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FAULT DETECTION IN IRIS REACTOR SECONDARY LOOP USING INFERENTIAL MODELS

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ABSTRACT

The development of fault detection algorithms is well-suited for remote deployment of small and medium reactors, such as the IRIS, and the development of new small modular reactors (SMR). However, an extensive number of tests are still to be performed for new engineering aspects and components that are not yet proven technology in the current PWRs, and present some technological challenges for its deployment since many of its features cannot be proven until a prototype plant is built.

In this work, an IRIS plant simulation platform was developed using a Simulink® model. The dynamic simulation was utilized in obtaining inferential models that were used to detect faults artificially added to the secondary system simulations. The implementation of data-driven models and the results are discussed.

1. INTRODUCTION

This research focuses on the use of IRIS which is an Integral Primary System Reactor (IPSR) that houses the reactor core, steam generators, circulation pumps, and the pressurizer inside one common vessel. With power output of about 330 MWe (design can be changed to 100 MWe), IRIS (International Reactor Innovative and Secure) was designed to fulfill the advantages of the integrated primary system reactor. It improves safety, reduces the site civil works, and improves plant availability for developed as well as developing countries with large or small electrical grids that can greatly benefit from such design.

Simulations based on such reactor design are used in this work as a platform for developing inferential models, interchangeably known as data-based models, which are in turn used to detect faults artificially added in new simulations. Significant variables are chosen to contribute with the inferential models. From secondary loop: feed water flow rate, feed water temperature, steam temperature and steam flow rate. From primary: reactor power and average core temperature.

The method of choice for detecting faults is the Sequential Probability Ratio Test (SPRT), and is based on the assumption that the residuals of a model are normally distributed and uncorrelated.

2. IRIS SYSTEM DESCRIPTION

The IRIS reactor is an IPSR with all main primary circuit components (core, control rods and drive mechanisms, steam generators, primary coolant pumps, and pressurizer) integrated into a single reactor vessel [1]. The upper head acts as the pressurizer to maintain constant primary pressure. Eight spool-type reactor coolant pumps, eight steam generators, and control rod drives are also housed in the reactor pressure vessel. Major components of the primary system are shown in Fig. 1, resulting in a pressure vessel diameter of 6.2 m, larger than a regular Pressurized Water Reactor (PWR), despite its lower power rating, but largely reducing the size and eliminating dozens of penetrations, virtually eliminating large Loss of Coolant Accidents (LOCA) and the number of possible small LOCAs [2]. The feed water flow to a pair of helical coil steam generators has a common feed line, with the primary water being pumped up through the core and the riser, the circulation then reverses in a downward direction and the water is forced down by the immersed pumps through the region surrounding the helical steam generator tubes. The primary flow through the downcomer flows into the lower vessel plenum and then flows up through the core.

IRIS is being designed to fulfill the advantages of the IPSR. It improves safety, reduces the site civil works, and improves plant availability for developed as well as developing countries with large or small electrical grids that can greatly benefit from such design. The development of autonomous and fault-tolerant control strategy is well-suited for remote deployment of small and medium reactors, such as the IRIS.

Such novel, integral design includes several advantages over other designs [3]-[6]. Major IRIS parameters can be found in the open literature [3].

IRIS plant is one of the next generation nuclear reactor designs, that uses mostly established LWR technology (due to its maturity), allowing an accelerated deployment, and is a design that houses the steam generators, circulation pumps, and the pressurizer inside one common vessel. However, an extensive number of tests are still to be performed for new engineering aspects and components that incorporate not yet proven technology in the current PWRs [7]. Certain parameters are not directly measurable, such as the level of water in the steam generator tubing where the superheated steam is generated.

