NUCLEAR POWER PLANT MONITORING USING DATA-DRIVEN MODELING TECHNIQUES

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Abstract

This paper presents a monitoring algorithm using the Group Method for Data Handling (GMDH) that creates algebraic models for system characterization. The monitoring system was applied to the IEA-R1 experimental reactor at IPEN, Brazil. The IEA-R1 is a 5 MW pool-type research reactor that uses light water as coolant and moderator, and graphite as reflector. The GMDH provides a general framework for characterizing the relationship among a set of state variables of a process and is used for generating estimates of critical variables in an optimal data-driven model form. The monitoring system developed in this work was used to predict the IEA-R1 reactor hall dose rate, based on nuclear power and rod position variables. The results obtained using the GMDH models agreed very well with the dose rates measurements.

Introduction

During the last two decades, *model-based fault diagnostics* methods have received increasing attention in both research and application. This approach is based on the concept of *analytical redundancy* as opposed to *physical redundancy* (hardware or parallel), which uses measurements from redundant sensors for fault diagnostics purposes. Analytical redundancy makes use of the prediction of signals generated by the mathematical model of the system being considered. These predictions are compared with the actual measurements from system sensors. The comparison is made using the residual quantities, which provide the difference between the measured signals and signals generated by the mathematical model.

In this work the models will be obtained by applying the Group Method of Data Handling (GMDH), which uses data generated for different normal conditions. These data are referenced as "fault-free database". The GMDH is based on sequential learning networks, which are networks of mathematical functions that characterize complex, nonlinear relationships in a compact and rapidly executable form. Such networks subdivide a problem into manageable sub-problems and then automatically apply advanced mapping techniques to solve each of these simple problems.

For the current application, data are acquired from the IEA-R1 reactor Data Acquisition System (SAD). The monitoring function is independent of the Instrumentation and Control panels indications installed in the Reactor Control Room. The SAD consists of a signal conditioning and processing module and a PC-based human-machine interface software. A total of 57 operational variables are monitored by the SAD. The monitoring system developed in this work was used to predict the IEA-R1 reactor hall dose rates, based on two process variables: nuclear power and rod position. The details of model prediction and reactor measurement techniques will be presented in the next sections.

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 [2]. 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.

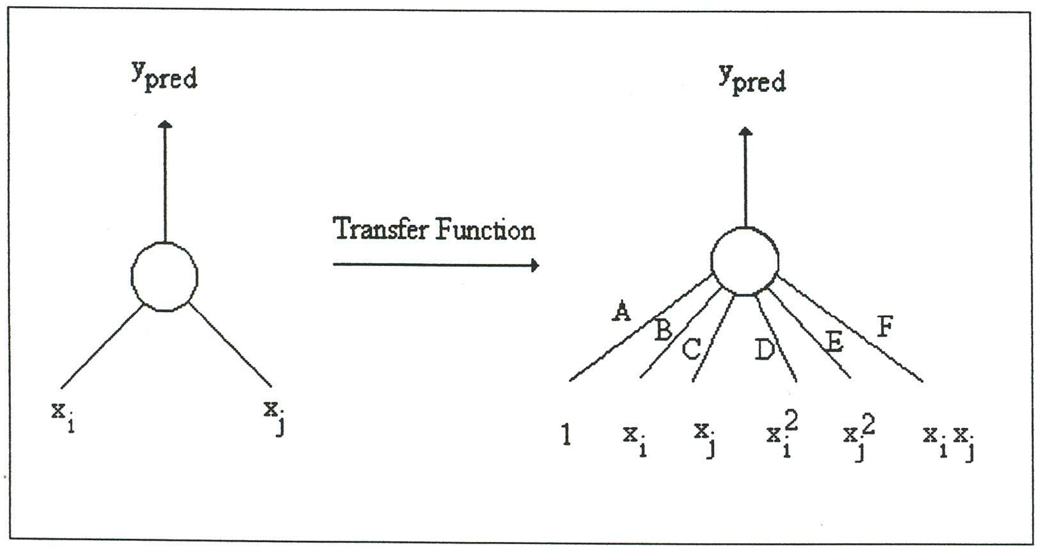

Figure 1. A node of the GMDH model structure. This node uses a second order polynomial transfer function.

