Review of On-Line Monitoring Techniques for NPP Instrument Channels

Jianping Ma
Department of Mechanical & Materials Engineering
The University of Western Ontario
London, Ontario, Canada, N6A 5B8
jma64@uwo.ca

Abstract: The nuclear industry has attempted to use the condition-based instrument maintenance strategy to overcome the drawbacks of the traditional maintenance practice. In the new strategy, the instrument channels are monitored using advanced on-line monitoring (OLM) techniques during operation. Principal Component Analysis (PCA), Autoassociative Neural Networks (AANN) and Multivariate State Estimation Technique (MSET) are three well-known OLM techniques. In this paper, a technical review of these three techniques and their applications in Nuclear Power Plants (NPPs) is presented.

1. Introduction

Traditionally, the instrument channels in a Nuclear Power Plant are manually calibrated periodically [1]. However, this practice is not optimal. Faulty instruments cannot be detected promptly and they may continue to operate in malfunction until the next calibration. The erroneous signals may lead to deteriorated NPP monitoring accuracy, incorrect control actions or even worse consequences. In the Three Mile Island (TMI) accident, instrument failures played a significant role. On the other hand, the unnecessary calibrations of healthy instrument channels may potentially affect their availability and reliability. The unnecessary instrument channel maintenance is also expensive in terms of human resources, staff radiation exposure and prolonged plant outage [2].

To overcome these drawbacks, the nuclear industry has attempted to use condition-based calibration strategies by monitoring the NPP instrument channels using advanced OLM techniques. Progress has been made around the world and applications to real NPP data also rendered promising results [2-9]. The U. S. Nuclear Regulatory Commission (NRC) has concluded that the generic concept of on-line monitoring for tracking instrument performance is acceptable and it is beneficial for NPP safety and economy, although some requirements have to be met before the OLM techniques can be used for instrument calibration reduction [2].

Successful applications of various OLM techniques in NPPs for instrument channel monitoring have been reported. A technical review of three popular OLM techniques is presented in this paper. These techniques are (1) Principal Component Analysis, (2) Autoassociative Neural Networks, and (3) Multivariate State Estimation Technique.

The paper is organized as follows: the general principle of NPP instrument channel OLM is presented in Section 2. Technical reviews of the three OLM techniques are given in Section 3. Some practical applications of OLM techniques in NPPs have been described in Section 4 and the conclusion is drawn in Section 5.

2. Principle of On-Line Monitoring of Instrument Channels

The general principle of instrument channel OLM is shown in Fig. 1. n correlated NPP instrument channel outputs y_1, y_2,…, y_n are acquired during operation. For convenience, they will be compactly shown as an output vector $y = (y_1 \quad y_2 \quad \ldots \quad y_n)^T$. OLM techniques are then applied to y so that each output in y can be predicted from the other correlated outputs. The predicted instrument channel outputs will be denoted as $\hat{y} = (\hat{y}_1 \quad \hat{y}_2 \quad \ldots \quad y_n)^T$. The conditions of the instrument channels can be monitored by analyzing the prediction residuals $r = y - \hat{y}$. So the central task of instrument channel OLM is to predict the instrument channel outputs from their correlated signals using OLM techniques. Even minor instrument faults can be detected swiftly when the predicted output of an instrument is not consistent with the measured value.

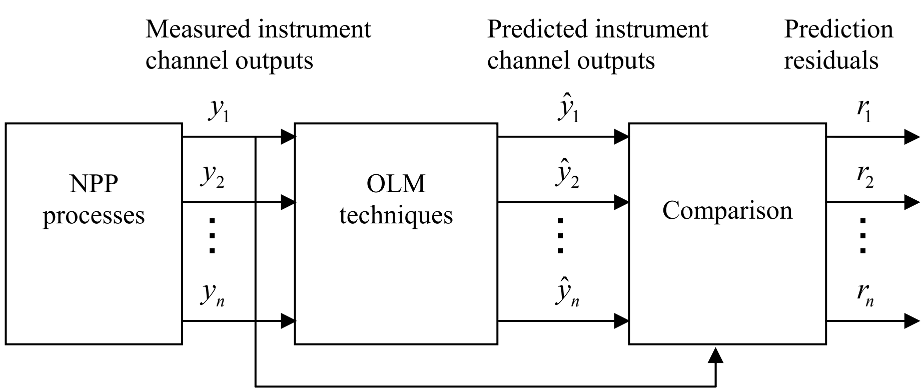

Figure 1: Principle of instrument OLM

Generally, existing OLM techniques can be classified into two categories: (1) model-based methods and (2) data-driven methods as summarized in Fig. 2 [10-19]. Although the model-based techniques are extensively applied in many fields for instrument fault detection and diagnosis, data-driven models are mostly used in the reported NPP instrument channel OLM systems. Therefore, only three popular data-driven OLM techniques will be reviewed in this paper.

