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PRODUÇÃO TECNICO CIENTÍFICA
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CENTRO DE ENGENHARIA NUCLEAR

Monitoração e Diagnóstico

Fault Detection and Isolation in Nuclear Plant Systems

ARCAL, December 2000

Artigo Científico
P&D.CEND.CEND.002.00
ARTC.03.00

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INSTITUTO DE PESQUISAS ENERGÉTICAS E NUCLEARES
SÃO PAULO/BRASIL

ARCAL XLIV "SEGURIDAD DE REACTORES DE INVESTIGACION"

"GESTION DE ENVEJECIMIENTO DE REACTORES DE PESQUISA"

REPORT:

"SAFETY OF RESEARCH REACTORS: SENSORS AND ACTUATORS FAULT DETECTION AND ISOLATION IN NUCLEAR RESEARCH REACTORS"

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CNEN ARCAL/OIEA

INDEX

1. INTRODUCTION

The objective of this research is to develop a robust fault detection and isolation (FDI) method, for detecting faults in process sensors, actuators, controllers and other field devices in a nuclear power plant.

Faults in different types of components normally have different influence on a system's dynamic behavior. For example, one would expect that a fault in a temperature detector would influence the system differently from a fault in a water flow valve. Other important consideration is the fact that although the system variables may change their values through time, it does not imply that a fault has occurred: the system may be operating at a different but normal condition. Therefore, a robust fault detection and isolation diagnostic system must not only be able to detect and isolate faults, but also be able to differentiate system changes due to a sensor's failure from system changes caused by changes in the process normal operational conditions.

Along with these aspects, an analytical redundancy should be used to improve the FDI robustness for more complex systems. In an analytical redundancy, a loop component's output is estimated through a mathematical relationship among different (but related) loop components. Normally these loop components are of different types. Two redundant devices, such as two pressure sensors, may degrade with a common-mode failure. Using different types of sensors for predicting a variable can significantly decrease the possibility of common failures. For example, one can estimate the pressurizer water level in a PWR using hot leg temperature, cold leg temperature, reactor power and primary pressure.

The first step in obtaining mathematical relationships for analytical redundancy is to identify related loop components. This first step may be accomplished through some mathematical tools such as correlation analysis or PCA (Principal Component Analysis) technique. After identifying related loop components, the characterization of these relationships through mathematical models are required. The models generate the necessary redundant sensor outputs for the FDI algorithm. In this work the models will be obtained by applying the Group Method of Data Handling (GMDH), which uses data generated from the loop for different normal set point conditions. These data are referenced as "fault-free database." All possible (or available) different normal system conditions must be considered when developing these relationships. This is an important aspect in avoiding future false alarms by the FDI algorithm.

The set of analytical models for loop component redundancy is then used to predict each loop component's state variables and control functions. During a normal operating condition each prediction error should be close to zero, that is, there should be a good agreement between the predicted value and the actual measurement from the system component. If a given component residual value is above some predefined threshold limit, then a fault has been detected. If a fault is detected, the isolation of the fault component is performed by an expert system.

The last step in the FDI analysis is the reconstruction of the faulty component signal output. In this step the FDI algorithm attempts to compensate the signal used by the faulty component. If it succeeds, the process can be kept in operation without losing performance until next programmed maintenance schedule. In summary, the required steps for developing an FDI algorithm are as follow:

1. Generation of a fault-free database. Many different system operational conditions must be considered here.
2. Determination of a qualitative relationship among different loop components through correlation coefficient and Principal Component Analysis techniques [2].
3. Determination of quantitative relationships among different loop components through the GMDH technique [1].
4. Development of a rule-based decision module for fault detection and isolation. This is accomplished by simulating and characterizing individual faults in each important loop component.