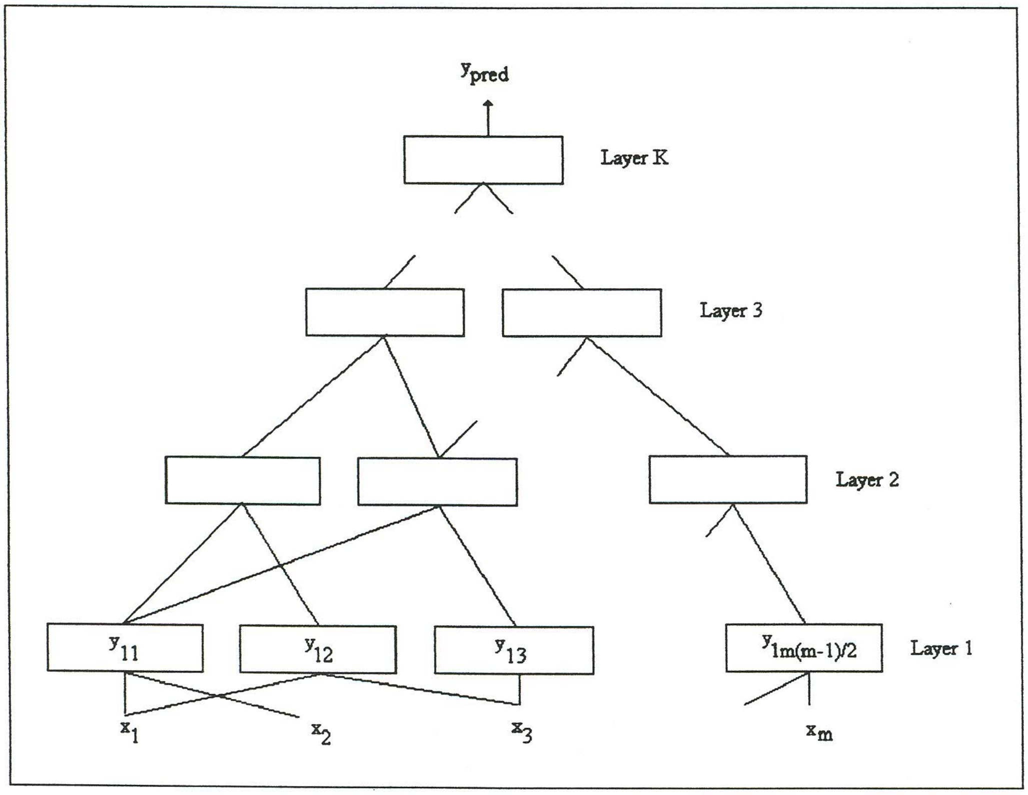

Figure 2. Self-organizing GMDH model structure with m-inputs and K-layers.

The following procedure is used for a given set of ***n*** observations of the ***m*** independent variables $\{x_1, x_2, \ldots, x_m)$ and their associated matrix of dependent values $\{y_1, y_2, \ldots, y_n\}$ (a multiple input single output system).

i) Subdivide the data into two distinct subsets. One for training and other for testing (Figure 3).

ii) For each pair of input variables x_i and x_j and the associated output y of the training set, compute the regression polynomial that best fits the dependent observations y in the training set.

iii) For each regression, evaluate the polynomial for all ***n*** observations. Store these ***n*** new observations into a new matrix Z. The other columns of Z are computed in a similar manner. These variables can be interpreted as new improved variables that have better predictability than those of the original generation $x_1, x_2, \ldots, x_m$.

iv) Screening out the least effective variables: For each column of Z matrix, the algorithm computes the root-mean-square value (also called the regularity criterion) rj over the test data set and is given by

$$r_j^2 = \frac{\sum_{i=1}^{nt} (y_i - z_{ij})^2}{\sum_{i=1}^{nt} y_i^2} \tag{2}$$

v) Order the columns of Z according to increasing r_j, and then pick those columns of Z satisfying $r_j < R$ (where R is some prescribed value chosen by the user) to replace the original columns of X.

vi) Testing for optimality: The above process is repeated and new generations are obtained until the method starts overfitting the data set. One can plot the smallest of the r_j's computed in each generation and compare it with the smallest r_j's of the previous generation.

