therefore, radiation exposure to plant personnel can be minimized.
b. *Enhance equipment reliability*: Equipment OLM is a beneficial supplement to periodic inspection. Early warnings of incipient faults allow corrective measures to be taken before critical situations happen.
c. *Avoid actuations of safety systems*: Fault detection at an early stage can prevent safety systems from actuating, thus reducing the number of unplanned events with potential safety significance.
d. *Assist with correct and timely decision making*: On the one hand, incipient fault detection reduces the chances of unexpected operational upsets. On the other hand, diagnosis of impending failures gains time for anticipative decision making and adequate countermeasure planning.
e. *Enhance safety margins*: FDD methods are used to achieve better reactor core monitoring. Reducing reactor core monitoring uncertainties means enhanced safety margins.

From the viewpoint of plant economics, benefits of FDD in NPPs include, but are not limited to:

a. *Optimize the maintenance schedule*: The current practice of time-based preventive maintenance has limitations for an NPP, such as unnecessary inspections (Hines and Seibert, 2006). By the OLM of instruments and equipment, condition-based maintenance can be adopted.
b. *Improve plant availability*: FDD applications contribute to improved plant availability for a number of reasons. Firstly, diagnosis of incipient faults prevents unexpected operational

Table 1
Potential faults in NPPs.

Faults	Examples	Impact on an NPP
Instrument steady state performance degradation	Sensor drift Sensor bias	Reduced reactor power output Substantial operation and maintenance (O&M) cost Radiation exposure to personnel
Instrumentation channel dynamic performance degradation	Pressure measurement slow response due to sensing line blockage	Affect system reliability Technical specifications not met
Faults in equipment	Damaged machine bearing Motor winding faults Poor lubrication	Reactor trip/scram Plant transients and safety system actuation Substantial O&M cost
Loose parts in reactor coolant system (RCS)	Detached RCS structures External objects	Damage to SG tubes and nuclear fuel Potentially affect safety functions Expensive to repair
Anomalies in reactor core	Undesirable power distribution Vibration of reactor internals	Conservative reactor power output Reactor trip/scram
Plant transients	Control rod ejection Loss of normal feedwater flow	Reactor trip Actuation of safety systems

Table 2
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	Multivariate state estimate technique (MSET)	Time-frequency analysis (TFA)
Kalman filters	Principal component analysis (PCA)	Wavelet transform (WT)
Parameter estimation	Partial least squares (PLS)	Autoregressive (AR) signal model
	Autoassociative kernel regression (AAKR)	Control charts

upsets and reduces unplanned shutdowns. Secondly, scheduled plant down time can be reduced through optimal maintenance planning. Finally, FDD applications help to avoid plant performance deteriorations due to equipment faults.

c. *Avoid escalation of minor problem into major event*: Diagnosing faults at early stage enables timely repairs, preventing the faults from developing into more serious problems.
d. *Support power uprates and life extension*: Power uprates and life extension are the two viable ways to improve power production in existing NPPs. Better plant performance monitoring and aging management, through applications of FDD, are important aspects to support power uprates and life extensions.

With progresses in FDD theory and NPP instrumentation and control (I&C) technologies, there is a growing interest in nuclear industry to apply FDD in existing plants. FDD will play ever important roles in future NPPs that have tighter requirements for safety and economy. Modern I&C systems make more plant data available for analysis and trending using state-of-the-art FDD methods. Contemporary plant information systems collect and archive plant-wide measurement data. Real-time and historical data can be analyzed for plant performance monitoring, and abnormal events can be swiftly delivered to pertinent plant personnel for subsequent actions. Applications of digital communication technologies (e.g., Ethernet) in motor control centers (MCC) make critical motor condition information accessible for real-time monitoring and fault diagnostics. The nuclear industry also starts to look at using wireless communication in NPPs, which makes cost-effective OLM increasingly feasible (Hashemian et al., 2009a) (Hashemian et al., 2009b) (Kadri et al., 2009).

This paper presents a review of FDD methods and their applications in NPPs. One of the objectives of this paper is to introduce current issues in the nuclear power industry to the FDD research community, and also to expose the concepts and techniques of FDD to the nuclear power industry so that these techniques can be adopted for practical applications. Due to the nature of the paper, more emphasis is placed on concepts and scope of methods. Technical details are left to the references.

The rest of the paper is organized as follows. In Section 2, FDD methods are surveyed in the order of model-based methods, data-driven methods, and signal-based methods. Principles of the three FDD approaches are explained, and characteristics of a number of popular techniques are summarized. In Section 3, six application areas of FDD methods in NPPs are overviewed following the same order in Table 3. For each application area, the problems are stated; principles of using FDD to solve the problems are explained; practical FDD methods for the application are highlighted; and trends for future development are examined. Section 4 contains a brief summary and discussion.

2. Review of FDD methods

2.1. Model-based FDD methods

Analytical redundancy (Willsky, 1976) (Chow and Willsky, 1984) is the core concept that most model-based FDD methods are based on. In model-based FDD, the normal behavior of a system is represented by a mathematical model. Sensory measurements are estimated analytically from other correlated measurements using the model that describes their relationships. The idea can be extended to analytically estimate other quantities such as model parameters and system states. The differences between the analytically estimated quantities and the actual measurements are called residuals. Faults result in violations of the normal relationships represented in the model, leading to statistically abnormal changes in the residuals. Therefore, faults can be detected by testing these residuals statistically (Gertler, 1988) (Isermann, 2006). Fault isolation techniques vary by model structures. Some popular techniques are isolation enhanced residuals (Gertler and Singer, 1990) (Li and Shah, 2002) (Li and Jiang, 2004), use of a set of specially designed models (Beard, 1971) (Clark, 1978) (Frank, 1990), recovery of physical coefficients (Isermann, 1992) (Jia and Jiang, 1994) (Jia and Jiang, 1995), and expert knowledge systems (Isermann, 1993). The processes of model-based FDD can be divided into the following subsystems: residual generation, residual evaluation and decision making as summarized in Fig. 1.

Among the most studied model-based FDD methods are parity equations (Chow and Willsky, 1984) (Lou et al., 1986) (Gertler and Singer, 1990) (Gertler, 1997), diagnostic observers (Beard, 1971) (Clark, 1978) (Frank, 1990) (Frank and Ding, 1997), Kalman filters (Willsky, 1986) (Basseville, 1988), and parameter estimation (Isermann, 1984) (Isermann, 1993) (Li and Jiang, 2004). Subspace system identification methods emerged in the 1990s for model-based FDD applications (Larimore, 1990) (Verhaegen and Dewilde, 1992) (Van Overschee and De Moor, 1994) (Van Overschee and De Moor, 1995) (Qin and Li, 2001) (Dong and Verhaegen, 2009) (Dong et al., 2009). As is shown in Table 4, system models used for model-based FDD include both state-space models and input-output models. Characteristics of the model-based FDD methods are summarized in Table 5. Model-based methods can be designed to detect and diagnose multiple faults simultaneously in dynamic systems (Clark, 1978). However, accurate system models are required, which can be difficult to obtain for complex systems. In

Table 3
Applications of FDD methods in NPPs.

Applications	Data-driven methods	Signal-model methods
Instrument calibration monitoring	Sensor output estimation	
Instrumentation channel dynamic performance monitoring	(e.g., ANN, MSET, PCA AAKR)	Analysis of measurement noises (e.g., power spectral density (PSD), AR model)
Equipment monitoring	Sensory data estimation (e.g., ANN, MSET)	Analysis of vibration, motor current, and acoustic emission (AE) signals (e.g., PSD, WT, TFA)
Loose part monitoring		Analysis of structural borne acoustic signals (e.g., spectrum analysis, TFA)
Reactor core monitoring	Reactor parameter estimation (e.g., ANN)	Analysis of neutron noises (e.g., PSD, WT, decay ratio estimation)
Transient identification	Pattern recognition (e.g., ANN)	

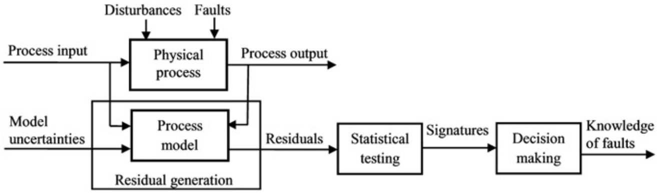

Fig. 1. Schematic of model-based FDD.

addition, faults that have not been considered in the modeling stage may not be detected at all. Further, robustness against disturbances and modeling uncertainties has to be considered (Chow and Willsky, 1984) (Lou et al., 1986) (Frank and Ding, 1997) (Patton and Chen, 1997). In summary, even though model-based FDD methods have been extensively studied, their practical applications in NPPs are still very limited at present.

2.2. Model-free FDD methods

FDD methods that do not rely on explicit mathematical models of a concerned system are collectively referred to as model-free methods in this paper. They are further classified into data-driven methods and signal-based methods.

Data-driven methods use multivariate statistical methods and machine learning tools for FDD. They also rely on relationships between correlated measurements within a system, but use them implicitly through analysis of fault-free training data obtained during normal operations. For this reason, such methods are also referred to as process history-based methods (Venkatasubramanian et al., 2003). Suppose that there is a training data matrix $D \in R^{l \times n}$ obtained from a system, where n is the number of concerned variables and l is the number of training data samples, and an empirical model f is trained using D. When a set of new measurements $d \in R^{1 \times n}$ becomes available, estimations of d can be obtained as $d = f(d)$ and the residuals can be generated as $e = d - d$. Any faults in the system will cause changes in the relationships between the variables in d. This results in statistically abnormal changes in the residuals. Consequently, faults can be detected and diagnosed by performing statistical tests on the residuals. The processes of data-driven FDD can be divided as following: model training, residual generation, and residual evaluation. A schematic of data-driven FDD is illustrated in Fig. 2. Note that Fig. 2 shows the principle of data-driven FDD in a general sense. In fact, the model f can be a mapping from the input variables d_{in} to the output variables d_{out} which are subsets of d and consist of different variables. It is not a necessary requirement for f to estimate every variable in d, but only those of interest for the diagnostic task. Since no explicit models are required, data-driven methods are more attractive to practical applications with complex systems. However, a key limitation of data-driven methods is that the empirical model only works well within the operational range represented by the training data.