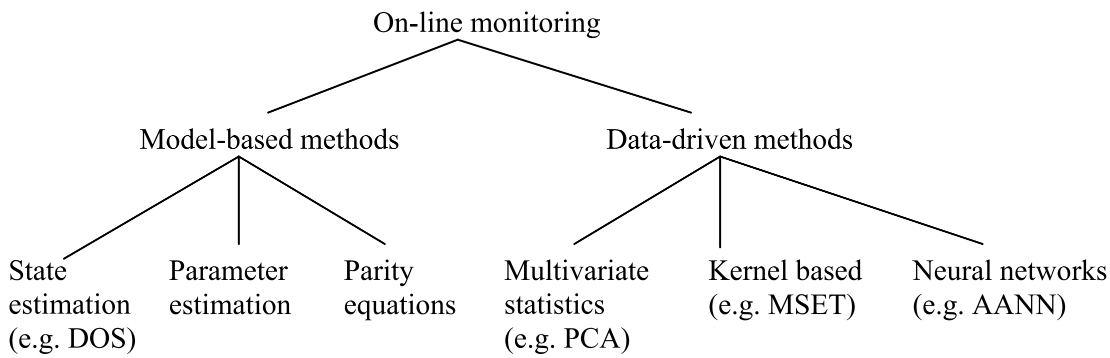

Figure 2: Summary of OLM techniques

3. Technical Reviews of Selected OLM Techniques

3.1 Principal Component Analysis (PCA)

In PCA, the prediction of the instrument channel outputs from the other correlated outputs is carried out as

$$\hat{y} = yPP^T \tag{1}$$

where P is a matrix composed of the so-called loadings that will be explained later. P^T is the transpose of P.

The prediction residuals can be calculated as

$$r = y - \hat{y} = y(I - PP^T) \tag{2}$$

where $I \in R^{n \times n}$ is a unity matrix. The instrument channels can be monitored by analysis of r [15-16] [20].

P in Eq. 1 is calculated using fault-free training data obtained from the instrument channels to be monitored. The training data are collected into a data matrix $Y \in R^{m \times n}$, where *m* is the size of the available training data and *n* is the number of correlated variables. After the data matrix Y is mean-centered and unit variance scaled, the correlation matrix of Y will be calculated as

$$\mathrm{cov}(Y) = \frac{Y^T Y}{m-1} \tag{3}$$

The eigenvalues and eigenvectors of the correlation matrix are calculated as

$$\mathrm{cov}(Y)p_i = \lambda_i p_i \tag{4}$$

where λ_i is the ith largest eigenvalues and p_i is the eigenvector corresponding to λ_i. The eigenvectors p_i are called loadings and they contain the information on how the n variables in Y are correlated to each other.

The data matrix Y can be decomposed into n components as

$$Y = \sum_{i=1}^{n} Yp_i p_i^T \tag{5}$$

But most of the information contained in Y can be captured by the first k ($k<n$) Principal Components (PCs) as

$$Y = \sum_{i=1}^{k} Yp_i p_i^T + \sum_{i=k+1}^{n} Yp_i p_i^T = YPP^T + E \tag{6}$$

where P is composed of the first k principal loadings $P = [p_1 \quad p_2 \quad \dots \quad p_k]$ and E is a residual matrix. The number k is determined so that $\sum_{i=1}^{k}\lambda_i \Big/ \sum_{i=1}^{n}\lambda_i$ is larger than certain percentage, for example 90%, which means at least 90% of the information contained in the measurement data is captured by the first k PCs.

Once P is obtained, it can be used to predict the values of new measurement data using Eq. 1, which can be computed on-line easily.