2. GMDH MODELS AND RATIONAL FUNCTION APPROXIMATION FOR STATE PREDICTION

The *Group Method of Data Handling (GMDH)* is an algebraic method for predicting system states, controller and actuator functions. The GMDH constructs a model, of a desired output as a function of a set of related inputs from a subsystem, by a successive polynomial approximation. The general relationship has the form shown in Equation (1) where $\{x_1, x_2, \ldots, x_m\}$ is a vector of input variables and y is the variable to be predicted. This formulation can be extended to the prediction of multiple outputs $\{y_1, y_2, \ldots, y_n\}$. [1]

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

Figure 1 shows a typical node of a GMDH modeling layer with the basic quadratic predictor. The model parameters such as {A,B,C,D,E,F}, are estimated from a least-squares fit using N observations of the input and output variables. Figure 2 illustrates that the predicted values of *Y* are propagated successively to higher layers of the algorithm, with the approximation of *Ypred* improving at successive stages. At each stage of the approximation, *Ypred* is formed from pairs of input signals (to that layer), and new values of the predicted variable 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 attains a desired value.

Parsimony in model fitting is achieved by comparing the fractional prediction errors from one generation to the next, and by terminating the algorithm when the error is a minimum or when the errors from successive approximation stages is less than a preset limit.

The GMDH approach described above uses polynomial approximation. This polynomial set may be satisfactory in establishing some of the relationships of interest. In characterizing the subsystems in a nuclear power plant it is necessary to use terms containing rational functions (for example, rations of polynomials in X1 and X2). Equation (2) represents a set of such terms, which forms a *complete* set of terms in a given domain. The new set should facilitate the development of prediction models with a minimum number of terms. The computational efficiency of establishing these models will be enhanced by a systematic choice of the terms in the set shown in Equation (2).

$$\left\{\begin{array}{l} 1,(x_1,x_2),(x_1^2,x_2^2),(x_1x_2),(\frac{1}{x_1},\frac{1}{x_2}),(\frac{1}{x_1^2},\frac{1}{x_2^2}),(\frac{1}{x_1+x_2},\frac{1}{x_1x_2}),(\frac{x_1}{x_2},\frac{x_2}{x_1}), \\ (\frac{x_1}{x_1+x_2},\frac{x_2}{x_1+x_2}),(\frac{x_1+x_2}{x_1},\frac{x_1+x_2}{x_2}),\ldots \end{array}\right\} \qquad (2)$$

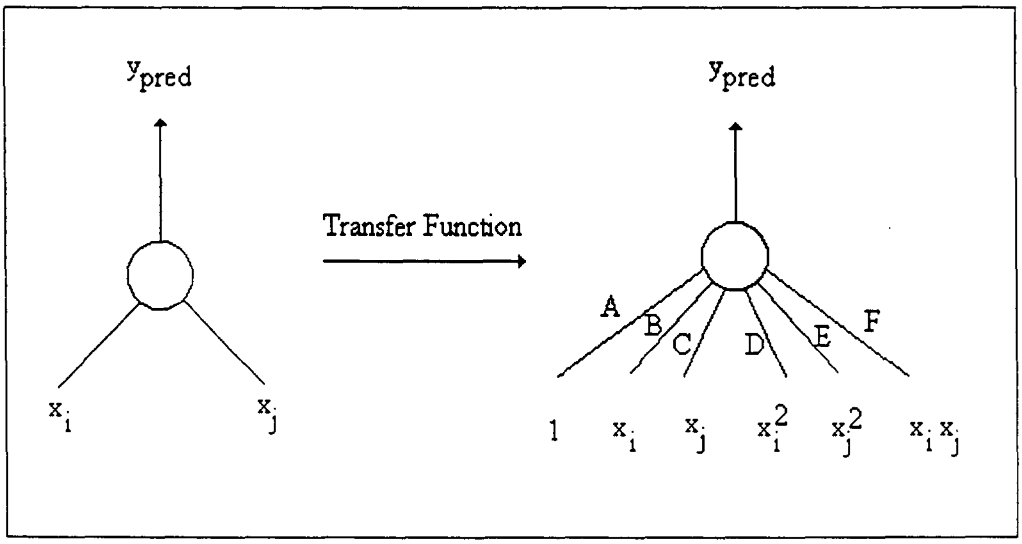

Figure 1. A node of the GMDH model structure. This node uses a second order polynomial transfer function.