A variety of data-driven FDD methods have been developed such as ANN (Anderson, 1995) (Watanabe et al., 1989) (Venkatasubramanian et al., 1990), MSET (Herzog et al., 1998) (Zavaljevskl and Gross, 2000), PCA (Wise and Gallagher, 1996) (Dunia et al., 1996) (Kaistha and Upadhyaya, 2001), PLS (MacGregor and Kourti, 1995) (Wise and Gallagher, 1996), AAKR (Garvey and Hines, 2006), independent component analysis (ICA) (Hyvarinen, 1999), cross-calibration (Hashemian, 2006), and their variants (Kramer, 1991) (Qin and McAvoy, 1992) (Dong and McAvoy, 1996) (Schölkopf et al., 1998) (Cho et al., 2005). Those methods have been extensively applied in various industries. In NPPs, data-driven methods have been studied for instrument calibration monitoring, equipment monitoring, reactor core monitoring, and transient identification. Among data-driven methods, PCA is one of the most used techniques due to its simple and flexible structure. It has been studied for FDD in NPP instruments (Kaistha and Upadhyaya, 2001) (Ma and Jiang, 2009). In addition, there are two other extensively used data-driven methods for applications in NPPs: MSET and ANN, particularly the autoassociative neural network (AANN) (Kramer, 1991) (Hines et al., 1998). Techniques based on MSET and ANN are used in the SmartSignal system (Hines and Davis, 2005) (SmartSignal, 2010) and PEANO (process evaluation and analysis by neural operators) system (Fantoni et al., 2003) (Fantoni, 2005) developed for OLM of NPPs. ANN has also been studied for NPP transient identification (Bartlett and Uhrig, 1992) (Embrechts and Benedek, 2004) and to estimate parameters important for reactor core monitoring (Dubey et al., 1998) (Souza and Moreira, 2006). Characteristics of PCA, MSET, and ANN are summarized in Table 6. Recently, kernel-based machine learning techniques (Shawe-Taylor and Cristianini, 2004) have been used for pattern recognition (Vapnik, 1995) (Burges, 1998) and fault detection (Lee et al., 2004) (Widodo and Yang, 2007) (Mahadevan and Shah, 2009) (Ma and

Table 4
System models for model-based FDD methods.

State space model	Input-output model
$x(t+1) = Ax(t) + Bu(t)y(t) = Cx(t)$ where t is time, x is state vector, u is input vector, y is output vector, and A, B and C are matrices with proper dimensions	$H(z)y(t) = G(z)u(t)$ or $y(t) = \varphi^T(t)\theta$ where, z is a shift operator, $G(z)$ and $H(z)$ are matrices consisting of elements that are polynomials of z, θ consists of model parameters and $\varphi^T(t)$ contains system past inputs and outputs (Isermann, 1993)

Table 5
Model-based FDD methods.

Method	Equation	Comments
Parity equations	$e(t) = G(z)u(t) - H(z)y(t)$ where $e(t)$ is residual	Advantageous for additive faults[a]
Diagnostic observer	$\hat{x}(t+1) = A\hat{x}(t) + Bu(t) + L(y(t) - C\hat{x}(t))$ $e(t) = y(t) - C\hat{x}(t)$ where x is estimate of x, and L is the observer feedback matrix	Advantageous for additive faults For deterministic settings
Kalman filter	$\hat{x}(t+1\|t) = A\hat{x}(t\|t) + Bu(t)$ $\hat{x}(t\|t) = \hat{x}(t\|t-1) + K'(t)e(t)$ $e(t) = y(t) - Cx^{(t\|t-1)}$ where $K'(t)$ is Kalman gain	Advantageous for additive faults For system with stochastic disturbances Some studies for NPP applications
Parameter estimation	$\theta = [\Psi^T\Psi]^{-1}\Psi^T Y$ where θ is estimation of θ, Ψ is a matrix consists of $\Psi^T(t)$, and Y is a vector consists of $y(t)$	Advantageous for multiplicative faults[b] Physical coefficients may be recovered for diagnosis Expensive on-line computation

[a] An additive fault such as sensor bias and process leak leads to residuals that are independent of values of an observed system variable.
[b] A multiplicative fault such as surface contamination reflects changes in plant parameters, leading to residuals that are dependent on system variables.

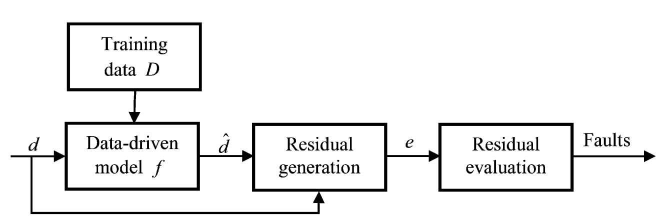

Fig. 2. Schematic of data-driven FDD methods.

Table 6
Data-driven FDD methods and their applications in NPP.

Method	Equation	Characteristics	NPP applications
PCA	$\hat{d} = \sum_{i=1}^{k} mp_i p_i^T$ where p_i is the eigenvector of the correlation matrix of D corresponding to the ith largest eivenvalue, and k is the number of retained principal components.	Simple and flexible Linear	Instrument monitoring Equipment monitoring
MSET	$\hat{d} = D \cdot (D^T \otimes D)^{-1} (D^T \otimes d)$ where $\otimes$ is a nonlinear kernel operator.	Nonlinear Popular for NPP applications	Instrument monitoring Equipment monitoring
ANN	$\hat{d} = F(\sum_i w_i h_i(d))$where F are activation functions, w_i are weights, and h_i are other functions that generate outputs using weighted sum of inputs, subjected to activation functions.	Nonlinear Popular for NPP applications Popular for pattern recognition Black-box structure	Instrument monitoring Equipment monitoring Reactor core monitoring Transient identification

Jiang, 2010) in various industries. Their applications in NPPs have not yet been fully explored.

Signal-based FDD methods make decisions by comparing features extracted from a signal with baseline characteristics that are considered to be normal. Features in both frequency domain and time domain have been used. This scheme is shown as Fig. 3. Signal-based methods do not rely on analytical relationships between different measurements.

Spectrum analysis is among the most used signal-based methods for FDD. The spectrum of a signal can be obtained using the fast Fourier transform (FFT). Spectrum analysis is a powerful tool to diagnose faults in NPP instrumentations, equipment, and processes. TFA (Cohen, 1989) (Hlawatsch and Boudreaux-Bartels, 1992) (Stockwell et al., 1996) and WT (Qian, 2002) are extensions to spectrum analysis. TFA maps a one dimensional signal into a two dimensional function space in both time and frequency. Therefore, the instantaneous spectrum of the signal can be obtained. WT uses time-scale decomposition of a signal. It can also generate the instantaneous spectrum of the signal as a function of time. WT and TFA demonstrated better results over spectrum analysis for transient signals and signals with low signal-to-noise ratios. They are increasingly used for FDD applications in various industries, including nuclear (Tandon and Choudhury, 1999) (Kim et al., 2003) (Peng and Chu, 2004) (Pokol and Por, 2006) (Park et al., 2006) (Sejdić et al., 2009). A summary of spectrum analysis, TFA, and WT is presented in Table 7. As shown in Table 8, those methods have been used in NPPs for instrumentation channel dynamic performance monitoring, equipment vibration monitoring, motor current signature analysis (MCSA), AE monitoring, loose part monitoring, and vibration monitoring of reactor internal mechanisms. Signal-based methods in time domain include control charts (Montgomery, 2005) (Hunt, 1986), AR model fitting for step response estimation (Hashemian et al., 1988) (Kitamura, 1989), and root mean squares (RMS), to name a few.

Due to the promising results in studies for NPP applications, a few FDD methods that process information qualitatively using tools such as if-then rules are also worth mentioning. These qualitative methods can process imprecise and incomplete information to make FDD decisions. Two popular techniques are fuzzy logic (Zhang and Morris, 1994) and expert systems (Nelson, 1982) (Bernard and Washio, 1989). Fuzzy logic, expert systems, genetic algorithms

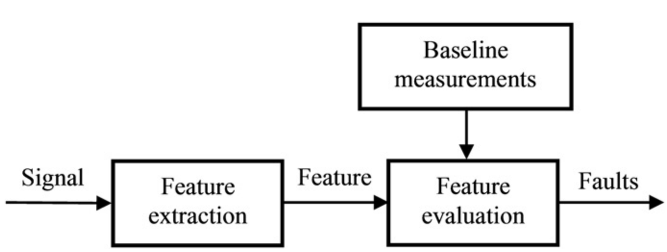

Fig. 3. Schematic of signal-based FDD methods.

(Holland, 1975), and ANN are among the most used techniques in the so called "soft computing" computational regime. Applications of soft computing methods in NPPs include sensor validation, equipment monitoring, and reactor core surveillance. Such applications prior to 1999 are reviewed in Uhrig and Tsoukalas, (1999). Some recent studies can be found in Na et al. (2001); Marseguerra et al. (2003); Embrechts and Benedek, (2004); Zio and Baraldi, (2005); Souza and Moreira, (2006); Razavi-Far et al. (2009); Zaferanlouei et al. (2010). Other qualitative methods studied in the literature include qualitative reasoning (De Kleer and Brown, 1984) (Weld and De Kleer, 1990) (Kuipers, 1994) (Iwasaki, 1997), signed directed graph (Iri et al., 1979) (Umeda et al., 1980) (Kramer and Palowitch, 1987), and case-based reasoning (Aamodt and Plaza, 1994) (Watson and Marir, 1994). Applications of such methods in NPPs are relatively limited at present.