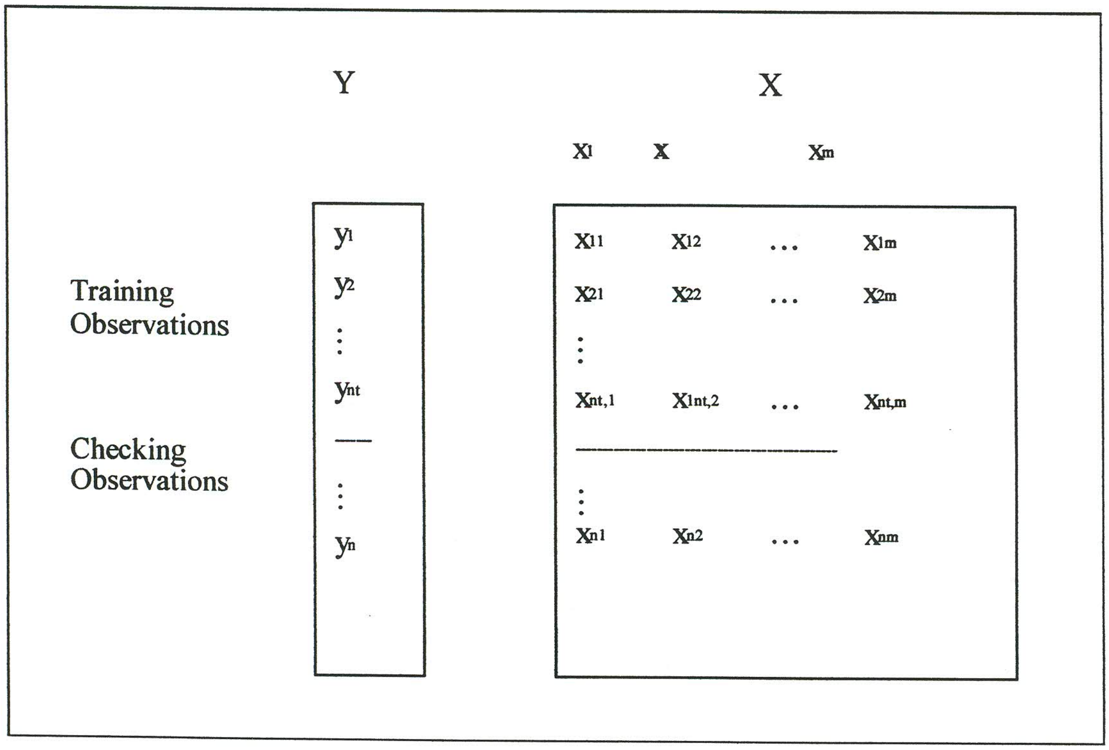

Figure 3. Input to the GMDH algorithm. The data is split into two sets. The first is used to fit the GMDH model and the second is used to evaluate the polynomial to avoid model overfitting.

Once all quadratic regression polynomials are stored in the computer, it is possible to compute the prediction $\hat{y}$ of the dependent variable y from these regressions. An algorithm was developed to select different combinations of basic functions [1]. The selected combination of functions is then used by the GMDH regression equation in a systematic manner. All possible combinations of terms are tested, such as one by one, two by two, three by three, etc. A binary number generator was used to make this selection automatically. For the case of a maximum of ***k*** candidate terms, this binary number goes from 1 to 2^k-1.

For each possible combination of the basic functions, the GMDH algorithm estimates the value of the dependent variable. Then an overall residual value between the data points and the predicted value of the best regression equation found by the GMDH is computed.