In application to nuclear plant subsystems, a systematic study has to be performed in establishing models that are valid for a range of operating conditions. The level of complexity of the fault detection and identification algorithm depends on the importance of the equipment or the asset being considered, the ease of real-time monitoring and communication, and the multiplicity of devices.

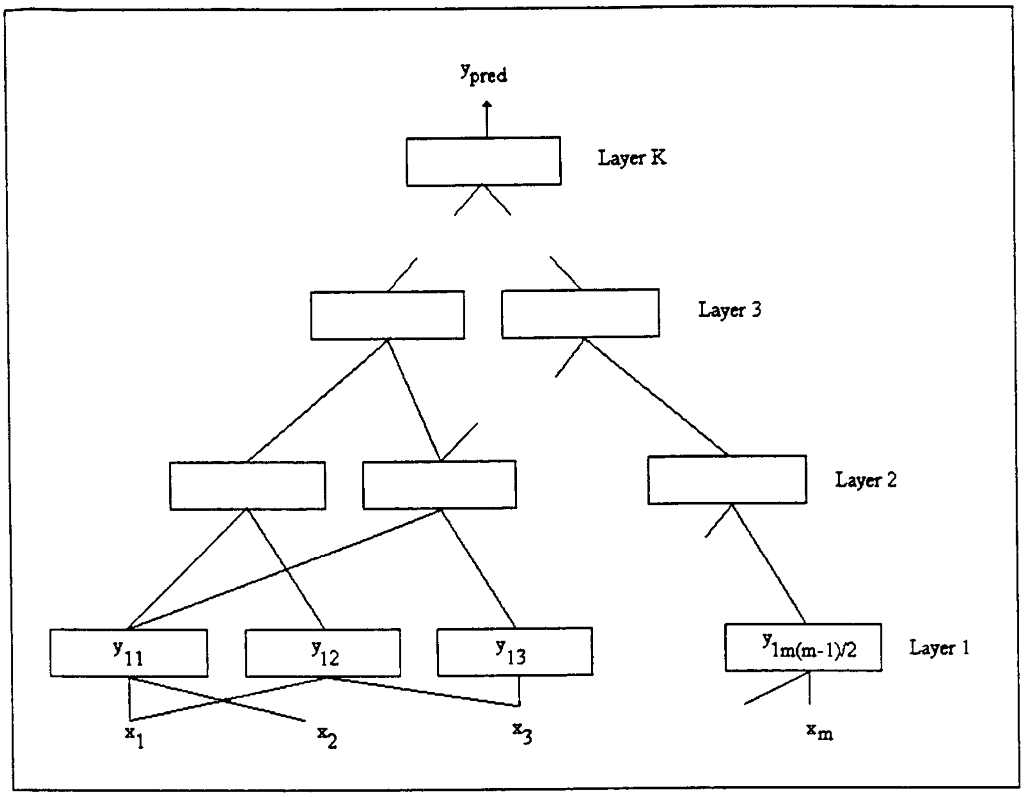

Figure 2. Self-organizing GMDH model structure with m-inputs and K-layers.

3. PRINCIPAL COMPONENT ANALYSIS

The PCA is mainly a method to transform a set of correlated variables into a smaller set of new variables that are uncorrelated and still keeps almost all the information of the original data. The PC model, with reduced dimension, can be use to detect and diagnose abnormalities in the original data in a robust way [2].

PCA decomposes the data matrix X (m samples, n variables) as the sum of the outer product of vectors $\mathbf{t}_i$ and $\mathbf{p}_i$ plus a residual matrix **E** [3]:

$$\mathbf{X} = \mathbf{t}_1\mathbf{p}_1^T + \mathbf{t}_2\mathbf{p}_2^T + \ldots + \mathbf{t}_k\mathbf{p}_k^T + \mathbf{E} = \mathbf{T}_k\mathbf{P}_k^T + \mathbf{E} \quad (1)$$