3. Applications of FDD methods in NPPs

3.1. Instrument calibration monitoring

The steady state performance of an instrument in an NPP can degrade over time, leading to problems such as drift and bias (Hashemian, 2004). To deal with these problems, currently, instruments in NPPs have to be calibrated periodically. This often requires a system shutdown or takes the instruments out of service. However, operational experience shows that less than 5% of the manual calibrations are even necessary (Hines and Seibert, 2006). The unnecessary calibrations increase plant outage time, staff workload, and radiation exposure. In addition, the reliability of an instrument may be adversely affected by manual intervention. Furthermore, a fault occurring between two consecutive time-based calibrations may not be detected, that could lead to more serious consequences. It is therefore desirable to monitor steady state performance of instruments during plant operation. This is referred to as calibration monitoring. Calibration monitoring can lead to optimal maintenance, enhanced instrument reliability, reduced O&M costs and less radiation exposure for personnel (James, 1996) (Evans, 2004).

A key component in calibration monitoring is accurate estimation of a sensor's output. Steady state performance of the sensor can be validated by comparing its actual output with the reference. To this end, two FDD approaches can be implemented: hardware redundancy and analytical redundancy. In hardware redundancy, redundant physical sensors are used to measure one variable. Outputs from the redundant sensors can serve as additional reference for cross-checking each other. This is the basic idea of the cross-calibration technique (Hashemian, 2006), where the average of a set of redundant sensors is considered to be the true value of a variable being measured. A fault in a sensor can be detected if the sensor shows any abnormal deviation from the average. Limitations

Table 7
Signal-based FDD methods.

Methods	Characteristics
Spectrum analysis	Simple frequency domain analysis Extensively used in NPP applications No time resolution
Time-frequency analysis	Time-dependent spectrum Computationaly more expensive than spectrum analysis Increasingly studied for recent NPP applications
Wavelet transform	Time-dependent spectrum with frequency-dependent resolution Good for transient signals and signals with spikes Popular for recent NPP applications

of hardware redundancy include the need for extra sensors, and it is difficult to detect faulty sensors that drift in the same direction. The other approach, known as analytical redundancy, estimates the output of a sensor analytically from other correlated measurements in the system. Most of data-driven FDD methods use such an approach. Model-based methods can also be used in theory, but this is difficult for practical NPP systems. The approach of analytical redundancy is illustrated in Fig. 4 using eight measurements of a pressurized water reactor (PWR), where PRZ, WR, and NR represent pressurizer, wide range, and narrow range, respectively. Fig. 5 shows calibration monitoring results for an SG level WR sensor throughout a fuel cycle. Presented in Fig. 5 are the differences between the actual level outputs and the estimated ones generated by a nonlinear PCA model (Ma and Jiang, 2010), using measurements shown in Fig. 4. It is observed that a drift has developed in the sensor over time.

MSET, ANN, and their variants are the most widely used FDD methods for calibration monitoring in NPPs. Some additional data-driven methods reported for calibration monitoring include PCA (Kaistha and Upadhyaya, 2001) (Ma and Jiang, 2009), ICA (Ding et al., 2004), nonlinear PLS (Rasmussen et al., 2000) (Fantoni et al., 2002), and AAKR (Garvey and Hines, 2006). Data-driven calibration monitoring methods have been demonstrated with success using real NPP data (Herzog et al., 1998) (Fantoni, 2005). In (Herzog et al., 1998), using an MSET model, the feedwater flow of a PWR plant can be estimated from 29 correlated measurements with an RMS error of only 0.13% of the flow rate at full power.

A safety evaluation report TR-104965 issued in 2000 by the U.S. Nuclear Regulatory Commission (NRC) concluded that the generic concept of on-line instrument performance monitoring is acceptable. However, some requirements such as uncertainty analysis must be addressed by plant specific license amendments if request to relax the calibration frequency of safety-critical instrumentation is made. Recently, uncertainty analysis and verification and validation of data-driven calibration monitoring methods are investigated (Hines and Rasmussen, 2005) (Hines and Davis, 2005) (Uhrig and Hines, 2005). Performance optimization of those methods has also been studied (Gribok et al., 2002) (Hines and Usynin, 2005). Overall, instrument calibration monitoring in NPPs has been extensively studied with potential benefits recognized (Evans, 2004). Plant monitoring systems developed based on these calibration monitoring methods have been implemented in a number of NPPs (Hines and Davis, 2005) (Fantoni, 2005) (SmartSignal, 2010).

3.2. Dynamic performance monitoring of instrumentation channels

Dynamic performance is an important aspect of instrumentation channels in NPPs. For temperature and pressure measurements, response time is very important, particularly for safety systems. Response time can be defined as the time it takes for the output of a sensor to reach 67.3% of its final steady-state value following a step change at the input. The time constant of an instrumentation channel should not exceed the maximum value assumed in the safety analyses. The response time of an instrumentation channel can degrade for various reasons. For a thermal-well mounted temperature sensor, its response time can increase due to air gap, obstructions or dirt between the sensor and the thermal-well (Hashemian, 2004). A sensing line is often used in NPPs to connect the process to the pressure transmitter. Problems in a sensing line, such as blockages, voids, and leaks, can increase the response time. Depending on the transmitter, such an increase could be over one magnitude (Hashemian, 2004). Testing the response time of an instrumentation channel often requires taking the measurement system out of service. Unfortunately, off-line tests cannot replicate the exact on-line operating conditions. Furthermore, it is very difficult and expensive to carry out these tests frequently. For a self-powered neutron detector (SPND) used in Canada Deuterium Uranium (CANDU) reactor shutdown systems (Rouben, 1999), its dynamic performance is influenced by the fraction of prompt signal. The signal of an SPND consists of a prompt component and a series of delayed components (Ma, 2006). Only the prompt signal is able to respond to neutron flux change instantaneously. Therefore, it is a requirement for the prompt fraction to be above a minimum limit so that the detector can respond fast enough to overpower accidents (Glöckler, 2003) (Demazière and Glöckler, 2004). The prompt fraction of an SPND changes over time due to material burn-up and defects. The prompt fraction is conventionally tested by comparing SPND outputs with signals from an ex-core ion chamber during a planned shutdown. This requires extensive preparation and the test frequency is very limited (Demazière and Glöckler, 2004).

Noise analysis, a signal-based method, provides a mean for dynamic performance monitoring of instrumentation channels during plant operation. On top of the steady-state value, noise-like fluctuations often exist at the outputs of an instrumentation channel. With the assumption that the fluctuations are driven by white noise from the process, a model of the instrumentation channel can be generated from the measurement noises, from which the response time can be estimated (Hashemian, 2006) (Hashemian and Jiang, 2010). Degradation of dynamic response can be diagnosed by comparing the recently computed response time with what is considered to be normal. The concept of this scheme is illustrated in Fig. 6. After signal acquisition and qualification, signal analysis in both time and frequency domains can be used to extract response

Table 8
Applications of signal-based FDD methods in NPPs.

Applications	Signals	Features	Methods
Instrumentation channel dynamic performance monitoring	Measurement noises	Break frequency Step response function	FFT AR model
Equipment vibration monitoring	Vibration measurements	Spectrum	FFT, TFA, WT
MCSA	Stator current of induction motors	Spectrum	FFT, TFA, WT
Vibration monitoring of reactor internals	Neutron detector noises	Spectrum Cross power spectral density	FFT, TFA, WT
Loose part monitoring	Structural borne acoustic signals	RMS, spectrum, frequency ratio	FFT, TFA, WT

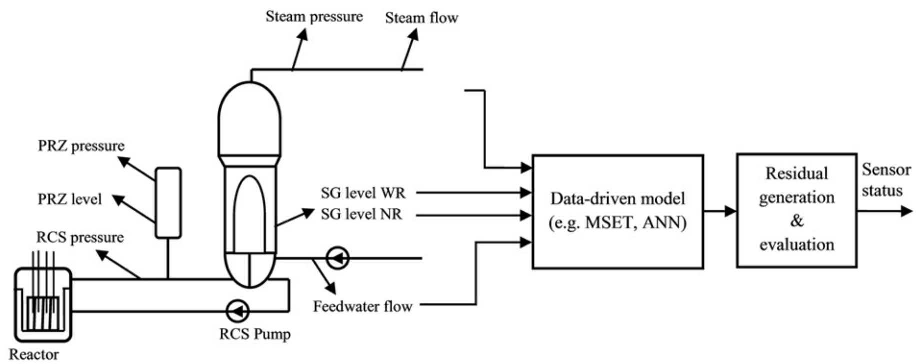

Fig. 4. Principle of data-driven instrument calibration monitoring.

time from the measurement noises. In the time domain, an AR model for the measurement noises can be obtained. The step response of the instrumentation channel can be calculated from the AR model coefficients (Hashemian et al., 1988) (Kitamura, 1989). In the frequency domain, PSD of the measurement noises is first obtained, from which the time constant can be estimated as the inverse of the break frequency (Hashemian, 2006). Noise analysis has also been studied for on-line determination of prompt fractions of SPNDs in CANDU reactors. It is based on the understanding that only the prompt signal of an SPND is able to follow the low frequency neutron flux fluctuation around 0.25 Hz in the reactor caused by reactor regulating systems (Demazière and Glöckler, 2004).