IEA-R1 Experimental Reactor

The monitoring system was applied to the IEA-R1 experimental reactor at IPEN, Brazil. Figure 4 shows, schematically, the IEA-R1 reactor primary and secondary circuits and the sensors. For the development of the monitoring algorithm using the Group Method for Data Handling (GMDH), data is being collected from the IEA-R1 reactor's SAD (Data Acquisition System). The IEA-R1 Data Acquisition System (SAD) [3] 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 variables monitored by the SAD are listed in Table I. The SAD allows to record data bases containing the time history of all monitored process variables. This database will be used to perform plant condition monitoring and sensor monitoring for fault detection.

All variables are acquired at every 1-minute, during one cycle operation, from start up to shut down. The IEA-R1 reactor full cycle is one-week long, starting on Monday and ending on Thursday. During the full cycle operating there are non-stationary periods of time: the start-up, moving control rod positions and the shutdown period. Only the steady-state reactor operation period was considered to build the model. 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.

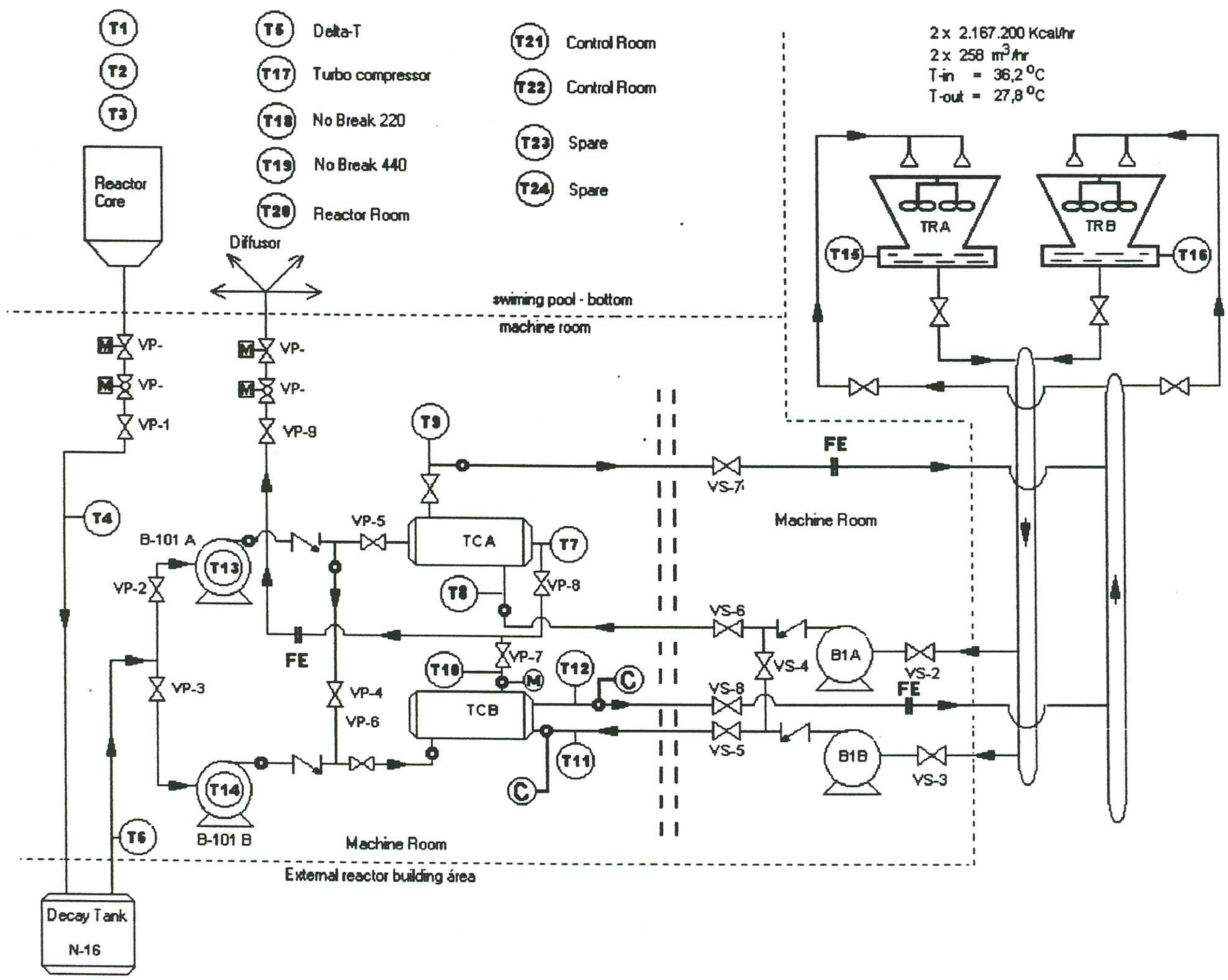

Figure 4 - Schematic Diagram of the IEA-R1 Reactor

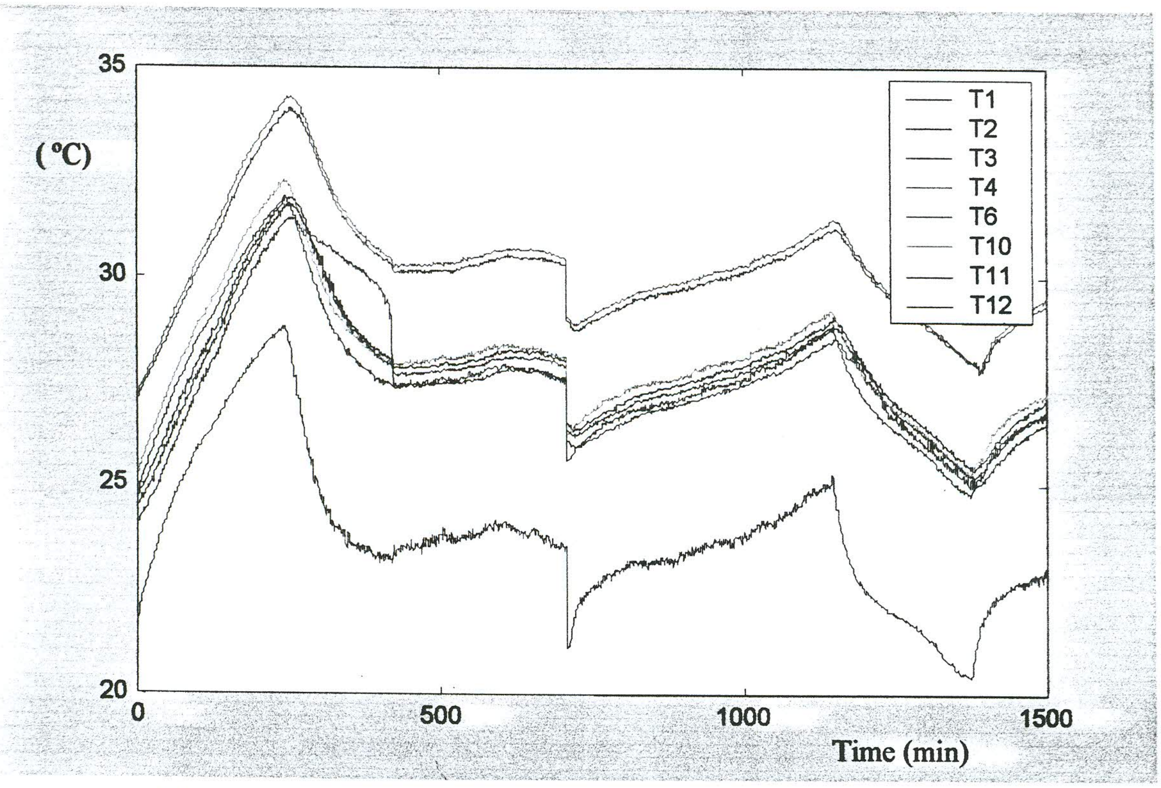

Figure 5 - Temperature Sensors time plot of Primary Circuit

Table I. SAD Variables

Variables Tags	Description
Z1 to Z4	control and safety rod positions
N1 to N8	period and % nuclear power
F1 to F3	flow rates
DP	core pressure drop
C1 to C2	pool water conductivity
L1	decay tank water level
R1 to R9	area dose rates
R10 to R14	ventilation system dose rates
T1 to T24	temperatures