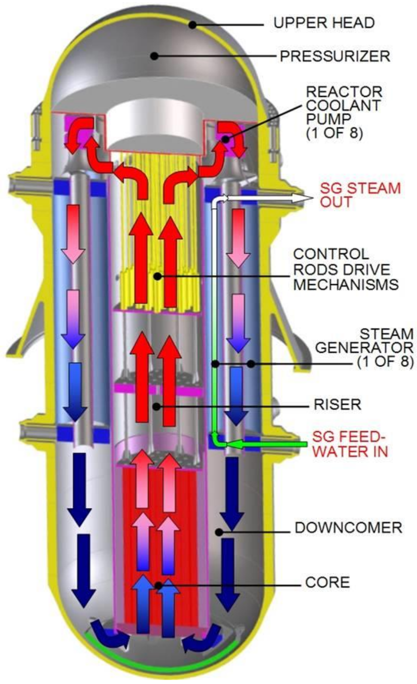

Figure 1: IRIS primary system layout [3]

3. HELICAL COIL STEAM GENERATOR (HCSG)

The steam generator is a helical coil, once-through steam generator producing superheated steam. The reactor control requirements specify constant average coolant temperature across the core at constant steam pressure. In the HCSG system the primary water is on the shell side flowing from the top to the bottom of the vessel. The primary side heat transfer is sub-cooled, forced convection along the entire steam generator height, while the secondary fluid flows upward inside the 656 coiled tubes from bottom to top. The feed water flows into the sub-cooled region of the steam generator, and in this region the heat transfer is mainly due to single phase turbulent and molecular momentum transfer and the pressure loss is mainly due to wall friction. The saturated region begins when the bulk temperature becomes saturated. The heat transfer in the saturated boiling region is dominated by nucleate boiling, which is much more efficient than single-phase liquid or steam heat transfer. In the saturated boiling region, the generated bubbles do not disappear in the liquid core and the pressure loss is not only due to the wall friction but also due to the interfacial drag between the bubbles and the liquid. The saturated boiling region ends when critical heat flux is reached. When the steam quality reaches unity, the liquid evaporation ceases and the steam becomes superheated. The use of helical tubing reduces the size of the steam generator, and results in an efficient heat transfer with a larger heat transfer area per unit volume than straight tube steam generators. The HCSG system is regulated to supply adequate amount of steam to meet the turbine demand. A programmed feed-forward controller is used to maintain the outlet steam pressure, while preventing the carryover of water to the turbine system or dry-out of the steam generator tubes, minimizing the mismatch between the steam outlet flow rate and the feed water inlet flow rate.

4. IRIS SIMULINK MODEL

4.1. IRIS Model

A single-unit Simulink model of the IRIS plant developed by Xu [8] is used in this research and includes reactor core and HCSG models. Originally, the main core model input was coolant inlet temperature (in degrees Fahrenheit), but was modified to accept power demand (in % power) by using a look up table that relates both input variables, based on North Carolina State University (NCSU) FORTRAN code [9]–[10].

The helical coil steam generator is one of the critical components and a major contributor to the cost of IRIS design. Typical once-through steam generator equations can be found in [11]. The model was developed based on a previous dynamic model [12] and a Simulink model [13] for a traditional PWR plant. The reactor core fuel-to-coolant heat transfer model was developed by using the Mann's nodal model [14], and the classic point kinetics reactor model equations with six delayed neutron groups.

The feed water flow rate is determined based on NCSU's code, and is set according to the power demand - feed water flow relationship program. In the simulations there is no feed-forward controller to quickly move the control rods based on changes on power load demands. The pressurizer model and the balance-of-plant (BOP) are not included in the simulation, and are assumed to be functioning well. Temperature of feed water is assumed to be fixed at 224 °C, which corresponds to 100% power. The main program is shown in Fig. 2 and the main outputs are:

- Moderator core inlet temperature (T_{cold}), referred to in the program as T_{pout}.
- Steam outlet pressure, P_{sout} in PSI.
- Steam flow rate, W_{sout} in lbm/s per tube, per steam generator.
- Steam outlet temperature, T_{sout} in °F.
- Steam generator boiling length, Lb in ft.
- Sub-cooled length, Lsc, in ft.
- Feed water flow rate, W_{fw}, in lbm/s per tube per steam generator.
- Power profile (P/P_0).
- Fuel temperature (°C).
- Coolant core outlet temperature, T_{hot} (°C).
- Average moderator temperature, which is defined as the average between moderator inlet and outlet temperatures, T_{ave} (°C).
- Core outlet moderator temperature, T_{hot} (°C).