Applications of noise analysis for instrumentation channel response time testing have been studied since the 1980s. Plentiful results have been accumulated from laboratory validations and tests using real NPP measurements (Hashemian et al., 1988) (Glöckler, 2003) (Hashemian, 2006). Those tests have confirmed that assumptions made in noise analysis-based response time test schemes can satisfiy most of the requirements in NPPs. In fact, noise analysis has already become an important diagnostic tool for pressure and temperature measurements in NPPs. The tests can be carried out using plant computer data without interrupting sensor operation. As a matter of fact, it is the only effective way to test the response time of pressure measurements during NPP operation (Hashemian and Jiang, 2010). Conventional tests can be carried out when a need is indicated by noise analysis. Thus, reliability of an instrumentation channel can be enhanced. Using noise analysis, on-line determination of prompt fractions of SPNDs in CANDU reactors also enhances the traditional way of monitoring the safety-related sensors.

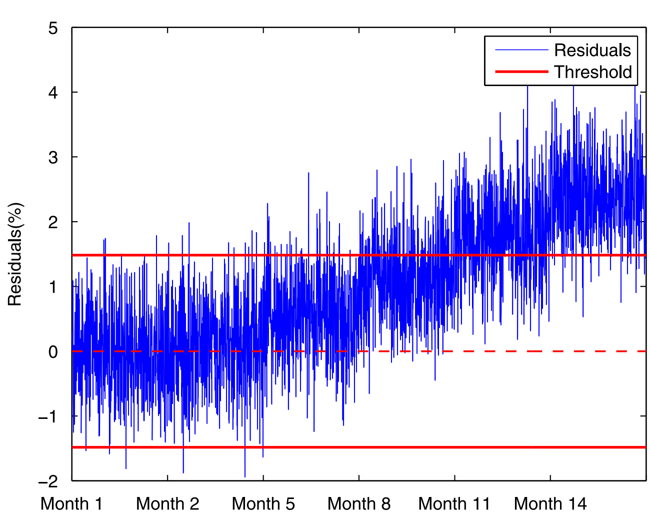

Fig. 5. Calibration monitoring results for an SG level WR measurement.

3.3. Equipment monitoring

Normal operation of an NPP depends on satisfactory operation of many subsystems, such as motors, pumps, valves, and compressors. Operational interruptions of these systems can result in million-dollar loss a day. Taking electric motors as an example, there are over 350 motors used to drive pumps, fans, and compressors in a typical PWR plant. Various faults can occur in a motor such as winding faults, insulation degradation, a broken rotor bar, bearing faults, and inadequate lubrication. These faults can result in motor breakdowns. Out of 147 motor failure-related events returned from a search of the licensee event report (LER) system maintained by the U.S. NRC, there are over 25 cases which result in a reactor trip or scram. Thus, it is highly desirable to detect equipment faults as early as possible before they become inoperable. Fault detection provides a way to ensure equipment reliability in addition to periodic inspections. The principle of using data-driven FDD methods for equipment monitoring is identical to instrument calibration monitoring. Several applications of signal-based FDD methods for equipment monitoring will be discussed next. They are vibration monitoring, MCSA, and AE monitoring.

Many faults in (mechanical) equipment are accompanied with abnormal vibrations (amplitudes and/or frequencies). For example, (LER5291997006, 1997) reports a reactor trip caused by reactor coolant pump vibration (and bearing temperature increases) due to bearing faults. Misalignment can also cause increased vibration levels for a motor. Vibration monitoring provides a way to monitor the equipment in an NPP. Spectrum analysis of vibration signals is a common technique for vibration monitoring. The spectrum of a vibration signal can be trended and compared with fault-free baseline measurements to detect developing faults in equipment. This process is shown in Fig. 7. Features in time domain, such as standard deviation and kurtosis of vibration signals are also frequently used for vibration monitoring (Reimche et al., 2003). Vibration monitoring has routinely been used in NPPs. New technologies are being developed for better vibration monitoring. One approach is to use advanced signal processing methods, such as TFA and WT, in vibration monitoring. Such methods have been considered for use in various industries (Tandon and Choudhury, 1999) (Peng and Chu, 2004) (Park et al., 2006) (Sejdić et al., 2009).

For induction motors, an interesting non-invasive monitoring technique is known as motor current signature analysis. It has been

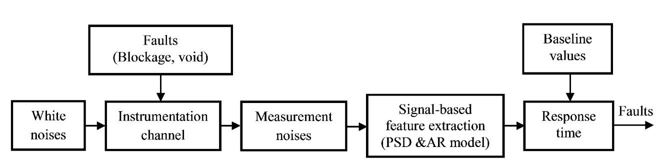

Fig. 6. Noise analysis for response time test.

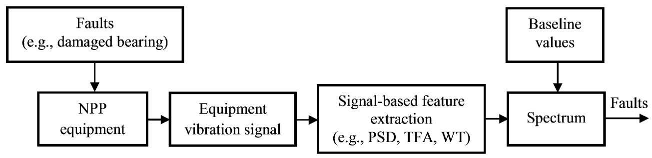

Fig. 7. Principle of vibration analysis for equipment monitoring.

demonstrated that the load of an induction motor is related to the stator current. Various mechanical and electrical faults can cause anomalies in the spectrum of stator current. By analyzing the spectrum of the motor current, MCSA has become an important diagnostic tool for detecting induction motor faults such as broken rotator bar, bearing damage, misalignment, and air gap eccentricity (Benbouzid, 2000) (Ye et al., 2003) (Mehala and Dahiya, 2007).

Acoustic emission (AE) monitoring is also considered for applications in NPPs. It mainly relies on signal-based analysis of changes in spectrum and intensity of acoustic signals emitted from equipment and pressure boundaries of NPPs. AE monitoring has been studied for diagnostic applications such as leakages in pressure boundaries (Hessel et al., 1999) (Kunze, 1999), bearing damages (Li and Li, 1995), valve wear (Lee et al., 2006), and faults in rotating machinery (Neill et al., 1997).

3.4. Reactor core monitoring

The quality of reactor core monitoring is extremely important for NPP plant safety and availability. To protect plant personnel, the public and the environment from radioactive hazards, conservative margins are established in NPPs (IAEA-TECDOC-1332, 2003). As a result, a reactor is only allowed to operate at a conservative power level. Important parameters for reactor core monitoring include power distribution, departure from nucleate boiling ratio (DNBR), and reactivity feedback coefficients. In practice, uncertainties in calculating these parameters can be as high as 20% (Souza and Moreira, 2006). Reduced uncertainties in reactor core monitoring can translate directly into enhanced safety margins and a potential increase in reactor power output. Both data-driven methods and signal-based methods have been studied for various reactor core monitoring applications. Three of such applications will be discussed in this subsection. They are data-driven methods for reactor core parameter estimation, neutron noise analysis for reactor internal vibration monitoring, and neutron noise analysis for reactor core parameter estimation.

Research has been performed to use data-driven methods, mostly ANN, to estimate parameters important for reactor core monitoring based on process measurements. Problems in a reactor core can be detected if the estimated reactor condition deviates from what is considered normal. It is demonstrated in (Souza and Moreira, 2006) that, using an ANN, the reactor power peak factor can be estimated with relative errors less than 1%, which may permit a reduction of previously set conservative safety margin by as much as 5%. Inputs to this ANN model are control rod position, neutron flux measurements, and several thermal–hydraulic parameters. Similar studies have been carried out to monitor CANDU reactor power distribution using ANN (Dubey et al., 1998), reconstruct CANDU reactor pin power using neuro-fuzzy model (Na et al., 2001), estimate control rod position using ANN (Andersson et al., 2003), and estimate critical heat flux using adaptive neuro-fuzzy model (Zaferanlouei et al., 2010). Despite promising results obtained in those studies, there are still a lot of work remains to be done before those methods can be fully deployed to relax the current technical specifications on reactor core surveillance.

A reactor core consists of internal structures, such as fuel bundles, core support barrel assembly, control rods, and in-core instrumentation guide tubes. It is difficult to measure vibrations of reactor internals directly, but it is still desirable to obtain such information indirectly, because excessive vibrations pose risks to their structural integrity. A signal-based technique, known as neutron noise analysis, proved to be successful for this application. Nuclear reactors are equipped with ex-core neutron flux detectors for reactor control and protection. Many reactors such as CANDU also have in-core neutron flux detectors for monitoring the in-core neutron flux distribution (Rouben, 1999). Vibrations of reactor internals induce reactivity perturbations, which are registered in the noise signals of the neutron detectors. Therefore, analysis of neutron noise provides an effective way to diagnose abnormal vibrations of reactor internals. This scheme is shown in Fig. 8. Spectrum analyses are commonly used for neutron noise analysis. Identifications of PWR core support barrel vibration using ex-core neutron detector noises are presented in (Robinson et al., 1977) (Yun et al., 1988) (Park et al., 2003). Features extracted from neutron noise for such identification works include PSD, CPSD, cohenrence function, and phase differences between ex-core detectors. Neutron noise analysis has also been studied for vibration monitoring of PWR pressure vessel, flux detector guide tubes (Arzhanov and Pázsit, 2002), fuel bundles (Glöckler, 2003), and control rods (Czibok et al., 2003). Neutron noise analysis has been extensively studied since 1960s with a lot of experience accumulated (Thie, 1981) (Michela and Puyala, 1988) (Kolbasseff and Sunder, 2003). New signal processing techniques, mostly WT and TFA, are considered for advanced neutron noise analysis. For example, (Arzhanov and Pázsit, 2002) presented applications of WT-based analysis of neutron noises to detect and quantify impacting of instrumentation tubes with nearby nuclear fuel assemblies in boiling water reactor (BWR) due to excessive instrumentation tube vibrations.