PCA is very simple and flexible for practical applications. Training a PCA model is easy. The relationships among the correlated variables can also be easily interpreted. It is extensively used in many industrial fields for process monitoring fault diagnosis and so on. However, PCA has a major limitation: it is linear in nature and it cannot accurately monitor a process where profound nonlinear effects exist.

3.2 Autoassociative Neural Networks (AANN)

AANN was originally developed as an extension to PCA for nonlinear applications by combining PCA with feedforward neural networks [17-18]. As shown in Fig. 3, an AANN has five layers: input layer, mapping layer, bottleneck layer, demapping layer, and output layer. The bottleneck layer has the lowest dimension so that information compression can be achieved. The outputs of an AANN are the predicted values of the inputs. An AANN can be trained as an ordinary neural network using fault-free training data obtained from the processes to be monitored.

When applied for instrument channel monitoring in NPPs, the inputs of an AANN will be the n correlated instrument channel outputs y and the outputs of the AANN are just the predicted values of the instrument channel outputs $\hat{y}$. The instrument channels can be monitored by analysis of the prediction residuals $r = y - \hat{y}$.

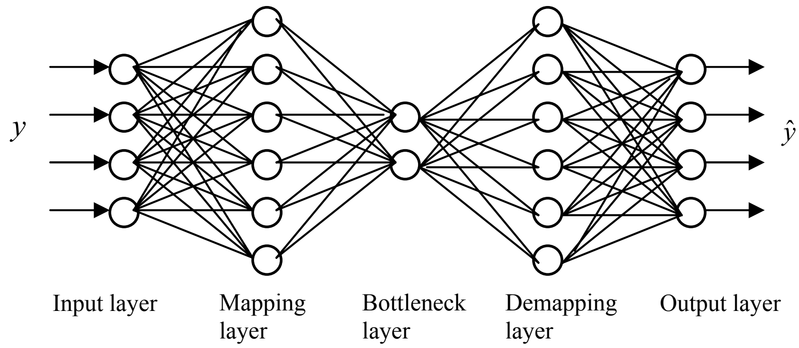

Figure 3: Structure of AANN

Nonlinear functions can be used when mapping from one layer to its subsequent layer. Therefore, AANN can deal with nonlinear effects and it can monitor the instrument channels more accurately when they are correlated nonlinearly. However, it is much more difficult to train an AANN than PCA, not only in terms of computation load but also in terms of choosing the proper model architecture.

3.3 Multivariate State Estimation Technique (MSET)

MSET was originally developed by the U. S. Argonne National Laboratory (ANL) for OLM applications in NPPs. It is an advanced nonlinear kernel based pattern recognition technique [8] [19].

MSET predicts the instrument channel outputs as

$$\hat{y} = D \cdot (D^T \otimes D)^{-1} \cdot (D^T \otimes y) \tag{7}$$

where $D \in R^{n \times m}$ is a process memory matrix containing fault free data obtained from the instrument channels to be monitored; n is the number of the correlated instrument channel outputs, and m is the size of the process memory data set. $\otimes$ is a nonlinear kernel operator, for example a Hermitian kernel.

The health of the instrument channels can be monitored by analyzing the prediction residuals, $r = y - \hat{y} = y - D \cdot (D^T \otimes D)^{-1} \cdot (D^T \otimes y)$, usually using the Sequential Probability Ratio Test (SPRT) technique.

Practical applications of MSET have rendered good results. It is claimed that MSET "possesses significant advantages in sensitivity, reliability, flexibility and computational efficiency over alternative process surveillance approaches currently available" [21]. However, some theoretical aspects of MSET, such as the proper choice of the kernel operator, are not well understood. Investigations have been carried out with certain success to avoid poor MSET performance by proper regularizations [7] [22].

4. Applications of OLM in NPPs

4.1 OLM applications of PCA in NPPs

PCA is among the mostly used process monitoring techniques. Successful applications of PCA for NPP OLM are also reported.

In [23], PCA is applied to the monitoring of a typical U-tube Steam Generator (UTSG) in a typical PWR. Measurements of sixteen variables related to the UTSG are monitored using PCA. Six single device faults are simulated and five of them can be successfully detected and isolated. The water level sensor drift is not detected because there is no measurement that is highly correlated with that variable. In [24], it is demonstrated again using a UTSG system that PCA is a robust and flexible technique for FDI applications in NPPs.