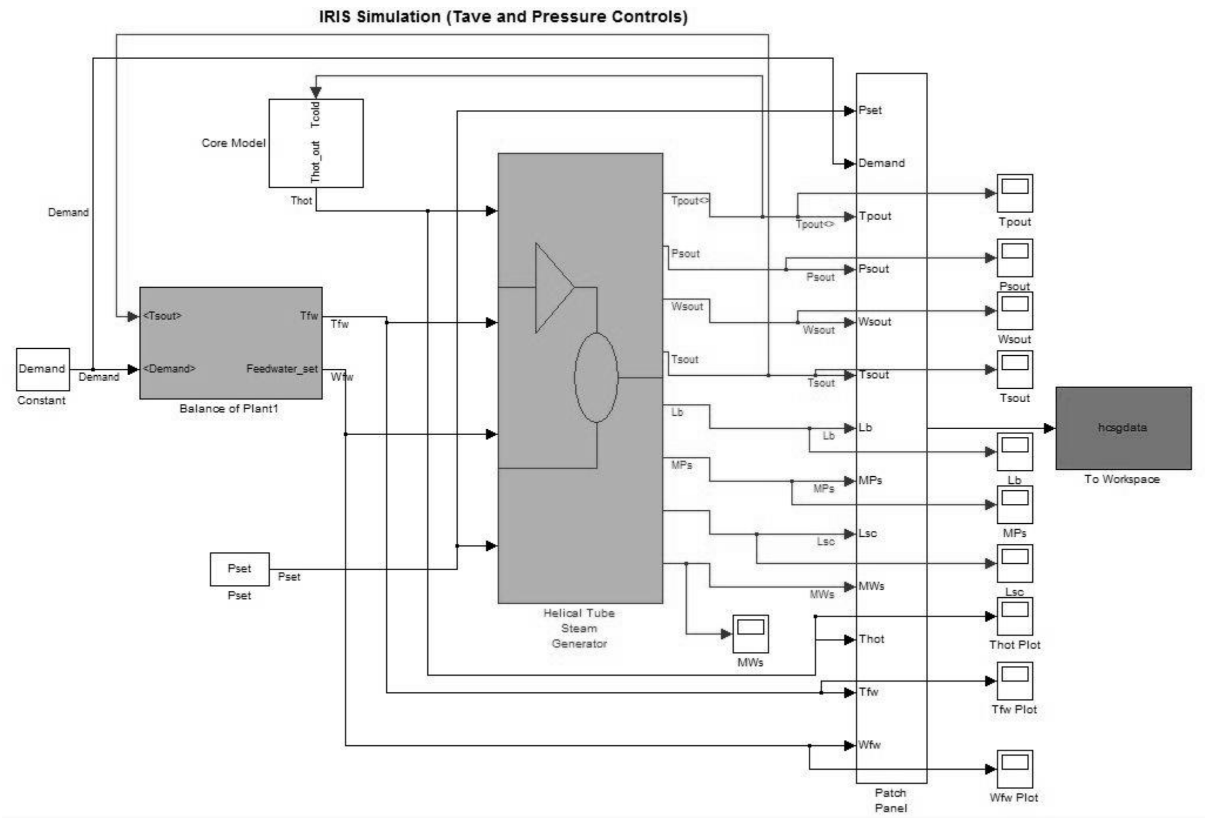

Figure 2: IRIS complete SIMULINK model main screen.

5. TOOLS FOR DEVELOPING EMPIRICAL MODELS

Various techniques are well established for on-line monitoring of equipment, systems and measurements in nuclear power plants. Since the early 1970s numerous efforts have been made to detect and identify anomalies and to provide alternative ways to measure critical and non-critical operating parameters in power plants, particularly reactor noise analysis which uses existing sensor signals to detect incipient faults, measure sensor response time, identify blockages in sensor lines, vibration of reactor internals, imbalance in rotating machinery, etc. Such techniques evolved into on-line monitoring to track the vibration of reactor internals, measure reactor stability, verify overall plant thermal performance, leak detection, estimation of remaining useful life of equipment, and others. Early detection of the onset of equipment and instrument channel degradation and failure can prevent loss of operational capability, reduce radiation exposure of plant personnel, enhance plant control, and minimize repair time [15].

The approach for detecting faults in measurements and/or equipment used in this research uses a data-based method for characterizing the relationship among a set of measurements and the Sequential Probability Ratio Test (SPRT).