Neutron noise analysis also provides a way to estimate some important reactor core parameters. For a BWR, power instability can be induced by undesirable power distribution and coolant flow, leading to reactor scram or shutdown. On-line stability monitoring is desirable to reduce the likelihood of such events or to avoid them completely. By analysis of neutron noises from local power range monitors in a BWR, the decay ratio of the reactor core can be estimated, from which the stability of the reactor core can be deduced (Andoh et al., 1983) (Nunez-Carrera and Espinosa-Paredes, 2006) (Torres-Fernández et al., 2010). Signal-based methods used in a BWR core monitoring system are summarized in (Mori et al., 2003). This system uses noise analyses to monitor reactor physical parameters, reactor stability, thermal-hydraulics, and reactor internal vibrations. Another application of neutron noise analysis is on-line estimation of reactor moderator temperature coefficient (MTC). MTC is a safety parameter for PWRs. Conventional methods of testing MTC may need to interrupt the normal plant operation and at the same time perturb other parameters whose effects need to be corrected. These tests are carried out only twice per fuel cycle, and they are costly and time consuming (Demazière and Pázsit, 2002). Noise analysis has been studied for on-line estimation of MTC by correlating neutron noise signals and core-exit temperature

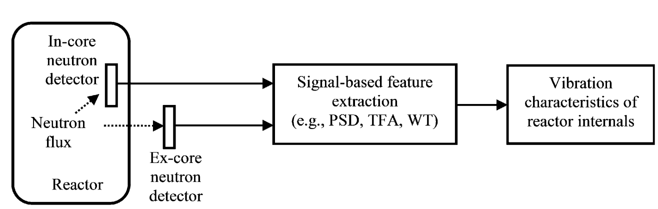

Fig. 8. Principle of neutron noise analysis for vibration monitoring of reactor internals.

noise signals (Demazière and Pázsit, 2002) (Demazière and Pázsit, 2004) (Demazière and Pázsit, 2009) (Kiss et al., 2010). The method can be performed throughout a fuel cycle without interrupting plant operation.

3.5. Loose part monitoring

Loose parts may exist in the reactor coolant system of an NPP. A loose part can come from internal structures of the RCS due to corrosion, fatigue, and friction. It can also be introduced externally during refuelling and maintenance tests. A loose part can cause damage to SG tubes, reactor internals, and coolant pumps. Such damage may cost millions of dollars to repair (Michela and Puyala, 1988) (Szappanos et al., 1999). Loose parts can also get stuck in the path of control rods, and poses safety hazards. In one case, a 7.7 kg austenite plate used to close the inlet hole of an SG during maintenance fell into the RCS of a VVER plant. In addition to causing damage to the SG, 41 fuel assemblies had to be removed from the core. The repair process also led to an additional collective radiation exposure of 370 person*mSv (Gor, 2005).

Loose part monitoring systems (LPMS) have been developed to detect the onset of a loose part, locate the loose part, and estimate the mass of the loose part. Depending on the nature of the loose part, decisions can be made on what actions should be taken. The principle of a LPMS is illustrated in Fig. 9. Detecting and diagnosing a loose part mainly relies on acoustic signals generated by the impact of the loose part with the RCS pressure boundary. The signals are picked up by accelerometers mounted at selected locations on the outer RCS boundary. Configurations of the LPMS for a VVER plant and a PWR plant are presented in (Szappanos et al., 1999) and (Kim et al., 2000), respectively. Filtering techniques are typically used for pre-processing to remove background noises. Loose part detection scheme relies on comparing the pre-processed acoustic signal with a pre-set threshold. Time delays between sensor pairs that detect the same event provide information to locate the detected loose part. Identifying the precise location of a loose part is still a challenge for existing LPMSs. Mass estimation of the loose part mostly relies on Hertz impact theory which supports the observation that low frequency signal components increase as the mass of the loose part increases. Therefore, the mass of a loose part can be estimated by referring the frequency characteristics of the acoustic signal to the baseline measurements. Two typical characteristic quantities are frequency ratio and center frequency (Olma, 1985) (Yoon et al., 2006).

Over the past three decades, significant amount of experience has been gained in the nuclear industry for loose part monitoring (Persion, 1999) (Szappanos et al., 1999) (Bechtold and Kunze, 1999). Diagnosis is done by experienced operators in first generation LPMSs. Systems with more autonomous diagnostic capabilities emerged later. Methods such as ANN, pattern recognition, and data mining are increasingly studied to enhance automatic diagnosis.

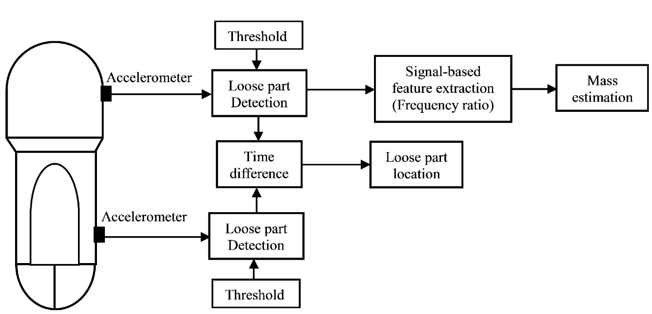

Fig. 9. Principles of loose part monitoring systems.

Currently, every NPP in Germany and the Republic of Korea has a LPMS (Uhrig and Hines, 2005). It is an ongoing research topic to apply advanced signal processing methods such as WT (Pokol and Por, 2006), TFA (Kim et al., 2003) (Park and Lee, 2006) (Yoon et al., 2006), and ANN (Figedy and Oksa, 2005) to achieve enhanced LPMS performance, e.g. reduced false alarms, more accurate time of detection, and more accurate mass estimation.

3.6. Transient identification

Transients in an NPP can be initiated by equipment failures or external disturbances. A transient must be correctly identified as soon as possible so that proper counter actions can be taken to minimize or mitigate the negative consequences. An automatic transient identification system can be a valuable addition to operator knowledge to safeguard the plant and to minimize the negative impacts on the plant safety and economy.

During a transient period, instrument outputs from an NPP may go through patterns that are different from those under normal conditions. The patterns can be different for different transients, severities, and initial conditions. Therefore, transient identification is essentially a pattern recognition problem, but the complexity of an NPP system makes it a very challenging task. Up to now, ANN is the mostly investigated method for NPP transient identifications (Barlett and Uhrig, 1992). Using simulator data, a set of ANNs can be trained to detect the presence of transients. An ANN can be trained such that it takes samples from a small number of sensors as inputs over the entire lifetime of a transient. It is a simple technique, but it cannot identify the transient quickly enough. An ANN can also be trained such that it takes instantaneous measurements from a larger number of sensors as inputs and diagnoses the problem as the transient develops. This scheme is more complex, but can diagnose the problem at an early stage. Such schemes are summarized in (Uhrig and Tsoukalas, 1999) (Uhrig and Hines, 2005). Performances of several ANN algorithms are compared in (Santosh et al., 2007). It is important to identify a transient not considered in the training stage as an unlabeled transient. Research work has been done to avoid incorrect identification of unlabeled transients using techniques such as probabilistic neural networks (Bartal et al., 1995) (Mol et al., 2002) (Embrechts and Benedek, 2004).

ANN is the core algorithm for most NPP transient identification studies. Other pattern recognition methods studied for NPP transient identification include variety of soft computing techniques (Cheon and Chang, 1993) (Uhrig and Tsoukalas, 1999) (Zio and Baraldi, 2005), hidden Markov models (Kwon, 2002), and recently particle swarm optimization (Antonio et al., 2008). Wavelet signal decomposition has also been studied for pre-processing of measurement data for transient identification (Roverso, 2002). Despite those developments, additional research is required before automated transient identification systems can be successfully used in NPP applications.

4. Summary and discussion

In this paper, an overview of FDD methods and their applications in six related areas in NPPs are presented. Vibration monitoring, neutron noise analysis, and loose part monitoring have been extensively applied with success in existing NPPs. In-situ instrumentation channel dynamic performance monitoring based on noise analysis has also been used in plants such as Ontario Power Generation in Canada. It is recognized that on-line condition monitoring of instruments and equipment in NPPs brings benefits to plant reliability and economy. Some commercial products have been developed and are increasingly used in NPPs. Encouraging results have been obtained for reactor core monitoring and transient identification. Applications of FDD in NPPs will become more feasible as I&C technologies and FDD theory progress.

Instrument calibration monitoring and reactor core monitoring applications, such as DNBR estimation are essentially the problem of estimating the true value of a variable from correlated quantities with as little uncertainty as possible. Data-driven FDD methods, such as ANN and MSET, have been the most studied for such applications. Applications of model-based FDD methods are very limited. Signal-based FDD methods have been proven useful for instrumentation channel dynamic performance monitoring, equipment vibration monitoring, MCSA, AE monitoring, LPMS, and vibration monitoring of reactor internals. Transient identification is basically a pattern recognition problem, with ANN dominating in this area. Emerging pattern recognition methods have not yet been explored.

There are issues that should not be overlooked when applying FDD in NPPs. False alarms can be induced by using an improper FDD system, leading to unnecessary maintenance workload. This must be taken into consideration during the design of a FDD system. Introduction of FDD systems in an NPP will also require modifications to existing plant maintenance procedures and the training of personnel in using these advanced technologies effectively.

Acknowledgment

This work is financially supported by the University Network of Excellence in Nuclear Engineering (UNENE) and the Natural Sciences and Engineering Research Council of Canada (NSERC).

