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A hybrid data-driven modeling method on sensor condition monitoring and fault diagnosis for power plants

Jianhong Chen, Hongkun Li, Deren Sheng *, Wei Li

Institute of Thermal Science and Power Systems, Zhejiang University, Hangzhou 310027, China

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ABSTRACT

This paper proposes a new hybrid data-driven soft measurement modeling method for power plant sensor condition monitoring and fault diagnosis. The method integrates Generalized Regression Neural Network (GRNN), Mean Impact Value (MIV), Partial-Least Squares Regression (PLSR) and B-Spline transformation techniques. First, the relevant parameters are obtained from mechanism analysis and a GRNN model is built to assess the average contribution rate of each independent variable and filter out the main modeling parameters by method of MIV. Then, the main modeling parameters are modeled with a PLSR method based on the cubic B-Spline transformation, which is an effective approach to the nonlinear modeling and multicollinearity problems. The final reliable model is completed to monitor and diagnose the sensors. Taking the active power sensor of a combined cycle generator unit of Siemens V94.3A as an example, the computational result shows that this modeling approach to sensor measurement data fits well in both accuracy and generalization ability under different conditions. Through fault signs and fault diagnosis methods analysis, this model could accurately identify sensor fault types. Most importantly, only a few model parameters need to be saved, and the model has low computation cost and strong robustness. Therefore the model is more suitable in solving the online real-time monitoring and diagnosis problems.

Introduction

In power plants, aircraft, and many other complex systems, a large number of sensors are used for monitoring and control. The safety, reliability, and performance of complex systems with many sensors are largely dependent on the accuracy and reliability of the sensors. Sensor readings play a key role in the assessments of system states. Many measurement sensors used in modern large-scale power unit are working in the complicated environment of high temperature, high pressure, high humidity, plenty of dust, corrosion and electromagnetic interference [1]. So compared to other parts of the system, they have a higher chance to fail and to measure inaccurately. Performance degradation, fault or failure of the sensors have great impact on the relevant monitoring, control and fault diagnosis system, leading to false diagnosis, false alarm, and even causing immeasurable loss [2,3]. Therefore, it is of great significance to research on how to detect faults in real time and rapidly diagnose sensors' faults.

Diagnosis of sensor faults is based on the residual signal between sensors' measured data and nominal value (estimated). Redundancy is the only way to generate residuals. According to the way of redundancy, sensor fault diagnosis can be divided into two categories, namely: the methods based on physical redundancy and the methods based on analytical redundancy [4,5]. The former are based on measuring/inferring a parameter or variable by/from more than one sensor. The latter provide redundancy for parameters or variables monitored through process model (analytical model) or knowledge from data.

Many automated techniques have been developed for the sensor Fault Detection and Identification (FDI), many of which have been summarized in [6–8]. The analytical redundancy methods do not require additional hardware, which can greatly save the cost for large systems. In some special applications like those in the aviation industry, additional sensors would be limited and analytical redundancy methods for sensor fault detection and diagnosis could only be adopted [5]. Other than that, the system can be more effectively controlled and optimized with the analytical redundancy methods. Therefore, they have been the hot spot of the current research. Compared to the physical redundancy methods, analytical redundancy methods are more difficult to achieve. Their validity and reliability of the sensor fault detection and diagnosis mainly depend on the reliability and validity of the model and diagnosis strategy. As for analytical redundancy

* Corresponding author. Tel./fax: +86 571 87951492.
E-mail address: ShengDR@zju.edu.cn (D. Sheng).

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methods, establishing an accurate model is the key to sensor fault diagnosis.

Many analytical redundancy methods have been applied for intelligent sensor data validation, fusion, and sensor fault detection. Kalman Filters and Luenberger Observers, because of their systematic design, noise disposal and enhance sensitivity, have been widely used for FDI in dynamic systems and are still receiving attention [9–11]. In [12], Gertler described the design of dynamic parity (consistency) relations for the detection and isolation of faults systematically and integrally. Mehranbod et al. [13] did lots of research on Bayesian belief network (BBN) and a multistage BBN model was developed to perform effective FDI in processes in transient or at steady-state. Artificial Neural Networks (ANNs), Principal Component Analysis (PCA), other model-based and data-based methods had the greatest potential among all analytical redundancy methods in development and application [14–18]. In [19], A nuclear power plants fault diagnosis system based on Genetic-RBF Neural Network (GRBFNN) made the neural network smaller in size and higher in generalization ability and the diagnosis speed and accuracy were also improved. Witczak M presented several effective approaches to solve robust fault diagnosis of nonlinear systems [20–23]. To realize robustness, adaptive threshold was obtained via the Model Error Modelling (MEM) and a robust Group Method of Data Handling (GMDH) neural network. MEM was applied to passive robust fault detection, fault isolation and fault identificationof a DC motor. Besides, Baraldi et al. [24] proposed a reconstruction model based on PCA, which has been applied to a real case study concerning 215 signals monitored at a Finnish nuclear pressurized water reactor. Because of the disadvantages of a single method, many hybrid methods have been proposed [25–28]. In [29], Simani and Fantuzzi proposed the method that the fault was detected on the basis of residuals generated from a bank of Kalman filters, while fault identification was obtained from pattern recognition techniques implemented by Neural Networks. Hybrid artificial neural network (HANN) integrating error back propagation algorithm with PLSR was proposed to overcome tendency to overfitting and difficulty to determine the optimal number of the hidden nodes of ANN [30]. In spite of so many methods at present, the problem is that these methods are not very fit for online application.

