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An integrated approach to sensor FDI and signal reconstruction in HTGRs – Part I: Theoretical framework

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ABSTRACT

Sensor fault detection and isolation (FDI) is an important element in modern nuclear power plant (NPP) diagnostic systems. In this respect, sensor FDI of generation II and III water-cooled nuclear energy systems has become an active research topic to continually improve levels of reliability, safety, and operation. However, evolutionary advances in reactor and component technology together with different energy conversion methodologies support the investigation of alternative approaches to sensor FDI. Within this context, the basic aim of this two part series is to propose, implement and evaluate an integrated approach for sensor FDI and signal reconstruction in generation IV nuclear high temperature gas-cooled reactors (HTGRs). In part I of this two part series, the methodology and theoretical background of the integrated sensor FDI and signal reconstruction approach are given. This approach combines techniques such as non-temporal parity space analysis (PSA), principal component analysis (PCA), sensor fusion and fuzzy decision systems to form a more powerful sensor FDI methodology that exploits the strengths of the individual techniques. An illustrative example of the PCA algorithm is given making use of actual data retrieved from a pilot plant called the pebble bed micro model (PBMM). This is a prototype gas turbine power plant based on the first design configuration of the pebble bed modular reactor (PBMR). In part II, the described integrated sensor fault detection approach will be evaluated by means of two case studies. In the first case study the approach will be evaluated on real PBMM data and in the second case study the approach will be evaluated on a highly detailed Flownex® model of the new generation PBMR.

1. Introduction

Economic constraints and reliability concerns are driving the electric power industry to seek improved methods for monitoring, controlling and sensor diagnosing systems in order to optimise plant performance, reduce unscheduled maintenance and establish long-term management of critical assets. Improvement of safety and operational levels in modern nuclear power plants (NPPs) are crucial, necessitating optimal health monitoring (Patton et al., 2000). With the assistance of early fault detection and proper fault classification, process and component malfunctions can be identified at an early stage, to reduce the risk of sudden failure as well as facilitating timely maintenance or repair (du Rand et al., 2009).

With the increased complexity of NPPs and the increased number of sensors installed in power plants, failure to identify the source of the indication of an ‘‘abnormal state'' and the inability to take appropriate corrective action could result in expensive and unnecessary system shutdowns, or accidents that endanger both the system and personnel (Patton et al., 2000). It is very important for a monitoring and diagnostic system to distinguish between the case of a sensor failure or a system fault (Alag et al., 2001). Sensor malfunctions can be classified into two types of fault classes: abrupt sensor faults and sensor degradation. Abrupt sensor faults result in either complete failure or erroneous readings from the sensor, whilst sensor degradation changes the performance of the sensor. During the lifespan of any engineering system, faults are unavoidable factors that degrade system performance.

Advanced sensor FDI techniques have been studied since the 1970s (Hwang et al., 2010; Patton, 2000) to improve chemical and power plant safety management and supervision systems. Yong-kuo et al. (2013) developed a distributed fault diagnosis system based on a fuzzy neural network (FNN) architecture for a NPP. The system combines local diagnosis and multi-source information fusion technology to allow for an advanced type of global fault diagnosis. Condition monitoring of a reactor core was also

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Nomenclature

Symbols (lower case)

c	constant value
$\mathbf{e}$	additive error vector
f	magnitude of the fault
$\mathbf{m}$	vector of redundant measurement
$\mathbf{p}$	parity vector
q	number of redundant measurements
$\mathbf{r}$	residual vector
$\mathbf{x}$	variable vector
$\mathbf{x}^*$	sample vector for normal operation

Symbols (upper case)

$E(\bullet)$	expected value
$\mathbf{H}$	measurement matrix
$\mathbf{P}$	parity matrix
$\mathbf{T}$	scores matrix
$\mathbf{V}$	projection matrix
$\mathbf{X}$	normalised data matrix
$\mathcal{S}_p$	principal component subspace
$\mathcal{S}_r$	residual subspace