The vectors $\mathbf{p}_i$ are orthonormal, and the vectors $\mathbf{t}_i$ are orthogonal, that is:

$$\mathbf{pi}^T\mathbf{pj} = 1, \quad \text{if } i = j \quad \text{and } \mathbf{pi}^T\mathbf{pj} = 0, \quad \text{if } i \neq j; \text{ and} \quad (2)$$

$$\mathbf{ti}^T\mathbf{tj} = 0 \quad \text{if } i \neq j \quad (3)$$

Also we can note that $\mathbf{t}_i$ is the linear combination of the original X data defined by $\mathbf{p}_i$:

$$\mathbf{X}\mathbf{p}_i = \mathbf{t}_i \quad (4)$$

The vectors $\mathbf{t}_i$ are known as the principal components *scores* and contain information on how the *samples* are related to each other. The $\mathbf{p}_i$ vectors are the *eigenvectors* of the

4. DEVELOPMENT OF A MATHEMATICAL MODEL OF THE IEA-R1 EXPERIMENTAL REACTOR

Theoretical and experimental studies will be performed for feasibility studies of the Fault Detection and Isolation (FDI) method proposed in this work. For the theoretical study, a simulation model of the IEA-R1 experimental reactor will be developed. This model will be implemented in Matlab-Simulink program environment. For experimental studies data is being collected from the SAD (Acquisition Data System). The figure 4 shows, schematically, the IEA-R1 Reactor primary and secondary circuits and the sensors.

The IEA-R1 Data Acquisition System (SAD) [6] has the main objective of monitoring and registering the main reactor operational parameters. The monitoring function is independent of the Instrumentation and Control panels indications installed in the Reactor Control Room. The SAD is composed by a signal conditioning and processing module and a PC-based man-machine interface software.

The SAD signals are compared with level alarm setting points and when these levels are violated an indication of occurrence is produced.

A total of 57 operational variables are monitored by the SAD, including temperature, flow, level, pressure, radiation, nuclear power and rod position variables.

The updated SAD allows to record data bases containing the time history of all monitored process variables. This database will be used to perform sensor monitoring for fault detection, fault isolation and sensor drift compensation [1].

The purpose of the model and the test system is to provide useful data and an environment for developing and testing the proposed FDI algorithm. Data from all available sensors for normal loop operation will be used to build a database.

To illustrate the IEA-R1 data, temperature variables of the primary circuit (loop B) of the IEA-R1 reactor are shown in figure 5. Each variable has 1500 samples and shows roughly one cycle operation, from start up to shut down. There were some time gaps when acquiring the data.

5. PRELIMINARY RESULTS

The following figures show some preliminary results using IEA-R1 data.

The GMDH method was used to construct a model to predict the area radiation, using control rod position and reactor power values.

Figures 6 and 7 show both the measured and the predicted area radiation value for the training and the testing data set. The error between these values (in percent) is shown in the Figure 8.

We applied PCA to the temperature data and extract the related eigenvalues (some times called *latents*). The eigenvalues are plotted in figure 9.

Using the criteria discussed [5], it can be seen from the plot that keeping two or three Principal Components could be a good choice for a PC temperature model. Then, it would be necessary to use only two or three variables instead of the eight variables to represent the temperatures in a PC model.

