# Development of three methods for control rod position monitoring based on fixed in-core neutron detectors

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A B S T R A C T

Nuclear reactor core power distribution on-line monitoring system is very important in core surveillance, and this system should have the ability to indicate some abnormal conditions, such as the unacceptable control rod misalignment. In this study, the methodologies of radial basis function neural network (RBFNN), group method of data handling (GMDH) and Levenberg–Marquardt (LM) algorithm are utilized separately to unfold the control rod position from the fixed in-core neutron detector measurements. For using these methods, a large number of in-core detector signals corresponding to various known rod positions are needed. These data can be generated by an advanced core calculation code. In this study, the neutronics code SMART was used. The simulation results show that all these methods can unfold the control rod position accurately, and the performance comparison shows that the regularized RBFNN performs best. Two correction strategies are proposed to correct the simulated fixed in-core detector signals and improve the rod position monitoring accuracy when there are mismatches between actual physical factors and modeled physical factors.

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## 1. Introduction

Core power distribution monitoring in operating power reactors is very important in core surveillance (Peng et al., 2014a), the power distribution is one of the basic operation parameters which can determine many other important parameters such as power peaking factor, enthalpy rising factor and quadrant tilt ratio used to evaluate the operation condition of reactor and the safe margin. The control rod has a strong local effect on power distribution, so the power distribution monitoring system should be able to detect the abnormity of the control rod. Traditionally, control rod positioning systems are based on electromechanical devices. The unacceptable rod misalignment may occur as a result of an electrical or mechanical failure. If the position of the rod cannot be verified, the rod positioning system must be considered inoperable. A reactor shutdown is usually necessary if more than one rod is considered inoperable. To detect de-calibration or abnormity of the standard rod positioning instrumentation, an alternative method is needed.

The idea of using the information that exists in the axial flux shape to determine the rod position was proposed by Garis and his co-workers (Garis et al., 1998). The flux shape can be measured

in the close vicinity of a fuel assembly containing a control rod assembly. The relationship between flux shapes and rod positions is rather implicit, so the neural network techniques are utilized to unfold the rod position from the axial flux shape which was measured by movable in-core detectors. Garis used a simple three-layered BP neural network and the training set was generated by the core master code SIMULATE. This BP neural network method was tested with good results on both fully simulated data as well as on a measurement taken at the Swedish pressurized water reactor Ringhals 4. Li and his co-workers (Li et al., 2010) proposed a Levenberg–Marquardt algorithm based method to unfold the rod position of high-temperature gas-cooled reactor from the ex-core detectors. The theoretical signals of the ex-core detector were formulated as the polynomials of the rod position, and these polynomials with real ex-core detector measurements formed an over-determined nonlinear system. The Levenberg–Marquardt algorithm was utilized to solve the over-determined nonlinear system. The simulation results showed that this method was accurate and robust.

Many works about the application of neural network and other nonlinear fitting methods in nuclear field have been published. Neural network has been used to predict the power peak factor accurately and in time in reactor protection systems (Souza and Moreira, 2006). The neural network inputs are the position of control rods and signals of ex-core detectors. The radial basis function

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network can produce slightly better results than the multilayer perceptron network, and the power peak factor safety margin can be decreased as much as 5%. In another work (Na et al., 2004), the axial Departure from Nucleate Boiling Ratio (DNBR) distribution at the hot pin position is predicted by the fuzzy neural networks using the measured signals of the reactor coolant system. The method has been applied to the first cycle of the Yonggwang 3 nuclear power plant. The simulation results show that this algorithm can provide reliable protection and monitoring information for the nuclear power plant operation and diagnosis by accurately predicting the DNBR each time step. Recently, Park introduced (Park et al., 2014) the group method of data handling (GMDH) algorithm to reconstruct 20-node axial core power shapes from five-level in-core detector power measurements. The GMDH algorithm is based on the evolutionary algorithm selecting the optimal representation of polynomial support functions that describe the optimal functional form of given measurements according to a specified criterion. The simulation results showed that the GMDH algorithm is a promising data driven modeling algorithm, hence tending to become an interesting option for engineering applications.

In this study, the methodologies of radial basis function neural network (RBFNN), group method of data handling (GMDH) and Levenberg–Marquardt (LM) algorithm are utilized separately to unfold the control rod position from the fixed in-core neutron detector measurements, and comparison has been made to show which method performs the best. The measurements belong to training data set and test data set are simulated by neutronics code SMART. In addition, two correction strategies are proposed to correct the detector measurements of training data set and improve the rod position monitoring accuracy when there are mismatches between actual physical factors and modeled physical factors.

## 2. Methodology

### 2.1. Levenberg–Marquardt algorithm

The Levenberg–Marquardt (LM) algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued function. It has become a standard technique for non-linear least-squares problem, and LM can be thought of as a combination of steepest descent and the Gauss–Newton method. Because the algorithm has been introduced in many papers, its mathematical formulations are not repeated in this paper.