In view of the above, each method has its own strength and weaknesses. Considering this, an integrated modeling method based on the GRNN, MIV, cubic B-Spline transformation and PLSR is proposed in this work for sensor FDI. In combination with the advantages of these methods, this hybrid method effectively performs with simple structure, high accuracy and good generalization ability, which is able to detect the fault accurately and in time.

Methodology

Overview

The method belongs to the methods based on model. The analytical value is obtained by the model, then the fault diagnosis is carried out by comparing sensor readings with analytical value. So establishing the accurate model is the key to data validation and sensor fault diagnosis. For a complex nonlinear system such as combined cycle generators, the soft measurement model to establish should be adapted to the various operating conditions (different loads and different seasons including spring, summer, autumn, winter, etc.). Therefore a large number of samples must be used for training so that the model conforms to the actual performance. However, it is not a good choice to save too many GRNN's training samples in the database. Otherwise parameters saved in the database will be increased exponentially. When the number of training samples is small, a good fitting effect still can be obtained for some data. However, due to the weak neural network generalization ability, for other data that is significantly different from the training samples, the prediction effect is poor. So GRNN is not suitable for establishing the model for online real-time applications. On the other hand, GRNN has excellent nonlinear fitting capability which can be used to interpret the influence of the parameter values and select the variables conveniently by using MATLAB software. PLSR based on B-Spline regression method is a good approach that uses quasi linear approximation to solve the nonlinear problems. The analytical model has good generalization ability, simple structure, and fewer parameters, but due to the complex modeling process, it cannot be achieved at the same time as variable selection. This lowers model precision given a lot of variables' weak correlation. In combination with the advantages of both methods, this paper integrates GRNN, PLSR, MIV and B-Spline to propose a new modeling method, as shown in Fig. 1.

As illustrated in Fig. 1, our methodology consists of four steps. (1) Mechanism analysis to acquire correlated variables with the sensor reading studied. (2) Variable selection which is based on GRNN–MIV. (3) Nonlinear modeling using PLSR based on B-Spline and estimating values of the sensor readings. (4) Fault detection is carried out by generating residue signals and monitoring their changes. The efficacy of our methodology is illustrated here by applying it to data from a gas turbine power plant. This approach is applicable to more general equipment monitoring and diagnostic applications.

First, mechanism analysis is performed to get all the correlated variables ($X_1 \sim X_p$) related to the dependent variables studied qualitatively, which has been ignored by almost all previous works.

After that, a GRNN modeling with good nonlinear fitting ability is obtained to investigate the MIV of each correlated variable to dependent variable Y for the purpose of selecting the main variables ($X'_1 \sim X'_m$). The main variables are selected and collated to constitute a new sample space by comparing the MIV. After that, Then by means of cubic B-Spline transformation, independent variable space X' is nonlinear mapped to independent variable space Z of PLSR. So the regression equation of the Y to Z based on PLSR can be calculated, and further the regression equation of the Y to X' also can be obtained, which is the final model. Our method takes full advantage of the GRNN's excellent nonlinear fitting ability to complete the selection of variables, and meanwhile, the method uses PLSR to complete the final model whose structure is relatively concise but with outstanding fitting ability.

When there are a large number of training samples, GRNN prediction model has a better convergence rate for complex nonlinear problems. Combining with MIV, it could easily quantitatively screen the main advantage of variables for model, which makes up for the disadvantages of model performance degradation caused by introduction of non-correlated variables. The quasi linear PLSR model based on B-Spline transformation has less parameters and good generalization ability, and more importantly its structure is simpler. So the eventual model can perform with simple structure, high accuracy and good generalization ability. The GRNN is often over-parameterized with too many training samples and therefore it is hard to generalize it to practical applications. However, this hybrid method effectively solves the problem with very few parameters, which is suitable for online real-time applications. In this way, the trouble of saving the mass parameters required by the GRNN for operation and maintenance of monitoring system is avoided.

In the next sub-sections, the four steps of the proposed hybrid method for sensor data validation and fault diagnosis would be explained in detail.