Development of a Mathematical Model of the IEA-R1 Experimental Reactor

The GMDH method finds a mathematical expression which maps a given dependent variable y to a set of independent variables {x1, x2, ... , xk}. The user qualitatively defines which independent variables are physically related to the dependent variable y. This definition can come from the knowledge of a system engineer, from theoretical simulations, or even from mathematical tools such as correlation coefficients.

The mathematical relationships generated by the GMDH are used for predicting the output value of each loop component. This predicted value (also called the analytical measurement) is compared to actual measurements.

In this work, the GMDH method was used to construct a model to predict the *radiation dose rate*, using *control rod position* and *reactor power values*. The IPEN experimental reactor's SAD monitors 14 nuclear radiation variables. The radiation dose rate variable predicted in this work is dose rate at the core support bridge, right side. The dose rate at the core support bridge is predicted based on the safety rod 1 position and the % load (automatic mode).

For this work we used data collected from August 2000 to September 2000, being 4 weeks in August, and two weeks in September. The GMDH model was built using August 07 loop data. Only the steady-state reactor operation period was considered to build the model.

The first step is to collect data from the system for normal operating conditions. The August 07 loop data was stored in a matrix. Each column represents a system variable and each row represents an observation. For better efficiency in the development of GMDH models, these data should be normalized.

For each chosen set of basic functions, the GMDH algorithm is processed. The main task of the GMDH algorithm is to find the model that best maps the input/output set for given basic functions. After finding the best model, a residual value is computed between the predicted value and the target value.

After obtaining the mathematical relationship among a set of loop variables, the model can be used for generating an analytical redundant measurement. This redundant measurement is the prediction of the GMDH model.

The algorithm splits the input data into two sets of data. The first set is used to find the best model, while the second monitors for model over fitting. Figure 6 plots the error (in percentage) between the predicted and the expected output results of the best GMDH model for predicting the dose rate as a function of *control rod position* and *reactor power values*, showing a mean value error of 0.00507%, which represents only the numerical processing rounding error. The plots indicate that the GMDH maps the input-output variables satisfactorily for both the training data and the test data.