In [25], PCA is applied to the OLM of redundant instruments in NPPs. The scheme is successfully validated using real NPP measurement data from three set of redundant instrument channels: three pressurizer level channels, five pressurizer pressure channels, and three Steam Generator (SG) pressure channels. In that research, a 0.33% drift in one of the five pressurizer pressure channels is detectable to PCA.

4.2 OLM applications of AANN in NPPs

In [26], AANN is applied to the monitoring of 22 critical plant sensors at the Crystal River-3 NPP and 56 sensors at the Oak Ridge National Laboratory (ORNL) High Flux Isotope Reactor (HFIR). It is shown in both cases that generally "sensor drifts are detectable at a nominal level of 0.5% of the instrument's full scale range." Also, the faulty sensors' outputs can be replaced from the other correlated fault free measurements.

AANN is the key monitoring technique of the Process Evaluation and Analysis by Neural Operators (PEANO) system developed by the OECD Halden Reactor Project [5]. In PEANO, measurements from the instrument channels of a plant are first classified into correlated clusters and the channels in each cluster are monitored by an AANN. In 1997, PEANO was tested using fourteen process signals of a 900MW PWR in different operating conditions provided by Electricite De France (EDF). Failures were put into the signals by EDF and they were successfully detected by PEANO. PEANO was also installed and ran in real time at the Halden Boiling Water Reactor (HBWR) for OLM. Since no instrument failed during on-line operation, drift to the measured steam flow was artificially added and this failure was monitored. A number of tests of PEANO using real measurement data from several U. S. NPPs were also successfully carried out. In one application, PEANO detected a span drift of a steam flow sensor one month earlier before the plant actually did.

4.3 OLM applications of MSET in NPPs

MSET attracts the most interest for OLM in U. S. NPPs. Venturi flow meters are usually used to measure the SG feedwater flow rates, however, the fouling of the venturi flow meters will result in overestimation of the actual flow rates, which will eventually cause an up to 3% reactor power derating. In [8], MSET is applied to the monitoring of the venturi flow meters at the Crystal River-3 NPP. 29 diagnostic sensors in loop A are monitored by a MSET model. It is shown that when the size of the process memory matrix D is 500, the rms error between the MSET predicted feedwater flow rate and the measured flow rate of the fouling free venturi flow meter is only 0.13%. 240 days later after the start of a new cycle, the measured feedwater flow rate exceeded the MSET prediction by about 1.1%, which was due to venturi flow meter fouling. MSET can predict the true feedwater flow rate more accurately, and it can, "in principle, be used to provide an improved estimate of the reactor power and hence avoid the revenue loss associated with derating the reactor based on a faulty feedwater flow rate indication."

Again at the Crystal River-3 NPP, MSET's ability to detect loss of time response capabilities of Rosemount pressure transmitters is verified. A loss of time response failure of the pressurizer level sensory system was identified by MSET about three months earlier than the plant operators [21].

Based on the MSET algorithm, the SmartSignal Inc. developed their commercial equipment condition monitoring software SmartSignal eCM™ and the Expert Microsystems Inc. produced their product SureSense [4]. Currently, the Limerick, Salem, Sequoyah, TMI, and VC Summer NPPs are using the system produced by Expert Microsystems Inc. for on-line monitoring and calibration of process instrumentation. And the Harris and Palo Verde NPPs are using the system developed by SmartSignal Inc. for the same purposes [4].

4.4 Applications of other OLM techniques in NPPs

Many more OLM techniques have been applied in NPPs with generally good results. The OLM applications of the relatively new Support Vector Machines (SVM) technique in NPPs also show promising results [27-28]. The Nonlinear Partial Least Squares (NLPLS) technique [29] and Autoassociative Kernel Regression (AAKR) technique [30] also have good testing results with real NPP data. In [31] and [32], applications of the model based OLM techniques in NPPs are reported.

5. Conclusion

Much progress has been made to monitor the NPP instrument channels using advanced OLM techniques to overcome the drawbacks of the traditional practice. In the new strategy, advanced OLM techniques are used to predict the output of an instrument channel from other correlated measurements. The prediction residuals can be analyzed to monitor the instrument channels. Three OLM techniques are reviewed in this paper. Their applications in real NPPs have rendered promising results, which imply great benefits in terms of NPP safety and economy.

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