DETECTION AND ISOLATION OF MULTIPLE FAULTS IN NUCLEAR POWER SYSTEMS

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The current and new generation nuclear power plants (NPPs) have economic and quality concerns as addressed by overall plant performance, unscheduled downtime, and long-term management of critical assets. The key to achieving these goals is to develop an integrated approach for monitoring, control, and fault detection and diagnosis of plant components such as sensors, actuators, control devices, and other equipment. Several methods for monitoring isolated faults in sensors and system components were developed in the past. These approaches assume that a system fault being monitored is relegated to a specific plant component and occurs in an isolated fashion. Fault detection and isolation (FDI) of sensors and field devices is an important step toward the implementation of a successful intelligent process control.

A large-scale system, such as an NNP, has a multitude of feedback control loops. This makes the task of FDI highly complex in these interconnected systems. The objective of the current research is to develop an on-line sensor and field device FDI system when simultaneous faults may occur in two or more of these devices. The focus of the new work also includes the detection of incipient failures in critical plant components so that timely maintenance tasks could be performed to avoid catastrophic consequences. The research generalizes the development and implementation of a single-fault detection technique¹ that was applied successfully to a process control loop.

DESCRIPTION OF THE ACTUAL WORK

The goals of this research are achieved by a two-step approach: (a) development of data-driven models for prediction state variables, controller, and actuator functions, using rational function approximation and group method of data handling² (GMDH), and (b) a decision-making module that utilizes system functional knowledge that is incorporated in a rule base.

The GMDH algorithm constructs a generalized data-driven polynomial-type model of a desired variable as a function of a set of related inputs from a plant subsystem by a successive polynomial approximation. The general relationship has the form shown in Eq. (1), where $\{x_1, x_2,, x_m\}$ is a vector of input variables to be predicted. This formulation can be extended to the prediction of multiple outputs $\{y_1, y_2,, y_n\}$:

$$y = a + \sum_{i=1}^{m} b_i x_i + \sum_{i=1}^{m} \sum_{j=1}^{m} c_{ij} x_i x_j + \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{m} d_{ijk} x_i x_j x_k + \cdots$$
 (1)

This is a self-organizing mapping method in that the predicted values of y are propagated successively to higher layers of the algorithm, with the approximation of y_{pred} improving at successive stages. As shown in Fig. 1, at each stage of the approximation, y_{pred} is formed from pairs if input signals (to that layer), and new values of the predicted values are propagated pairwise to the next layer. The iteration is continued until the mean-squared error between the predicted and the measured values of the output variable y attains a desired value, thus achieving parsimony in model fitting or learning.

The foregoing GMDH approach is generalized by using rational functions of (x_1, x_2) instead of polynomial functions. An example of a set of rational functions is presented in Eq. (2). This new set is established from phenomenological relationships among and the variables and should facilitate the development of prediction models with a minimum number of terms. In applications to NPP subsystems, a systematic study must be carried out in establishing models that are valid for a range of operating conditions. The GMDH approach has the advantages over artificial neural networks of not requiring tedious network learning and of updating with ease the prediction models during plant operation.

$$\left\{
1, (x_{1}, x_{2}), (x_{1}^{2}, x_{2}^{2}), (x_{1}x_{2}), (\frac{1}{x_{1}}, \frac{1}{x_{2}}), (\frac{1}{x_{1}^{2}}, \frac{1}{x_{2}^{2}}), (\frac{1}{x_{1} + x_{2}}, \frac{1}{x_{1}x_{2}}), (\frac{x_{1}}{x_{2}}, \frac{x_{2}}{x_{1}}), (\frac{x_{1}}{x_{2}}, \frac{x_{2}}{x_{1}}), (\frac{x_{1}}{x_{2}}, \frac{x_{2}}{x_{1}}, \frac{x_{2}}{x_{2}}), (\frac{x_{1} + x_{2}}{x_{1} + x_{2}}, \frac{x_{1} + x_{2}}{x_{1}}, \frac{x_{1} + x_{2}}{x_{2}}), \dots \right\}$$
(2)

The fault detection and isolation are performed in two modules. The first module monitors the system variables and checks if the changes in them are due to changes in system operating levels or due to device faults. The second module is activated when an incipient fault is detected. A rule-based decision algorithm is then used to associate the measurements to one or more fault types. The fault types and the rule base are system-specific and must be thoroughly evaluated by extensive plant simulation.

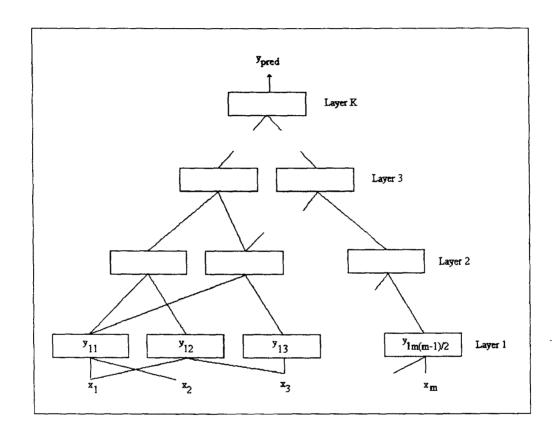


Figure 1. Self-organizing GMDH model structure with m-inputs and K-layers.

RESULTS

The effectiveness of the detection and isolation of multiple faults in sensors and field devices was studied using a Simulink model of a process control loop.² The low-pressure control loop consists of flowmeters, a water level sensor, motor-operated valves with position indicators, and a digital proportional-integral controller for regulating the water level. The system was initially characterized by prediction models that were developed using normal operational data for different system conditions. A complete rule base for fault detection and isolation was established. Multiple faults were introduced in one or more of these devices in various combinations. Both single and dual faults are introduced simultaneously. The new FDI system was able to detect and isolate 28 cases of incipient fault situations, except for two cases. In the latter cases, the prediction error was not sufficiently large to detect the impeding fault.

The development of the multiple-fault detection method is a significant step toward integrating control and system diagnostics functions. The method will be applied for incipient fault detection in a pressurized water reactor steam generator system. The GMDH algorithm may also be generalized to account for transient system operation.

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