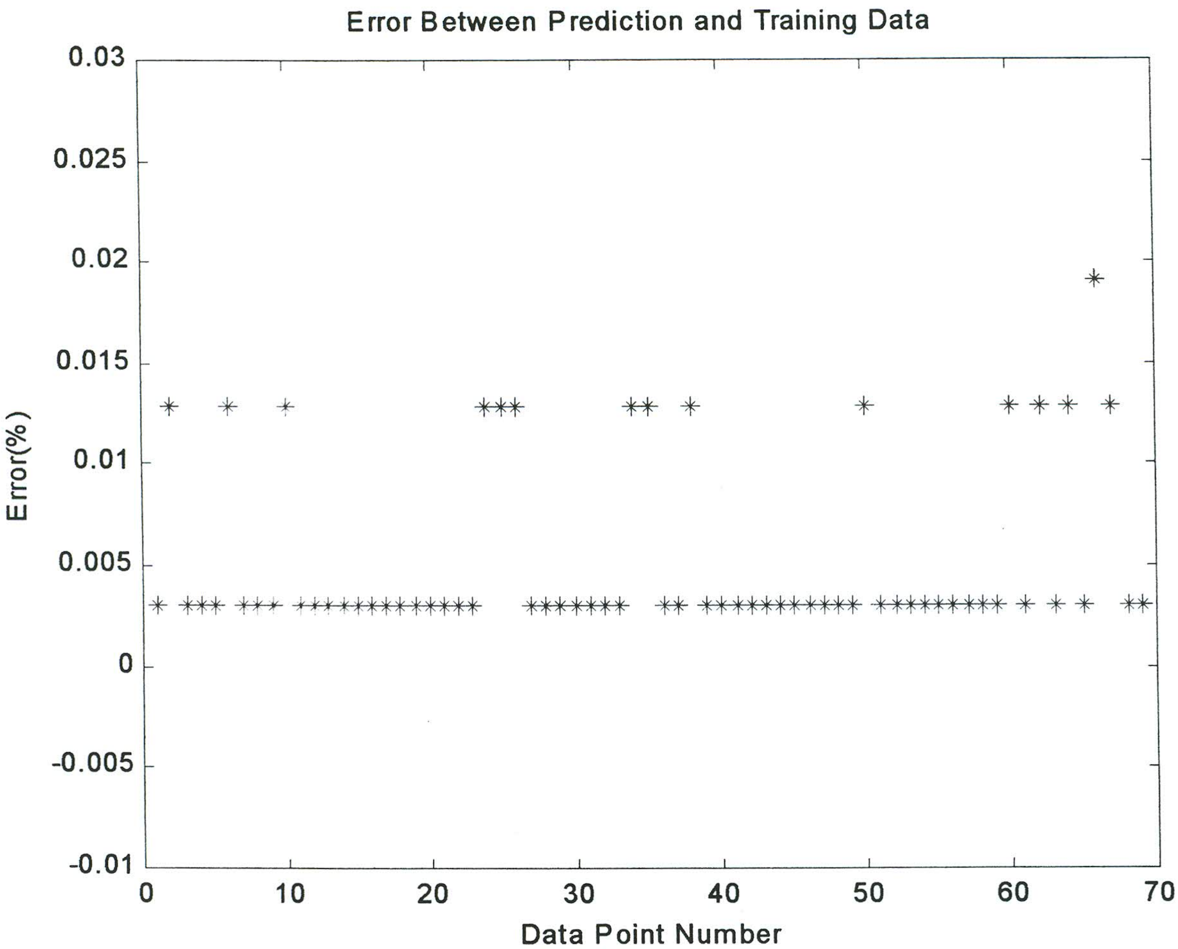

Figure 6. Error between GMDH model prediction and measured reactor dose rate.

This model was used to predict the IEA-R1 reactor's *radiation dose rate* in the following weeks operation cycles, starting in August 14, August 21, August 28, September 04, and September 11, respectively. The GMDH method was applied to these experimental data, predicting reactor dose rate during the steady-state operation period. At every minute of data acquisition, the GMDH model calculates the predicted dose rate, using nuclear power and rod position at this time. Figure 7 shows the error between IEA-R1 measured radiation dose rate, and predicted dose rate using GMDH model, where one can see the good agreement between predicted and measured values, with errors bounded in 4 percent.