### 2.2. Radial basis function neural network

The RBF network is a standard three-layer $(J_1 - J_2 - J_3)$ neural network, with the first input layer consisting of $d$ input nodes, one hidden layer consisting of $m$ radial basis functions in the hidden nodes and a linear output layer. There is an activation function $\phi(\bullet)$ for each of the hidden node. The hidden layer performs a nonlinear transform of the input, and the output layer is a linear combiner mapping the nonlinearity into a new space. Usually, the same RBF is applied on all nodes; that is, the RBF nodes have the nonlinearity $\phi_i(\vec{x}) = \phi(\|\vec{x} - \vec{c}_i\|)$, $i = 1, \ldots, J_2$, where $\vec{c}_i$ is the center of the $i$-th node and $\phi(\vec{x})$ is a RBF. The biases of the output layer neurons can be modeled by an additional neuron in the hidden layer, which has a constant activation function.

For input $\vec{x}$, the output of the RBF network is given by

$$y_i(\vec{x}) = \sum_{k=1}^{J_2} w_{ki} \phi(\|\vec{x} - \vec{c}_k\|), \qquad i = 1, \ldots, J_3, \tag{1}$$

where $y_i(\vec{x})$ is the $i$-th output, $w_{ki}$ is the connection weight from the $k$-th hidden unit to the $i$-th output unit, and $\|\bullet\|$ denotes the Euclid-

ean norm. The RBF $\phi(\bullet)$ is typically selected as the Gaussian function, i.e. $\phi(r) = \exp\left(-\frac{r^2}{2\sigma^2}\right)$, where $\sigma$ is known as width.

For a set of $N$ samples $\{\vec{x}_k, y_k\}_{k=1}^{N}$, Eq. (1) can be expressed in the matrix form

$$Y = W^T \Phi \tag{2}$$

where $W = [\vec{w}_1, \ldots, \vec{w}_{J_3}]$ is a $J_2 \times J_3$ matrix, $\vec{w}_i = (w_{1,i}, \ldots, w_{J_2,i})^T$, $\Phi = [\vec{\phi}_1, \ldots, \vec{\phi}_N]$ is a $J_2 \times N$ matrix, $\vec{\phi}_p = (\phi_{p,1}, \ldots, \phi_{pJ_2})^T$ is the output of the hidden layer for the $p$th sample, that is, $\phi_{p,k} = \phi(\|\vec{x}_p - \vec{c}_k\|)$, $Y = [\vec{y}_1, \ldots, \vec{y}_N]$ is a $J_3 \times N$ matrix, and $\vec{y}_p = (y_{p,1}, \ldots, y_{pJ_3})^T$ (see Fig. 1).

The learning in RBF is done in two stages. Firstly, the widths and the centers are fixed. Next, the weights are found by solving the linear equation. The center $\vec{c}_i$ can be selected by clustering. The width usually is fixed. Once the centers have been selected, the weights that minimize the output error are computed by solving a linear pseudo-inverse solution

$$W = \left(\Phi^T\right)^{\dagger} Y^T = \left(\Phi\Phi^T\right)^{-1} \Phi Y^T. \tag{3}$$

### 2.3. Group method of data handling (GMDH)

The GMDH algorithm is based on an inductive self-organizing approach to the estimation of black box models with unknown relationships between variables. Fig. 2 shows the branch structure of the GMDH algorithm. It begins with the basic inputs at the first level and becomes more complex according to the increasing number of layers. The general form of original GMDH model is as follows:

$$y = f(x_i, x_j) = A + Bx_i + Cx_j + Dx_i^2 + Ex_j^2 + Fx_i x_j \tag{4}$$

The coefficient parameters which is written such as $A, B, \ldots, F$ can be obtained by using a least square method in an arbitrary pair $(x_i, x_j)$ from independent variables $\vec{x} = (x_1, x_2, \ldots, x_m)$. The GMDH model uses the Kolmogorov–Gabor form of a high-order polynomial as follows:

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} a_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} a_{ijk} x_i x_j x_k \ldots \tag{5}$$

The GMDH model can determine the structure of the model and also calculate the system output of the most important inputs simultaneously. This uses the composition of the lower-order polynomials, which means that the GMDH model amalgamates lower order polynomials at each generation to reach the subsequent generation. The process of the algorithm is stopped and the optimum fit of the previous generation is selected as the optimized model if over-fitting has been found.

The main steps in the implementation of the GMDH algorithm are as follows:

(1) Construct each of input and output variables or data of the system. The data structure is modeled and divided into the training and checking data sets.
(2) Choose the external inputs to the GMDH network. Calculate the regression polynomial parameters for each pair of input variables involved in the training data set using the least squares method. Calculate the high-order variables in place of the original input variables in order to predict the output.
(3) Calculate the output for all checking observations not included in training set and store the observations into the matrix O.