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Study on Instrument Fault Detection using OLM Techniques for PHM Application in NPPs

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1. Introduction

In I&C fields, surveillance and diagnosis mean that is detecting abnormal conditions by monitoring process variables and determining whether the instrument or equipment failure. The diagnosis system is relatively being mature owing to many research. Among the various models, this paper introduces some On-Line Monitoring (OLM) models for instrument health monitoring and review applicability on NPPs. In recent years, many researchers are being focused on the prognostics which is predicting the future failure of instruments or equipment by using the status monitoring data. By using the prognostic techniques, we can expect a lot of advantages such as ease of control, power optimization, or optimal use of maintenance resources. And we have performed the test for detecting fault of safety-critical instruments and analyzed the fault detection sensitivity for various instrument failure modes using OLM techniques.

2. Current Trends of Prognostics & Health Monitoring using OLM techniques

The OLM techniques make possible to automatically analyze the accuracy and reliability of the instruments in operation environment [1]. Various models are widely used in commercial OLM systems. Following figure 1 shows the data-driven based OLM system flow chart. From a variety of OLM techniques, introduces data-driven based AAKR and AANN model [2].

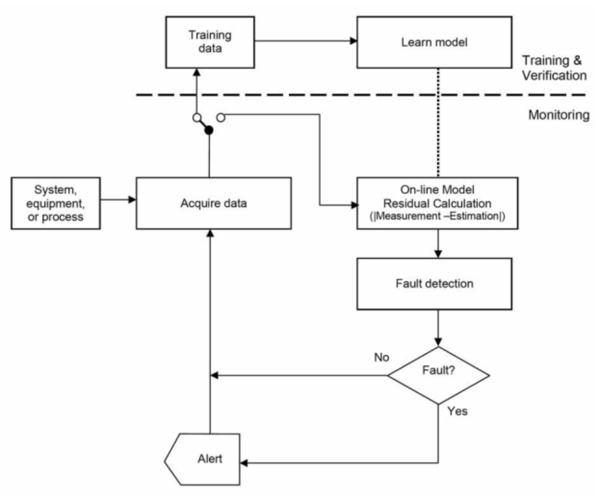

Fig. 1. Data-driven based OLM system flow chart.

2.1 Auto-Associative Kernel Regression Model

The Auto-Associative Kernel Regression (AAKR) model is non-linear, non-parametric, non-multiple kernel regression analysis method [1]. An AAKR model has similar structures for many commercial On-Line Monitoring models. The AAKR method is mainly used for predicting correct values on inputs. About query observation of model input, kernel regression estimating process is divided into three steps as follows.

Step 1 – Distance calculation: calculate the distance of query from each input exemplar.

Step 2 – Similarity Quantification: calculated distance is provided to a kernel function as an input value. Here, the distance is converted to weighting factor.

Step 3 – Output Estimation: these weighting factors are used for predicting model outputs.

The auto-associative has a structure that can predict the correct values of a group of sensors, even though it contains the defects such as sensor drift with noise or complete failure of the instrument. Figure 2 shows the auto-associative model architecture.

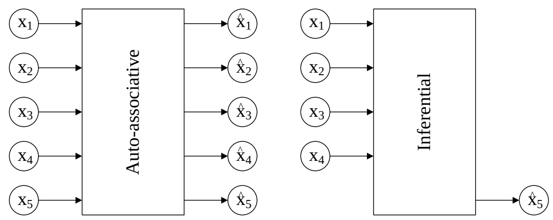

Fig. 2. The Auto-associative model architecture [3].

2.2 Auto-associative Artificial Neural Network Model

The Auto-associative Artificial Neural Network (AANN) model is a three hidden layer network forces a compact representation of the data in the bottleneck layer [3]. Commonly, it is called non-linear principal component network. Each output is a function of all of the inputs.

The AANN model requires comparatively long training time. However, with the improvement of modern computing performance, this is no longer a major problem. Figure 3 shows the basic structure of neural networks. An AANN model is trained for each group of correlated sensors. Several correlated sensor values become inputs, and through estimation process, Best estimates of several correlated sensor values are produced as outputs. Abnormal changes in an input affect the output to a much lesser degree. And by comparing the inputs to the outputs, faults can be detected.

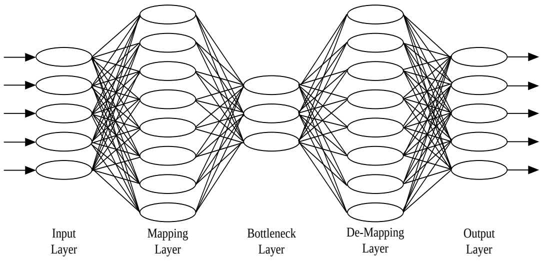

Fig. 3. The basic structure of neural networks.

2.3 Current Trends in Prognostics

Prognostics is an important part of the plant monitoring system. While the monitoring and diagnostics part is well established over several decades, the prognostics have recently had attention in many industrial fields. Prognostics modules are developed to predict the Remaining Useful Life (RUL), Time To Failure (TTF), and Probability Of Failure (POF). Prognostic model can be classified into the following several types according to the structure, operating method, and produced results.

Type 1 - Time-to-failure data-based model: these methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of an average component under average usage conditions. The most common method is Weibull Analysis [4].