5.1. Principal Components Analysis

Principal Component Analysis (PCA) is a multivariate method used to capture the relationships in the data while reducing the dimensionality of an input space without losing a significant amount of information (variability). The method also makes the transformed vectors orthogonal and uncorrelated and is particularly useful for analysis of ill-conditioned data; hence such transformed vectors can be used by regression techniques without having the problems of collinearity. A lower dimensional input space will also usually reduce the time necessary to train a data-based model and the reduced noise will improve the mapping. The objective of PCA is to reduce the dimensionality and preserve as much of the relevant information as possible. PCA can also be thought of as a method of preprocessing data to extract uncorrelated features from the data.

Consider *m* samples of *n* random variables in a matrix **X** where the n columns are the variables and the m rows are the observations. PCA decomposes **X** into a product of scores **T** and orthogonal loadings **P** as:

$$\mathbf{X} = \mathbf{T}\mathbf{P}^{\mathbf{T}} + \mathbf{E} \qquad (1)$$

where **E** contains the residuals.

The principal components (PCs) in the successive columns of **P** are obtained such that maximum variance in **X** is explained. Thus, in case the data is highly collinear, the first few PCs explain most of the variability in the data and are retained. The residuals in **E** constitute the unexplained variation in the data and contain the higher PCs that are rejected. PCA is thus a very efficient method for data compression. The scores so obtained are uncorrelated, meaning $\mathbf{T}^{\mathbf{T}}\mathbf{T}$ is a diagonal matrix. The PCs can be easily obtained as the right singular vectors of **X** using Single Value Decomposition (SVD), described below.

The Singular Value Decomposition (SVD) algorithm decomposes a matrix **X** of dimension (*n x p*) into a diagonal matrix **S** of the same dimension as **X** containing the singular values, and unitary matrix **U** of principle components, and an orthonormal matrix of right singular values **V**. It is important to use the mean centered data (***X***) to give all variables the same importance, resulting in:

$$\boldsymbol{X} = \mathbf{A}\mathbf{L}\mathbf{U}^{\mathbf{T}} \qquad (2)$$

Where:

X is an arbitrary (n x p) matrix.

A is a (n x r) matrix of standardized PC scores with variance=1/(n-1).

L is a (r x r) diagonal matrix, where r is the rank of **X**.

U is a (p x r) matrix of eigenvectors.

Both A and U have orthonormal columns resulting in:

$$\mathbf{A'A} = \mathbf{I}, \text{ and } \mathbf{U'U} = \mathbf{I}$$

5.2. Auto-Associative Kernel Regression (AAKR)

AAKR is a non-parametric, empirical modeling technique that uses historical, fault-free observations and can be used to correct any errors present in current observations. Further details can be found in Hines & Garvey [16]. The exemplar or memory vectors used to develop the empirical model are stored in a matrix **X**, where $X_{i,j}$ is the ith observation of the jth variable. For n_m observations of p process variables, this matrix can be written as:

$$\mathbf{X}=\begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,p} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,p} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n_m,1} & X_{n_m,2} & \cdots & X_{n_m,p} \end{bmatrix} \tag{3}$$

Using this format, a query vector is represented by a 1×p vector of process variable measurements: **x**.

$$\mathbf{x}=[\, x_1 \quad x_2 \quad \ldots \quad x_p \,] \tag{4}$$

The corrected version of the input is calculated as a weighted average of historical, error-free observations termed memory vectors ($\mathbf{X}_i$). The mathematical framework of this modeling technique is composed of three basic steps. First, the distance between a query vector and each of the memory vectors is computed. There are several distance functions that may be used, but the most commonly used function is the Euclidean distance, whose equation for the ith memory vector is as follows:

$$d_i\,(\mathbf{X}_i,\mathbf{x})=\sqrt{\left(X_{i,1}-x_1\right)^2+\left(X_{i,2}-x_2\right)^2+\cdots+\left(X_{i,p}-x_p\right)^2} \tag{5}$$

For a single query vector, this calculation is repeated for each of the n_m memory vectors, resulting in an $n_m \times 1$ matrix of distances: **d**.