Subscripts

i	sensor channel
j	sensor signal

Greek letters

ξ_q	threshold
λ_i	eigenvalue
$\mathbf{\Sigma}$	correlation matrix
δ^2	confidence limit for SPE
$\boldsymbol{\varepsilon}_i$	fault vector
σ	standard deviation
σ_s	maximum process change
γ	skewness

Abbreviations

AANN	auto-associative neural networks
BBN	Bayesian belief network
CM	common mode
FDI	fault detection and isolation
FNN	fuzzy neural network
FSN	fault semantic network
HTGR	high temperature gas-cooled reactor
ICA	independent component analysis
ICMP	instrumentation and calibration monitoring plan
MPS	main power system
MSE	mean squared error
MSET	multivariate state estimation
NPP	nuclear power plant
NLPLS	non-linear partial least squares
NTPS	non-temporal parity space
PBMR	pebble bed modular reactor
PBMM	pebble bed micro model
PCA	principal component analysis
PSVR	probabilistic support vector regression
SPE	square prediction error
VRE	variance of the reconstruction error

conducted by West et al. (2014) and relies on models derived from laboratory experiments combined with current operation plant data to infer the underlying health status of a nuclear reactor core. Probabilistic approaches have also been followed towards sensor fault diagnosis. These techniques are normally based on Bayesian belief networks (BBNs). Sharifi and Langari (2013) proposed a method that is different compared to these techniques in the sense that a probabilistic model is directly extracted from a parity equation. The relevant parity equation can be found using a model of the system or through principal component analysis (PCA). In the same probabilistic paradigm, (Liu et al., 2013) introduced a modified version of the probabilistic support vector regression (PSVR) method. This approach is proposed for the prediction of parameters of NNP components under fault conditions. It includes preprocessing, data reconstruction, model selection, and PSVR for estimation of the prediction interval and conditional predictive distribution of the target of interest. A combination of probabilistic and artificial intelligence methods for sensor fault detection and classification was also implemented by Nasimi and Gabbar (2014), where a fault semantic network (FSN) methodology is proposed for fault classification, identification and fault detection. Sensor readings are obtained and processed using PCA and weighted PCA methods for dimensionality reduction. A neural network is used for sensor fault identification and prediction. Even though research shows that these diagnostic systems are essential in prolonging the lifespan of the plant, only a few real systems are actually installed in operational units (Gertler, 1998; Johnson, 1989).

Sensor FDI of nonlinear systems is particularly difficult from a theoretical point of view (Zakharov et al., 2013). In addition, obtaining a sufficiently accurate analytical model for complex processes like those used in NPPs, could take years. Traditionally, two sensor FDI schemes are used: (1) limit value checking and (2) signal processing. Limit value checking techniques have been proven to perform well if the plant operates close to its' steady state. However, implementing a diagnostic system that only performs well during steady state conditions is not desirable. The difficulty with the approach to signal processing fault diagnosis, is distinguishing between changes in the signal properties due to faults. More recent approaches to sensor fault diagnosis can be found in the field of computational intelligence (Wang, 2003). These methods are however data-driven and dependent on the quality and amount of data used for model development. Acquiring such data for the entire operating range in the next generation NPPs are proven to be very difficult due to time and financial constraints. All these abovementioned factors necessitate the development of a new approach to NPP sensor fault diagnosis. The goal is therefore to realise an integrated sensor fault diagnostic methodology that is simplistic, reliable and most importantly, accurate for the whole spectrum of states in the NPP.

The methodology described in this paper builds on the ideas and methods that have been advanced by many investigators. This paper's contribution lies in the integration of these ideas to form a consistent comprehensive methodology. Previous work on sensor validation includes the parity space approach, filtering techniques, and probability ratio tests that have been used to evaluate sensor values by comparing them with redundant measurement values. These techniques can be read in detail in Venkatasubramanian et al. (2003) and Yan and Goebel (2003). Lee (1994) developed a technique that systematically explores the redundancies embedded in a system where numerous sensors are installed at various locations to evaluate the sensor values. This