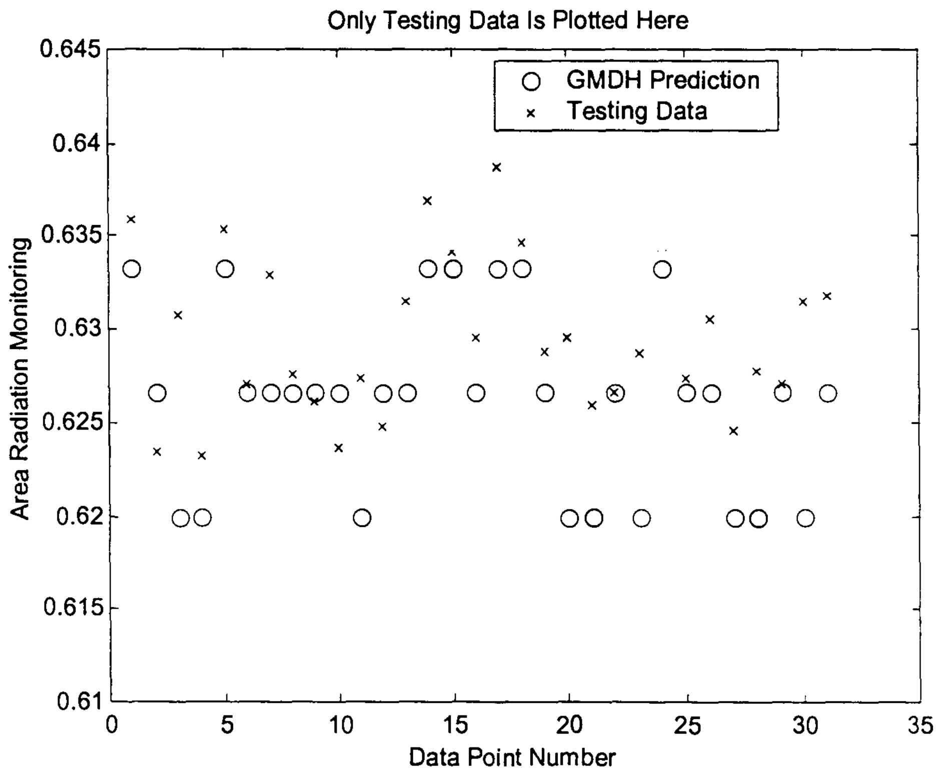

Figure 6. Comparison between prediction GMDH model and testing data

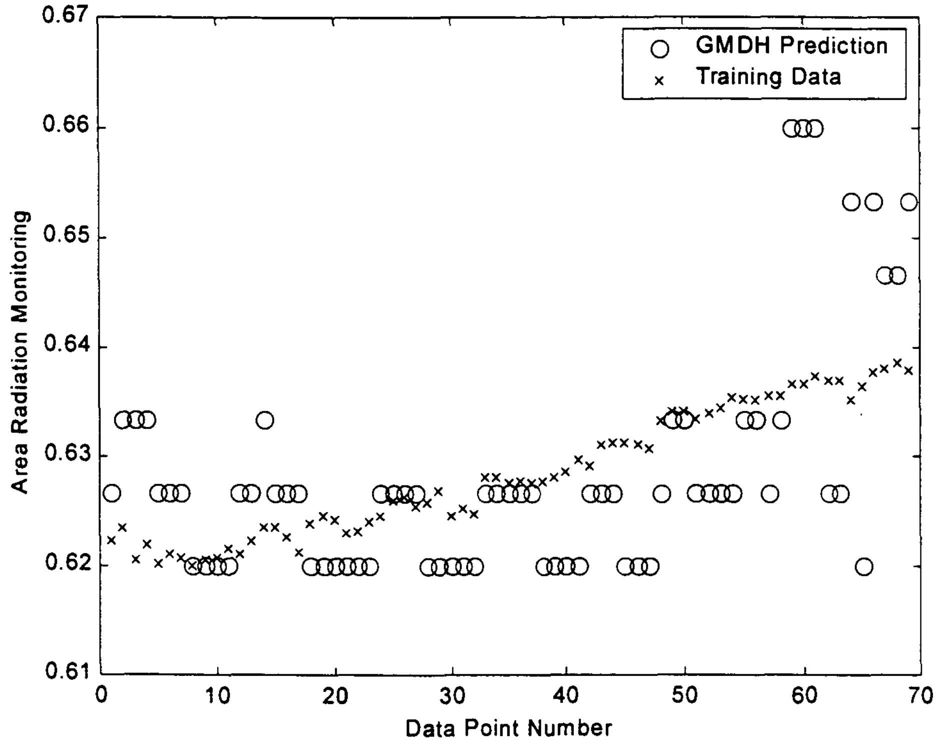

Figure 7. Comparison between prediction GMDH model and training data.