Next, these distances are transformed to similarity measures used to determine weights by evaluating the Gaussian kernel, expressed by:

$$\mathbf{w} = K_h\,(\mathbf{d}) = \frac{1}{\sqrt{2\pi h^2}}\, e^{-\mathrm{d}^2/h^2} \tag{6}$$

Where h is the kernel bandwidth, **w** are the weights for the n_m memory vectors.

Finally, these weights are combined with the memory vectors to make the predictions according to:

$$\hat{x} = \frac{\sum_{i=1}^{n_m}\left(w_i \mathbf{X}_i\right)}{\sum_{i=1}^{n_m} w_i} \tag{7}$$

If the scalar a is defined as the sum of the weights, i.e.

$$a = \sum_{i=1}^{n_m} w_i \ , \tag{8}$$

then equation 6.7 can be represented in a more compact matrix notation:

$$\hat{\mathbf{x}} = \frac{\mathbf{w}^{\mathbf{T}}\mathbf{X}}{a}$$

The parameters to be optimized in an AAKR model are the memory matrix (**X**) and the kernel bandwidth (*h*). The researcher must decide how many vectors to include in the memory matrix and how large to make the bandwidth which indirectly controls how many memory vectors are weighted heavily during prediction.

5.3. Sequential Probability Ratio Test (SPRT)

The method chosen to detect faults in the data is the Sequential Probability Ratio Test (SPRT), and is based on the assumption that the residuals of your model are normally distributed and uncorrelated. This method, which was originally developed by Wald [17] and applied by many investigators [18], detects changes in signal properties, such as mean and standard deviation of a signal, and is used to identify drifts and changes in noise levels, while minimizing the probability of false alarms.

Depicted in Fig. 3, rather than computing a new mean and variance at every new sample, the SPRT monitors the performance by processing the residuals in a sequential fashion. The residual signals, which are the differences between the data and the estimates from the model, are used to generate a likelihood ratio (ratio of joint probability density of residuals) based on the statistical properties of the incoming data compared with the statistics in the model. In other words, based on the statistics of the new data coming in, the method is capable of detecting differences in such statistical properties and inform if the new data comes from a similar statistical distribution or not. This process of comparing the model predictions with new data is depicted in Fig. 4, where the likelihood ratio is evaluated by the SPRT threshold for the specified component to make a logical decision concerning its status.

6. PROCESS FOR OBTAINING THE MODELS

As depicted in the flowchart in Fig. 5, the dataset was acquired in such a way to cover all power demands ranging from 100% down to 70% over a period of 60 hours, as seen in Fig. 6. The raw data acquired was then visually inspected for outliers and spurious values. It was then mean-centered, unit variance scaled to give all variables the same importance and a chance to contribute to the models. The scaled dataset was then divided up in to three different blocks using venetian blind method.

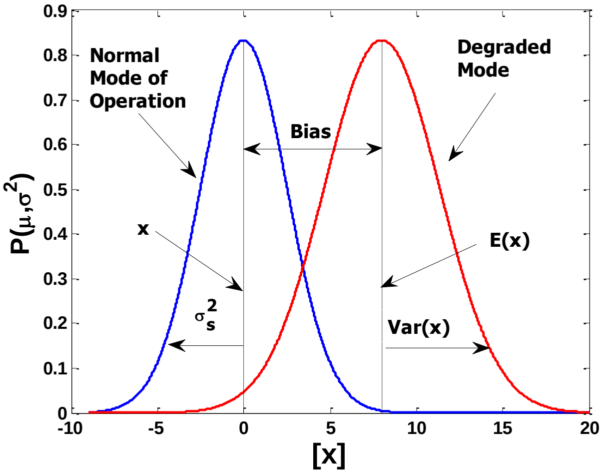

Figure 3: SPRT is based on comparing statistical differences.

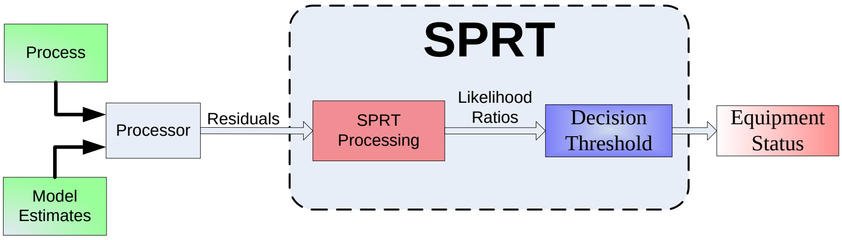

Figure 4: SPRT analysis diagram.