Type 2 - Stress-based model: these methods also consider environmental stresses (e.g. temperature, load, vibration, etc.) under which the component operates. They estimate the life for an average component under the given usage conditions. A common method is the Proportional Hazards Model [5].

Type 3 - Effect-based model: these methods also consider the measurable or inferred component degradation. An example is the General Path Model [6].

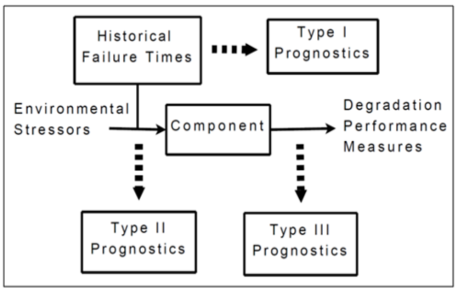

Fig. 4. Prognostic Method Types. [7]

Prognostics founded in root cause analysis allow accurate physics-based diagnostic and prognostic determinations for nuclear plant equipment to be derived. Some research studies for understanding and controlling the aging processes of safety-critical nuclear plant components are currently in progress [8, 9].

2.3 Instruments Failure Detecting Test by On-Line M techniques

We have performed the test as case study about various types of artificial fault that can occur in real operation conditions.

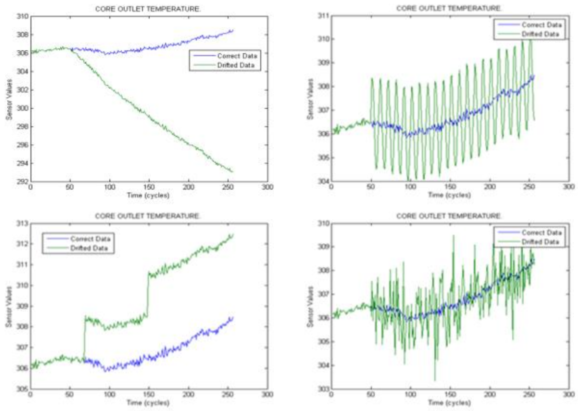

Fig. 5. Various types of artificially generaged fault for test.

For the test, we obtained the plant operation data set by using Compact Nuclear Simulator (CNS) [10]. This is a PWR type simulator, which is having a three-loop system. Among the obtained data set, most important variables have been selected as 23 kinds of major instrument variables for the testing.

For model development and evaluation, three data sets such as Training data, test data, and validation data are used. In the first step of this analysis, training data is used for the initial model development. In this step, exemplar observations are chosen from the training data to form a subset of memory vectors; this accounts for all the “training” needed by an AAKR model.

The second step involves optimizing the model architecture. This optimization is accomplished using the test data set. The models presented in this research are optimized for the kernel bandwidth, the number of memory vectors, the vector selection method, and the distance measure.

Finally, the validation data set is used to evaluate the model that was optimized in the previous step. Following figure 6 shows the methodology used for model development and analysis.

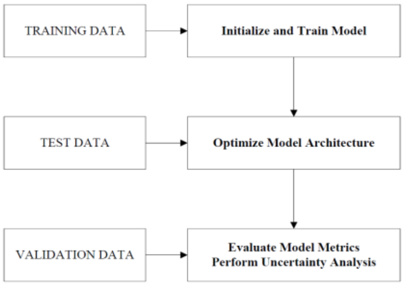

Fig. 6. Methodology for model development and analysis.

As the training data, following normal operation mode data set was used. And about 10% of training data set was used for test data optimizing a model. To see the fault detection performance, we have added a drift fault to a specific variable. Figure 7 shows the sensor degradation by 1% drift, which was artificially generated for the fault detection test and the test result of fault detection.

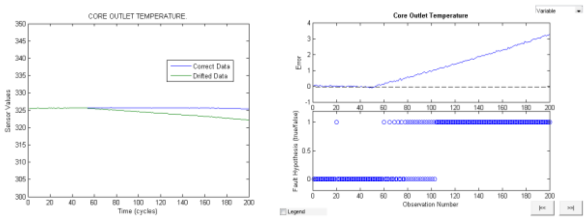

Fig. 7. Sensor degradation artificially generated for the fault detection test (left), result of fault detection about 1% drifted sensor (right).

In the test condition, the instrument fault is occurring in 50 time cycles. Shortly after the fault occurs, the model has shown that the sensor is on abnormal state, and after 110 time cycles, this sensor has been determined to be defective. we can see the result of fault detection sensitivity by various cases through following table.

Table I. The result of fault detection sensitivity by various cases.

Case	Degree of fault	Drift (%, of mean value)	Oscillation (°C, of amplitude)	Step change (°C, per step)	White Gaussian Noise (%, of std. deviation)
1	0.1	11.26	1.99	13.91	3.31
2	0.5	52.32	18.54	44.37	13.25
3	1	76.16	29.80	83.44	33.77
4	5	95.36	90.07	100	80.80
5	10	97.35	90.07	100	91.39

4. Conclusions

OLM techniques using data-driven based model such AAKR or AANN can be useful tools for securing integrity of safety-critical instrument that should always keep healthy conditions for the plant safety. Whereas a variety of diagnostic techniques are being applied to nuclear power plants, prognostics techniques are still stuck in elementary stage. In other industries such as railway or defence, prognostics have being shown significant achievement of maintenance efficiency increasing and cost effectiveness. Similarly, in the nuclear power field, prognostics can be a means to enhance the safety and reliability of plant operatings. For this, plant owner's interest and cooperation are required.

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