References

Aamodt, A., Plaza, E., 1994. Case-based reasoning: foundational issues, methodological variations, and system approaches. AI Communications 7, 39–59.
Anderson, J.A., 1995. An Introduction to Neural Networks. MIT Press, Cambridge, MA, USA.
Andersson, T., Demazière, C., Nagy, A., Sandberg, U., Garis, S.N., Pázsit, I., 2003. Development and applications of core diagnostics and monitoring of the Ringhals PWRs. Progress in Nuclear Energy 43, 35–41.
Andoh, Y., Naito, N., Kanemoto, S., Yamamoto, F., Ikeda, K., Kawai, K., Hashimoto, Y., 1983. Development of BWR plant diagnosis system using noise analysis. Journal of Nuclear Science and Technology 20, 769–780.
Antonio, J., Medeiros, C.C., Schirru, R., 2008. Identification of nuclear power plant transients using the particle swarm optimization algorithm. Annals of Nuclear Energy 35, 576–582.
Arzhanov, V., Pázsit, I., 2002. Detecting impacting of BWR instrument tubes by wavelet analysis. In: Ruan, D., Fantoni, P.F. (Eds.), Power Plant Surveillance and Diagnostics: Applied Research and Diagnostics. Springer, pp. 157–174.
Barlett, E.B., Uhrig, R.E., 1992. Nuclear power plant status diagnostics using an artificial neural network. Nuclear Technology 97, 272–281.
Bartal, Y., Lin, J., Uhrig, R.E., 1995. Nuclear power plant transient diagnostics using artificial neural networks that allow 'Don't-Know' classifications. Nuclear Technology 110, 436–449.
Basseville, M., 1988. Detecting changes in signals and systems-A survey. Automatica 24, 309–326.
Beard, R.V., 1971. Failure Accommodation in Linear Systems through Self-Reconfiguration. MIT, Cambridge, MA, USA.
Bechtold, B., Kunze, U., 1999. KUES'95-the modern diagnostic system for loose parts monitoring. Progress in Nuclear Energy 34, 221–230.
Benbouzid, M.E.H., 2000. A review of induction motors signature analysis as a medium for faults detection. IEEE Transactions on Industrial Electronics 47, 984–993.
Bernard, J., Washio, T., 1989. Expert Systems Applications Within the Nuclear Industry. American Nuclear Society, La Grange Park, IL.
Burges, C.J.C., 1998. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery 2, 121–167.
Chan, A.M.C., Ahluwalia, A.K., 1992. Feedwater Flow Measurement in U.S. Nuclear Power Generation Stations. Electric Power Research Institute.
Cheon, S.W., Chang, S.H., 1993. Application of neural networks to a connectionist expert system for transient identification in nuclear power plant. Nuclear Technology 102, 177–191.
Chiang, L.H., Russell, E.L., Braatz, R.D., 2001. Fault Detection and Diagnosis in Industrial Systems. Springer, New York.
Cho, J., Lee, J., Choi, S., Lee, D., Lee, I., 2005. Fault identification for process monitoring using kernel principal component analysis. Chemical Engineering Science 60, 279–288.
Chow, E.Y., Willsky, A.S., 1984. Analytical redundancy and the design of robust failure detection systems. IEEE Transactions on Automatic Control 29, 603–614.
Clark, R.N., 1978. Instrument fault detection. IEEE Transactions on Aerospace and Electronic Systems 14, 456–465.
Cohen, L., 1989. Time-frequency distributions-A review. Proceedings of the IEEE 77, 941–981.
Czibok, T., Kiss, G., Kiss, S., Krinizs, K., Végh, J., 2003. Regular neutron noise diagnostics measurements at the Hungarian Paks NPP. Progress in Nuclear Energy 43, 67–74.
De Kleer, J., Brown, J.S., 1984. A qualitative physics based on confluences. Artificial Intelligence 24, 7–83.
Demazière, C., Glöckler, O., 2004. On-line Determination of the Prompt Fraction of In-Core Neutron Detectors in CANDU Reactors. PHYSOR, Chicago, IL, USA.
Demazière, C., Pázsit, I., 2002. Theoretical investigation of the MTC noise estimate in 1-D homogeneous systems. Annals of Nuclear Energy 29, 75–100.
Demazière, C., Pázsit, I., 2004. Development of a method for measuring the moderator temperature coefficient by noise analysis and its experimental verification in Ringhals-2. Nuclear Science and Engineering 148, 1–29.
Demazière, C., Pázsit, I., 2009. Numerical tools applied to power reactor noise analysis. Progress in Nuclear Energy 51, 67–81.
Ding, J., Gribok, A.V., Hines, J.W., Rasmusse, B., 2004. Redundant sensor calibration monitoring using independent component analysis and principal component analysis. Real-Time Systems 27, 27–47.
Dong, D., McAvoy, T.J., 1996. Nonlinear principal component analysis—based on principal curves and neural networks. Computers and Chemical Engineering 20, 65–78.
Dong, J., Verhaegen, M., 2009. Subspace based Fault Detection and Identification for LTI Systems. In: Proceedings of 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes. Barcelona, Spain.
Dong, J., Kulcsar, B., Verhaegen, M., 2009. Subspace based Fault Detection and Identification for LPV Systems. In: Proceedings of 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes. Barcelona, Spain.
Dubey, B.P., Jagannathan, V., Kataria, S.K., 1998. Quick and reliable estimation of power distribution in a PHWR by ANN. Annals of Nuclear Energy 25, 567–579.
Dunia, R., Qin, S.J., Edgar, T.F., McAvoy, T.J., 1996. Identification of faulty sensors using principal component analysis. AIChE Journal 42, 2797–2812.
Embrechts, M.J., Benedek, S., 2004. Hybrid identification of nuclear power plant transients with artificial neural networks. IEEE Transactions on Industrial Electronics 51, 686–693.
Evans, M.G., 2004. U.S. Nuclear Regulatory Commission Perspectives Regarding On-Line Monitoring. In: Presentation at the Technical Meeting on Increasing Instrument Calibration Interval through On-Line Calibration Technologies. Halden, Norway.
Fantoni, P.F., 2005. Experiences and applications of PEANO for online monitoring in power plants. Progress in Nuclear Energy 46, 206–225.
Fantoni, P.F., Hoffmann, M., Rasmussen, B., Hines, J.W., 2002. The use of non-linear partial least squares methods for on-line process monitoring as an alternative to artificial neural networks. FLINS 2002, 1–10 (Gent, Belgium).
Fantoni, P.F., Hoffmann, M.I., Shankar, R., Davis, E.L., 2003. On-line monitoring of instrument channel performance in nuclear power plant using PEANO. Progress in Nuclear Energy 43, 83–89.
Figedy, S., Oksa, G., 2005. Modern methods of signal processing in the loose part monitoring system. Progress in Nuclear Energy 46, 253–267.
Frank, P.M., 1990. Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy-A survey and some new results. Automatica 26, 459–474.
Frank, P.M., Ding, S.X., 1997. Survey of robust residual generation and evaluation methods in observer-based fault detection systems. Journal of Process Control 7, 403–424.
Garvey, D.R., Hines, J.W., 2006. An Adaptive Distance Measure for Use with Nonparametric Models. NPIC&HMIT, Albuquerque, NM, USA (335–342).
Gertler, J.J., 1988. Survey of model-based failure detection and isolation in complex plants. IEEE Control Systems Magazine 8, 3–11.
Gertler, J.J., 1997. Fault detection and isolation using parity relations. Control Engineering Practice 5, 653–661.
Gertler, J.J., Singer, D., 1990. A new structural framework for parity equation-based failure detection and isolation. Automatica 26, 381–388.
Glöckler, O., 2003. Reactor noise measurements in the safety and regulating systems of CANDU stations. Progress in Nuclear Energy 43, 75–82.
Gor, P., 2005. Early Warning Acoustic System for Nuclear Power Plant. TCM-IAEA, Knoxville, Tennessee, U.S.
Gribok, A.V., Hines, J.W., Urmanov, A., Uhrig, R.E., 2002. Heuristic, systematic, and informational regularization for process monitoring. International Journal of Intelligent Systems 17, 723–749.
Hashemian, H.M., 2004. Sensor Performance and Reliability. The Instrumentation, Systems, and Automation Society, Research Triangle Park, NC.
Hashemian, H.M., 2006. Maintenance of Process Instrumentation in Nuclear Power Plant. Springer-Verlag, Berlin Heidelbert.
Hashemian, H.M., Feltus, M.A., 2006. On-Line Condition Monitoring Applications in Nuclear Power Plants. NPIC&HMIT, Albuquerque, NM, USA (568–577).
Hashemian, H.M., Jiang, J., 2010. Using the noise analysis technique to detect response time problems in the sensing lines of nuclear plant pressure transmitters. Progress in Nuclear Energy 52, 367–373.