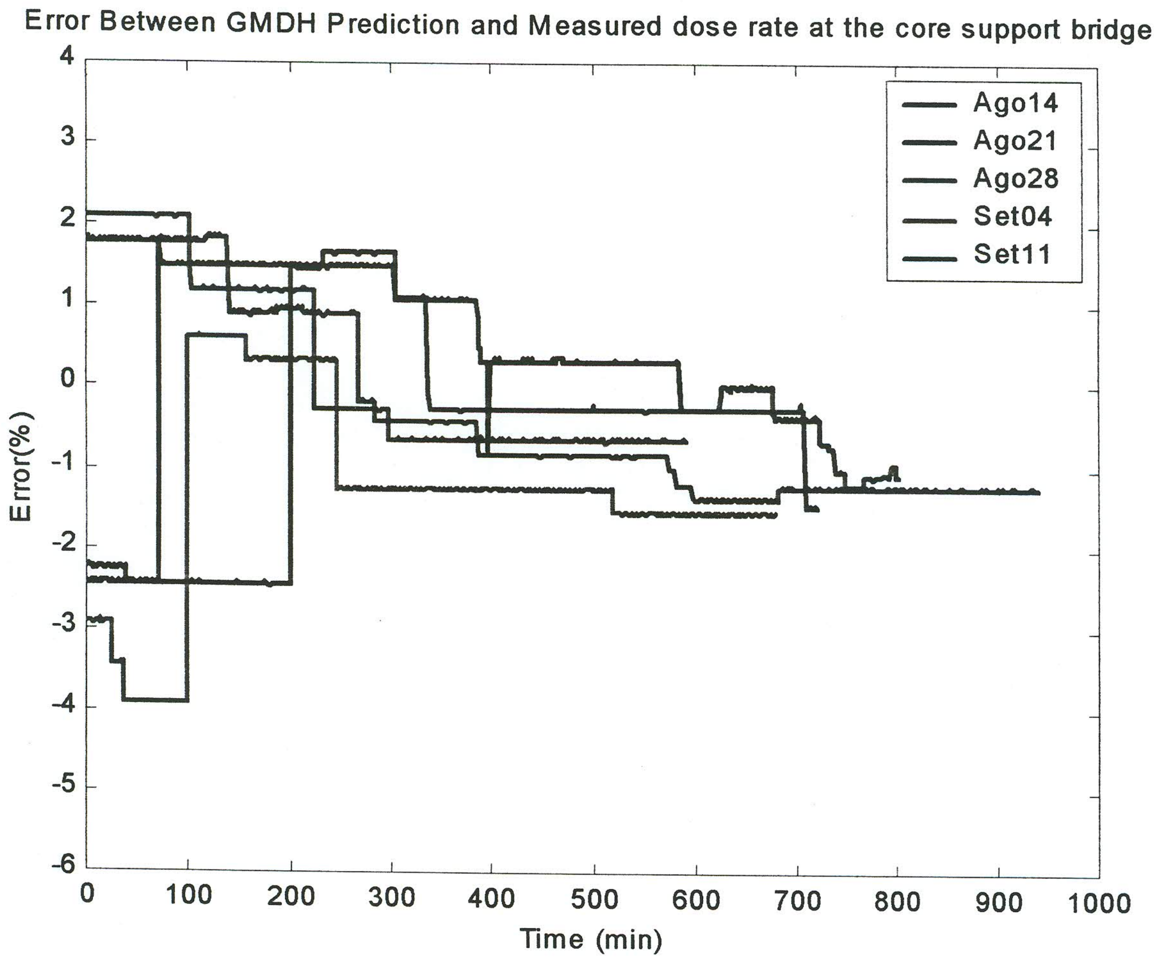

Figure 7. Error between GMDH model prediction and measured dose rate at the core support bridge, right side.

Conclusions and Future Work

In this work the IPEN IEAR1 reactor dose rate was predicted using nuclear power and rod position variables. The prediction was made using the Group Method for Data Handling (GMDH) that creates algebraic models for system characterization. For the development of the monitoring algorithm, data is being collected from the IEA-R1 reactor's SAD (Data Acquisition System). The model was built using data from August 07 reactor full cycle operation, showing a mean error between GMDH model and training data of 0.00507%, indicating that the GMDH maps the input-output variables satisfactorily for the training data.

The monitoring algorithm was then tested for the following weeks operation cycles: August 14, August 21, August 28, September 04, and September 11 showing an error less than 4 percent between measured and predicted values. This can demonstrate that the methodology is adequate for dose rate prediction.

This work is a first step towards a Monitoring and Fault Detection System for the IPEN nuclear reactor IEAR1. This work started at the Nuclear Engineering Department at the University of Tennessee, where a Single and Multiple Fault Detection System was developed for an Experimental Control Water Loop using GMDH model [1] [4]. The next step is to infer nuclear dose rate using another variables, such as temperature or flow rate. The same procedure will be performed for the 14 nuclear radiation dose variables monitored by the SAD IEAR1 reactor. Another interesting variable to be monitored and predicted using GMDH algorithm is the reactor nuclear power. All of these redundant measurements can help operators' decisions regarding initiation of necessary control actions, improving the reliability of the operation system.

References

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