Monitoring the performance of Aux. Feedwater Pump using Smart Sensing Model

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1. Introduction

If the transient or accidents occur in nuclear power plants, the plant operators are generally provided with only partial information. However, if the incorrect information is provided to operators, it will be caused to severe accident. Therefore, the accurate monitoring systems are needed in NPPs. From 1980's, monitoring systems have been developed based on the concept of prognostics. However, the monitoring systems which are related to safety injection have not been developed in NPPs yet.

Many artificial intelligence (AI) techniques equipped with learning systems have recently been proposed to monitor sensors and components in NPPs. Therefore, the objective of this study is the development of an integrity evaluation method for safety critical components such as Aux. feedwater pump, high pressure safety injection (HPSI) pump, etc. using smart sensing models based on AI techniques.

In this work, the smart sensing model is developed at first to predict the performance of Aux. feedwater pump by estimating flowrate using group method of data handing (GMDH) method [1]. If the performance prediction is achieved by this feasibility study, the smart sensing model will be applied to development of the integrity evaluation method for safety critical components.

Also, the proposed algorithm for the performance prediction is verified by comparison with the simulation data of the MARS code for station blackout (SBO) events.

2. Smart Sensing Model

In this work, a smart sensing model is developed to estimate the performance for Aux. feedwater pump using a group method of data handing (GMDH) algorithm. Therefore, the GMDH algorithm is briefly explained below.

2.1 Basic GMDH Algorithm

The GMDH algorithm [2] is the way to find a function that can well express a dependent variable from independent variables. This method uses a data structure similar to that of multiple regression models. The data set can be divided into the training data and test data. The reason of dividing the data set is to prevent over-fitting and maintain model parsimony.

The GMDH uses a self-organizing modeling algorithm with the flexibility of deciding nonlinear forms of the basic inputs $[x_1, x_2, \cdots, x_m]$. Fig. 1 shows the branch structure of the GMDH model. It starts with the basic inputs at the first layer and becomes more complex according to the increasing number of layers.

The original GMDH method employed the following general form at each level of the successive approximation:

$$y = f(x_i, x_j) = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_i x_j \qquad (1)$$

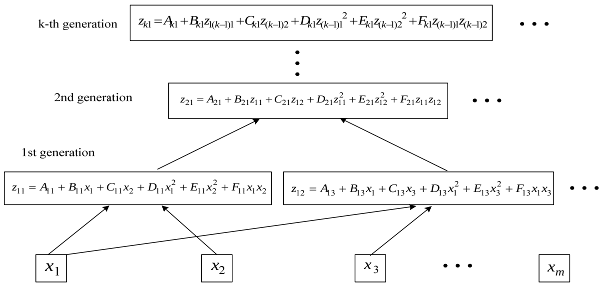

Fig.1 Branch structure of the GMDH model

The GMDH algorithm employs a high-order polynomial in the Kolmogorov-Gabor form. The Kolmogorov-Gabor (called as Ivakhnenko polynomial) is expressed as follows [2]:

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} a_{ijk} x_i x_j x_k \ldots \qquad (2)$$

where $\mathbf{x} = (x_1, x_2, \cdots, x_m)$ is an input variable vector and $\mathbf{a} = (a_0, a_i, a_{ij}, a_{ijk,} \cdots)$ is a vector of coefficients or a weight of the Kolmogorov-Gabor polynomial. Components of the input vector **x** can be independent variables, functional forms or finite difference terms.

2.2 Optimality Test

The GMDH algorithm has been developed and improved in many applications. The main steps in its implementation are given below.

The first step is to classify the data. That is, after constructing the input and corresponding output data for GMDH model, it is divided into training and test sets.

The second step is to establish a new variable. The external inputs have to be chosen to the GMDH network. And then calculate regression polynomial parameters for each pair of input variables **x** and combined output y in the training sets. Thus least-squares error (LSE) linear regression parameters are calculated.

The next step is to remove the variables which have little contribution. A measure used to evaluate the new variables at each generation is the fractional error defined as:

$$r_j^2 = \frac{\sum_{i=1}^{n} (y_i - z_{ij})^2}{\sum_{i=1}^{n} y_i^2} \quad \text{for } j = 1, 2, \cdots \qquad (3)$$

The last step is to take the optimality test. The process above is performed repeatedly until over-fitting is found through cross checking; that is, when the root mean square error (RMSE) of current layer is larger than the last layer. The minimum value of those r_j for generation k is denoted as $R_{\min k}$, if $R_{\min k} > R_{\min}$, then the training and testing processes of the algorithm stop and the polynomial with the minimum value of the error criterion in layer $k-1$ is selected to be the final approximate model. Otherwise, the algorithm moves to the next layer and repeats the above steps.

3. Application of the Proposed Algorithm

To apply the proposed algorithm, it is essential to acquire the data required to train the GMDH model from a number of numerical simulations because the Aux. feedwater pump is standby state in normal operation.

In this study, the GMDH model was trained using simulation data set (training data) prepared for training and was confirmed using another simulation data set (test data) independent of the training data. A total of 1000 simulations data were acquired using the MARS code. Among a total of 1000 simulation data for divided into 3 data case: 600 training data, 100 test data and 200 verification data by subtractive clustering (SC) method. The measured signals are as follows:

SG steam flowrate, SG pressure, SG temperature, SG wide-range level, Hot-leg flow, Cold-leg flow, Pressurizer pressure, Pressurizer temperature, Pressurizer water level, Aux. feed water temperature, Reactor power, Aux. feed-water pump suction pressure and core water level

Actually, the GMDH model did not use all the measured signals because all the signals has little relationship with Aux. feedwater flowrate. Also, it takes considerable time to train and optimize the GMDH model if many inputs are used in the GMDH model.

Fig. 2 shows that the Aux. feedwater flowrate is declined since Aux. feedwater pump performance was degraded to 80%. Also, Table 1 shows the RMS errors of proposed model for each data type.

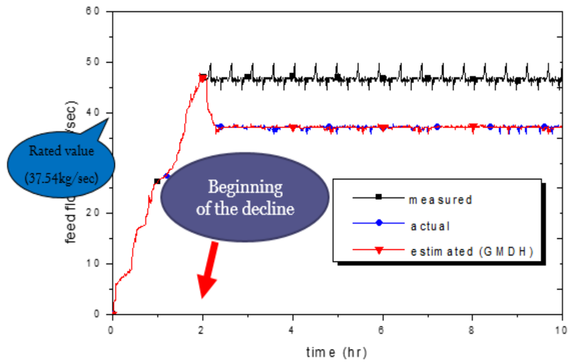

Fig.2 Measured Aux. feedwater flowrate and their estimation errors.

Table I: RMS errors

	No degradation	Degradation up to 80%
Training data (%)	0.2154	0.3346
Verification data (%)	0.1741	0.89
Test data (%)	0.1493	0.3126

4. Conclusions

In this study, the smart sensing model for the prediction performance of Aux. feedwater pump has been developed. In order to develop the smart sensing model, the GMDH algorithm is employed. The GMDH algorithm is the way to find a function that can well express a dependent variable from independent variables. This method uses a data structure similar to that of multiple regression models. The proposed GMDH model can accurately predict the performance of Aux. feedwater pump by estimating flowrate. In the simulations, the RMS error and the Max. relative error is 0.1493% and 1.976%, respectively for the test data. Also, In case of performance degradation up to 80%: RMS error and the Max. relative error is 0.3126% and 3.012% for the test data. Therefore, the proposed smart sensing model based on the GMDH algorithm can be successfully applied to monitor the status of the components.

REFERENCES

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