Hashemian, H.M., Riggsbee, E.T., Seibel, J.C., Hashemian, M., Sexton, C.D., Linn, M., Manges, W., Kuruganti, T., Rothrock, B., Feltus, M.A., 2009a. Wireless Sensors for Predictive Maintenance of Rotating Equipment in Research Reactors. NPIC& HMIT, Knoxville, Tennessee, USA.
Hashemian, H.M., Kiger, C.J., Morton, G.W., Shumaker, B.D., Carter, C., Feltus, M.A., 2009b. Wireless Sensor Applications in Nuclear Power Plants. NPIC&HMIT, Knoxville, Tennessee, USA.
Hashemian, H.M., Thie, J.A., Upadhyaya, B.R., Holbert, K.E., 1988. Sensor response time monitoring using noise analysis. Progress in Nuclear Energy 21, 583–592.
Herzog, J.P., Wegerich, S.W., Gross, K.C., Bockhorst, F.K., 1998. MSET modeling of Crystal River-3 Venturi flow meters. In: The 6th International Conference on Nuclear Engineering May 10–15, San Diego, CA.
Hessel, G., Schmitt, W., Van der Vorst, K., Weiss, F.P., 1999. A neural network approach for acoustic leak monitoring in the VVER-400 pressure vessel head. Progress in Nuclear Energy 34, 173–183.
Hines, J.W., Davis, E., 2005. Lessons learned from the U.S. nuclear power plant on-line monitoring programs. Progress in Nuclear Energy 46, 176–189.
Hines, J.W., Rasmussen, B., 2005. Online sensor calibration monitoring uncertainty estimation. Nuclear Technology 151, 281–288.
Hines, J.W., Seibert, R., 2006. Technical Review of On-Line Monitoring Techniques for Performance Assessment Volume 1: State-of-the-Art (NUREG/CR-6895). United States Nuclear Regulatory Commission, Washington DC.
Hines, J.W., Uhrig, R.E., Wrest, D.J., 1998. Use of autoassociative neural networks for signal validation. Journal of Intelligent and Robotic Systems 21, 143–154.
Hines, J.W., Usynin, A., 2005. MSET performance optimization through regularization. Nuclear Engineering and Technology 37, 177–184.
Hlawatsch, F., Boudreaux-Bartels, G.F., 1992. Linear and quadratic time-frequency signal representations. IEEE Signal Processing Magazine 9, 21–67.
Holland, J.H., 1975. Adaptation in Natural and Artificial Systems. University of Michigan Press, Ann Arbor, MI.
Hunt, J.S., 1986. The exponentially weighted moving average. Journal of Quality Technology 18, 203–209.
Hyvarinen, A., 1999. Survey on independent component analysis. Neural Computing Surveys 2, 94–128.
IAEA-TECDOC-1147, 2000. Management of Aging of I&C Equipment in Nuclear Power Plant. International Atomic Energy Agency, Vienna, Austria.
IAEA-TECDOC-1332, 2003. Safety Margins of Operating Reactors: Analysis of Uncertainties and Implications for Decision Making. International Atomic Energy Agency, Vienna, Austria.
IAEA-TECDOC-1402, 2004. Management of Life Cycle and Aging at Nuclear Power Plants: Improved I&C Maintenance. International Atomic Energy Agency, Vienna, Austria.
Iri, M., Aoki, K., O'Shima, E., Matsuyama, H., 1979. An algorithm for diagnosis of system failures in the chemical process. Computers and Chemical Engineering 3, 489–493.
Isermann, R., 1984. Process fault detection based on modeling and estimation methods-A survey. Automatica 20, 387–404.
Isermann, R., 1992. Estimation of physical parameters for dynamic processes with application to an industrial robot. International Journal of Control 55, 1287–1298.
Isermann, R., 1993. Fault diagnosis of machines via parameter estimation and knowledge processing-tutorial paper. Automatica 29, 815–835.
Isermann, R., 2006. Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerancr. Springer-Verlag.
Isermann, R., Balle, P., 1997. Trends in the application of model-based fault detection and diagnosis of technical processes. Control Engineering Practice 5, 709–719.
Iwasaki, Y., 1997. Real-world applications of qualitative reasoning. IEEE Expert 12, 16–21.
James, R.W., 1996. Calibration Through On-Line Monitoring of Instrument Channels. Conference Record of 1996 IEEE Nuclear Science Symposium, Anaheim, CA, USA (996-999).
Jia, F., Jiang, J., 1994. Diagnosis in DC servo systems-A comparative study of three fault diagnosis schemes. European Journal on Fault Diagnosis and Safety in Automation 4, 357–374.
Jia, F., Jiang, J., 1995. A robust fault diagnosis scheme based on signal modal estimation. International Journal of Control 62, 461–475.
Kadri, A., Rao, R.K., Jiang, J., 2009. Low-power chirp spread spectrum signals for wireless communication within nuclear power plants. Nuclear Technology 166, 156–169.
Kaistha, N., Upadhyaya, B.R., 2001. Incipient fault detection and isolation of field devices in nuclear power systems using principal component analysis. Nuclear Technology 136, 221–230.
Kim, J.S., Hwang, I.K., Lee, D.Y., Ham, C.S., Kim, T.H., 2000. Development of a mass estimation algorithm using the impact test data of nuclear power plant. Journal of Korean Nuclear Society 32, 227–234.
Kim, Y.B., Kim, S.J., Chung, H.D., Park, Y.W., Part, J.H., 2003. A study of technique to estimate impact location of loose part using Wigner-Ville distribution. Progress in Nuclear Energy 43, 261–266.
Kiss, S., Lipcsei, S., Végh, J., 2010. Monitoring MTC using cold leg thermocouple and background neutron detector noise signals in a VVER-440 reactor during a whole fuel cycle. Annals of Nuclear Energy 37, 827–834.
Kitamura, M., 1989. Fault detection in nuclear reactors with the aid of parametric modelling methods. In: Patton, R., Frank, P.M., Clark, R. (Eds.), Fault Diagnosis in Dynamic Systems: Theory and Applications. Prentice Hall, London, UK, pp. 311–360.
Kolbasseff, A., Sunder, R., 2003. Lessons learned with vibration monitoring systems in German nuclear power plants. Progress in Nuclear Energy 43, 159–165.
Kramer, M.A., 1991. Nonlinear principal component analysis using autoassociative neural networks. AIChE Journal 37, 233–243.
Kramer, M.A., Palowitch Jr., B.L., 1987. A rule-based approach to fault diagnosis using the signed directed graph. AIChE Journal 33, 1067–1078.
Kuipers, B., 1994. Qualitative Reasoning: Modeling and Simulation with Incomplete Knowledge. The MIT Press, Cambridge, MA, USA.
Kunze, U., 1999. Experience with the acoustic leakage monitoring system ALUES in 17 VVER plants. Progress in Nuclear Energy 34, 213–220.
Kwon, K.C., 2002. Hidden Markov model based transient identification in NPPs. In: Ruan, D., Fantoni, P.F. (Eds.), Power Plant Surveillance and Diagnostics: Applied Research and Diagnostics. Springer, pp. 91–106.
Larimore, W.E., 1990. Canonical Variate Analysis in Identification, Filtering, and Adaptive Control. In: Proceedings of the 29th IEEE Conference on Decision and Control, (596–604). Honolulu, Hawaii, USA.
Lee, J., Lee, M., Kim, J., Luk, V., Jung, Y., 2006. A study of the characteristics of the acoustic emission signals for condition monitoring of check valves in nuclear power plants. Nuclear Engineering and Design 236, 1411–1421.
Lee, J., Yoo, C., Choi, S., Vanrolleghen, P.A., Lee, I., 2004. Nonlinear process monitoring using kernel principal component analysis. Chemical Engineering Science 59, 223–234.
LER5291997006, 1997. United States Nuclear Regulatory Commission. https://nrcoe.inel.gov/secure/lersearch/index.cfm?fuseaction=SearchResults.showLER&doc=5291997006R00.pdf Retrived on: 02.06.10.
Li, W., Jiang, J., 2004. Isolation of parametric faults in continuous-time multivariable systems: a sampled data-based approach. International Journal of Control 77, 173–187.
Li, C.J., Li, S.Y., 1995. Acoustic emission analysis for bearing condition monitoring. Wear 185, 67–74.
Li, W., Shah, S.L., 2002. Structured residual vector-based approach to sensor fault detection and isolation. Journal of Process Control 12, 429–443.
Lou, X.C., Willsky, A.S., Verghese, G.C., 1986. Optimally robust redundancy relations for failure detection in uncertain systems. IEEE Transactions on Automatic Control 31, 333–344.
MacGregor, J.F., Kourti, T., 1995. Statistical process control of multivariate processes. Control Engineering Practice 3, 403–414.
Mahadevan, S., Shah, S.L., 2009. Plant Wide Fault Identification using One-class Support Vector Machines. In: 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes. Barcelona, Spain.
Ma, J., 2006. Self-Powered Detectors for Power Reactors: An Overview. 30th Annual CNA/CNS Student Conference. Toronto, Canada.
Ma, J., Jiang, J., 2009. A Fault Detection and Isolation Technique for In-Core Flux Detectors. NPIC&HMIT, Knoxville, Tennessee, USA.
Ma, J., Jiang, J., 2010. Fault Ddetection and Identification in NPP Instruments Using Kernel Principal Component Analysis. In: The 18th International Conference on Nuclear Engineering. Xi'an, China.
Marseguerra, M., Zio, E., Torri, G., 2003. Power density axial oscillations induced by Xenon dynamics: parameter identification via genetic algorithms. Progress in Nuclear Energy 43, 365–372.
Mehala, N., Dahiya, R., 2007. Motor current signature analysis and its applications in induction motor fault diagnosis. International Journal of systems applications, Engineering and Development 2, 29–35.
Michela, B., Puyala, C., 1988. Operational and economical experience with vibration and loose parts monitoring systems on primary circuits of PWRs. Progress in Nuclear Energy 21, 469–473.
Mol, A.C. de A., Martinez, A.S., Schirru, R., 2002. A new approach for transient identification with "Don't Know" response using neural networks. In: Ruan, D., Fantoni, P.F. (Eds.), Power Plant Surveillance and Diagnostics: Applied Research and Diagnostics. Springer, pp. 253–272.
Montgomery, D.C., 2005. Introduction to Statistical Quality Control (5th). John Wiley.
Mori, M., Kaino, M., Kanemoto, S., Enomoto, M., Ebata, S., Tsunoyama, S., 2003. Development of advanced core noise monitoring systems for BWRs. Progress in Nuclear Energy 43, 43–49.
Na, M.G., Yang, W.S., Choi, H., 2001. Pin power reconstruction for CANDU reactors using a neuro-fuzzy inference system. IEEE Transactions on Nuclear Science 48, 194–201.
Neill, G.D., Reuben, R.L., Sandford, P.M., Brown1, E.R., Steel, J.A., 1997. Detection of incipient cavitation in pumps using acoustic emission. Proceedings of the Institution of Mechanical Engineers, Part E. Journal of Process Mechanical Engineering 211, 267–277.
Nelson, W.R., 1982. REACTOR: an expert system for diagnosis and treatment of nuclear reactor accidents. Proceedings of AAAI 82, 296–301.
Nuclear Power Plants Information, 2010. International Atomic Energy Agency. http://www.iaea.org/cgi-bin/db.page.pl/pris.reaopag.htm Visited on: 26.04.10.
Nunez-carrera, A., Espinosa-paredes, G., 2006. Time-scale BWR stability analysis using wavelet-based method. Progress in Nuclear Energy 48, 540–549.
Olma, B.J., 1985. Source location and mass estimation in loose parts monitoring of LWR's. Progress in Nuclear Energy 15, 583–594.
Park, J.H., Lee, J.H., 2006. Application of continuous wavelet transform to the impact location estimation of the loose part monitoring system (LPMS). International Journal of Nuclear Science and Technology 2, 233–240.
Park, J., Lee, J.H., Kim, T.R., Park, J.B., Lee, S.K., Koo, I.S., 2003. Identification of reactor internals' vibration modes of a Korean standard PWR using structural modeling and neutron noise analysis. Progress in Nuclear Energy 43, 177–186.