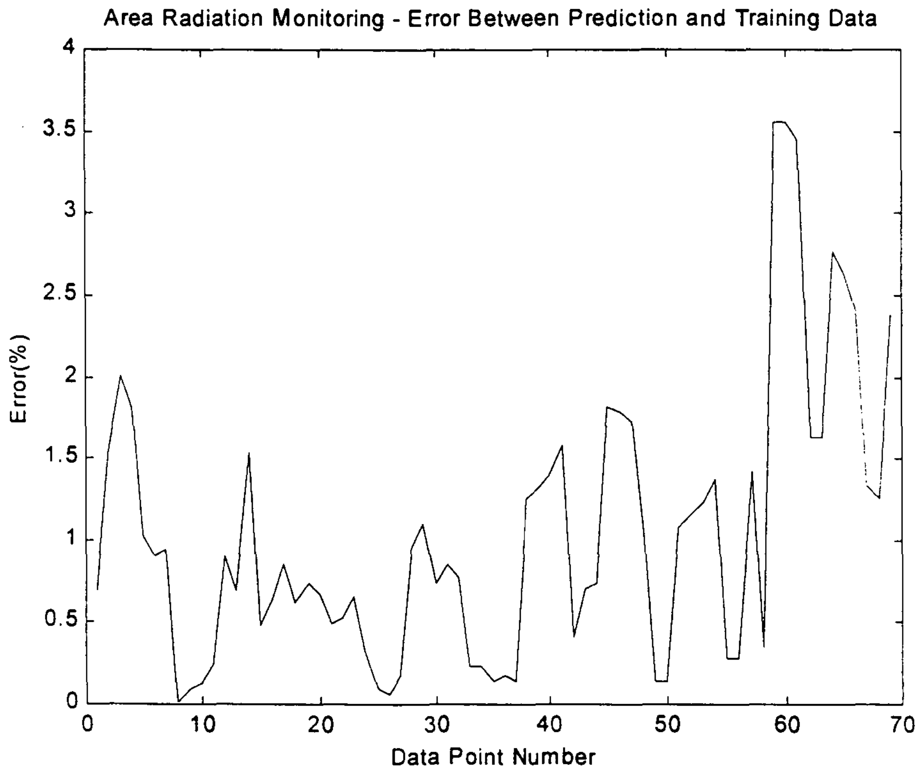

Figure 8. Error between measured and GMDH model.

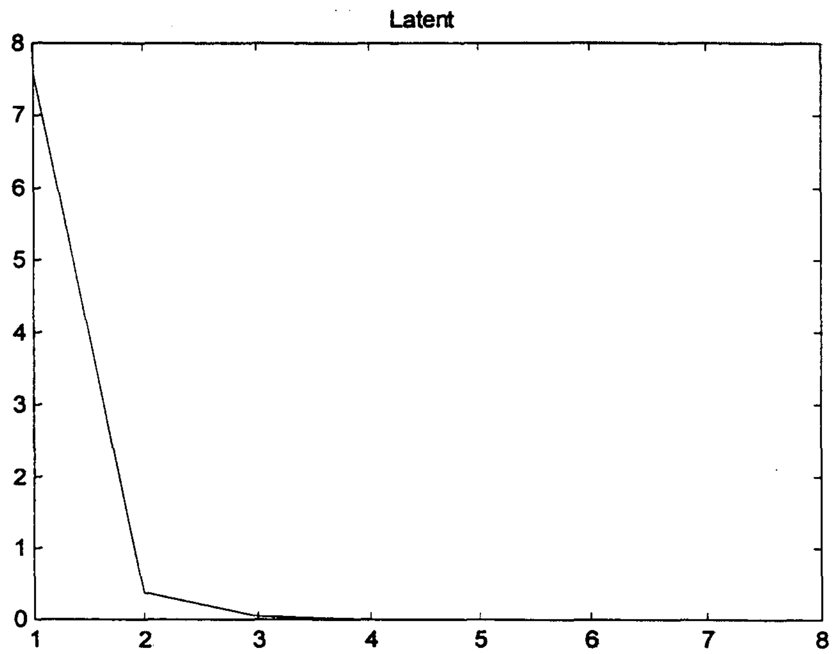

Figure 9 – Eigenvalues versus Principal Components

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