Park, G.Y., Lee, C.K., Kim, J.T., Ryu, J.S., Jung, H.S., 2006. Identification of Nuclear Components Degradation by Time-Frequency Ridge Pattern. NPIC&HMIT, Albuquerque, NM (1082–1087).

Patton, R.J., Chen, J., 1997. Observer-based fault detection and isolation: robustness and applications. Control Engineering Practice 5, 671–682.

Peng, Z.K., Chu, F.L., 2004. Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography. Mechanical Systems and Signal Processing 18, 199–221.

Persion, J.V., 1999. Commercial nuclear reactor loose part monitoring setpoints. Progress in Nuclear Energy 34, 203–211.

Pokol, G., Por, G., 2006. The advanced loose part monitoring system (ALPS) and wavelet analysis. International Journal of Nuclear Science and Technology 2, 241–252.

Qian, S., 2002. Introduction to Time-Frequency and Wavelet Transforms. Prentice Hall, Upper Saddle River, N.J.

Qin, S.J., Li, W., 2001. Detection and identification of faulty sensors in dynamic processes. AIChE Journal 47, 1581–1593.

Qin, S.J., McAvoy, T.J., 1992. Nonlinear PLS modeling using neural networks. Computers and Chemical Engineering 16, 379–391.

Rasmussen, B., Hines, J.W., Uhrig, R.E., 2000. Nonlinear Partial Least Squares Modeling for Instrument Surveillance and Calibration Verification. The Maintenance and Reliability Conference. MARCON, Knoxville, TN, USA.

Razavi-Far, R., Davilu, H., Palade, V., Lucas, C., 2009. Neuro-Fuzzy Based Fault Diagnosis of A Steam Generator. In: 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes. Barcelona, Spain.

Rehorn, A.G., Sejdić, E., Jiang, J., 2006. Fault diagnosis in machine tools using selective regional correlation. Mechanical Systems and Signal Processing 20, 1221–1238.

Reimche, W., Südmersen, U., Pietsch, O., Scheer, C., Bach, F.W., 2003. Basics of vibration monitoring for fault detection and process control. In: 3rd Pan-American Conference for Non-Destructive Tesing. Rio de Janeiro, Brazil.

Robinson, J.C., Hardy, J.W., Shamblin, G.R., Wolff, C.L., 1977. Monitoring of core support barrel motion in PWRs using ex-core detectors. Progress in Nuclear Energy 1, 369–378.

Rouben, B., 1999. CANDU Fuel Management Course. CANTEACH. http://canteach.candu.org/library/20031101.pdf Visited on: 24.04.10.

Roverso, D., 2002. Plant diagnostics by transient classification: the ALADDIN approach. International Journal of Intelligent Systems 17, 767–790.

Santosh, T.V., Vinod, G., Saraf, R.K., Ghosh, A.K., Kushwaha, H.S., 2007. Application of artificial neural networks to nuclear power plant. Reliability Engineering and System Safety 92, 1468–1472.

Schölkopf, B., Smola, A.J., Müller, K.R., 1998. Nonlinear component analysis as a kernel eigenvalue problem. Neural Computation 10, 1299–1319.

Sejdić, E., Djurović, I., Jiang, J., 2009. Time–frequency feature representation using energy concentration: an overview of recent advances. Digital Signal Processing 19, 153–183.

Shawe-Taylor, J., Cristianini, N., 2004. Kernel Methods for Pattern Analysis. Cambridge University Press, Cambridge, UK.

SmartSignal, 2010. Visited on: 26.04.10, from: SmartSignal: http://www.smartsignal.com.

Souza, R.M.G.P., Moreira, J.M.L., 2006. Neural network correlation for power peak factor estimation. Annals of Nuclear Energy 33, 594–608.

Stockwell, R.G., Mansinha, L., Lowe, R.P., 1996. Localization of the complex spectrum: the S transform. IEEE Transactions on Signal Processing 44, 998–1001.

Szappanos, G., Kiss, J.J., Por, G., Kiss, J.M., 1999. Analysis of measurements made by HELPS loose part detection system during installation and operation periods. Progress in Nuclear Energy 34, 185–193.

Tandon, N., Choudhury, A., 1999. A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings. Tribology International 32, 469–480.

Thie, J.A., 1981. Power Reactor Noise. American Nuclear Society, La Grange Park, Illinois.

Torres-Fernández, J.E., Prieto-Guerrero, A., Espinosa-Paredes, G., 2010. Decay ratio estimation based on time–frequency representations. Annals of Nuclear Energy 37, 93–102.

Uhrig, R.E., Hines, J.W., 2005. Computational Intelligence in nuclear engineering. Nuclear Engineering and Technology 37, 127–138.

Uhrig, R.E., Tsoukalas, L.H., 1999. Soft computing techniques in nuclear engineering applications. Progress in Nuclear Energy 34, 13–75.

Umeda, T., Kuriyama, T., O'Shima, E., Matsuyama, H., 1980. A graphical approach to cause and effect analysis of chemical processing systems. Chemical Engineering Science 35, 2379–2388.

Van Overschee, P., De Moor, B., 1994. N4SID: subspace algorithms for the identification of combined deterministic-stochastic systems. Automatica 30, 75–93.

Van Overschee, P., De Moor, B., 1995. A unifying theorem for three subspace system identification algorithms. Automatica 31, 1853–1864.

Vapnik, V.N., 1995. The Nature of Statistical Learning Theory. Springer-Verlag, New York.

Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., Yin, K., 2003. A review of process fault detection and diagnosis: Part III: process history based methods. Computers and Chemical Engineering 27, 327–346.

Venkatasubramanian, V., Vaidyanathan, R., Yamamoto, Y., 1990. Process fault detection and diagnosis using neural networks I: steady State processes. Computers and Chemical Engineering 14, 699–712.

Verhaegen, M., Dewilde, P., 1992. Subspace model identification Part I. The output-error state-space model identification class of algorithms. International Journal of Control 56, 1187–1210.

Watanabe, K., Matsura, I., Abe, M., Kubota, M., Himmelblau, D.M., 1989. Incipient fault diagnosis of chemical processes via artificial neural networks. American Institute of Chemical Engineers Journal 35, 1803–1812.

Watson, I., Marir, F., 1994. Case-based reasoning: a review. The Knowledge Engineering Review 9, 355–381.

Weld, D.S., De Kleer, J., 1990. In: Readings in Qualitative Reasoning about Physical Systems. Morgan Kaufmann Publishers Inc, San Francisco, CA, USA.

Widodo, A., Yang, B., 2007. Support vector machine in machine condition monitoring and fault diagnosis. Mechanical Systems and Signal Processing 21, 2560–2574.

Willsky, A.S., 1976. A survey of design methods for failure detection in dynamic systems. Automatica 12, 601–611.

Willsky, A.S., 1986. Detection of abrupt changes in dynamic systems. In: Basseville, M., Benveniste, A. (Eds.), Detection of Abrupt Changes in Signals and Dynamical Systems. Springer Verlag, pp. 27–49.

Wise, B.M., Gallagher, N.B., 1996. The process chemometrics approach to process monitoring and fault detection. Journal of Process Control 6, 329–348.

Ye, H., Wu, B., Sadeghian, A., 2003. Current signature analysis of induction motor mechanical faults by wavelet packet decomposition. IEEE Transactions on Industrial Electronics 50, 1217–1228.

Yoon, D.B., Park, J.H., Choi, Y.C., Sohn, C.H., Park, O.K., 2006. An Improvement of Mass Estimation Capability in Loose Parts Monitoring by Using Time-Frequency Analysis. NPIC&HMIT, Albuquerque, NM (331–334).

Yue, H.H., Qin, S.J., 2001. Reconstruction-based fault identification using a combined index. Industrial and Engineering Chemistry Research 40, 4403–4414.

Yun, W.Y., Koh, B.J., Park, I.Y., No, H.C., 1988. Neutron noise analysis for PWR core motion monitoring. Journal of the Korean Nuclear Society 20, 253–264.

Zavaljevskl, N., Gross, K.C., 2000. Sensor Fault Detection in Nuclear Power Plants Using Multivariate State Estimation Technique and Support Vector Machines. In: Presentation at the Third International Conference of the Yugoslav Nuclear Society YUNSC. Belgrade, Yugoslavia.

Zhang, Y., Dudzic, M.S., 2006. Online monitoring of steel casting processes using multivariate statistical technologies: from continuous to transitional operations. Journal of Process Control 16, 819–829.

Zhang, J., Morris, A.J., 1994. On-line process fault diagnosis using fuzzy neural networks. Intelligent Systems Eengineering 3, 37–47.

Zaferanlouei, S., Rostamifard, D., Setayeshi, S., 2010. Prediction of critical heat flux using ANFIS. Annals of Nuclear Energy 37, 813–821.

Zio, E., Baraldi, P., 2005. Evolutionary fuzzy clustering for the classification of transients in nuclear component. Progress in Nuclear Energy 46, 282–296.

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