The training block included the most significant data points, and both lowest and highest values from each variable to make sure the resulting training set included all the variance present in the dataset. The test set was used to test the models, and the validation set was used as new queries to gauge how well the obtained models performed using unseen or new data.

Next, a PCA test was performed using the covariance matrix to obtain the principal component coefficients, also known as loadings. Fig. 7 shows a graphical representation of how each variable is correlated with each other using the absolute values of the correlation coefficient matrix for all candidate variables, with dark blue meaning the variables are either weakly or not correlated at all, and dark brown meaning they are highly correlated with each other.

6.1. Models Obtained

A few variables used to simulate the secondary side of the plant were selected as candidates to obtain the inferential models, and are: feed water flow rate (Wfw), feed water temperature (Tfw), steam temperature (Tsout), steam flow rate (Wsout), reactor power (P/P_0) and average core temperature (Tavg). All variables but one are highly correlated with each other, with the exception of reactor power, therefore being removed from the models.

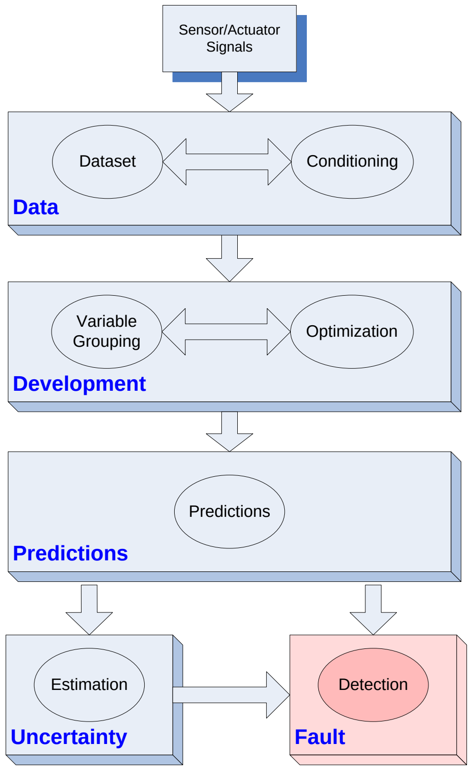

Figure 5: Model development flowchart.

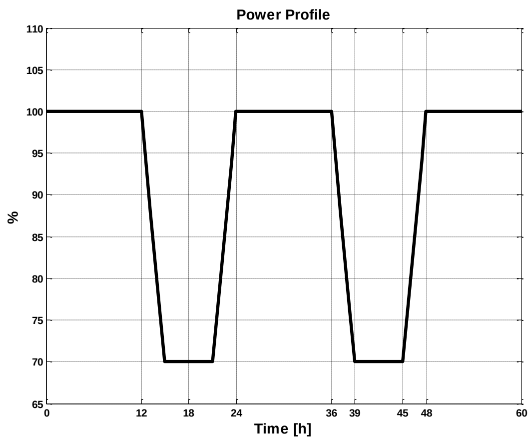

Figure 6: Power Profile.

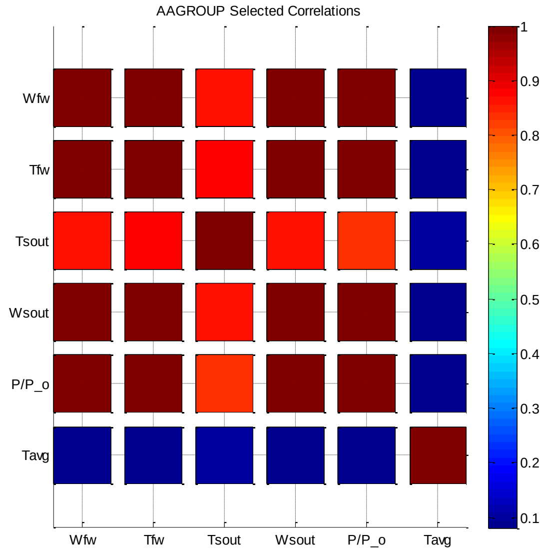

Figure 7: Correlation coefficient matrix (absolute values).

Three different models were investigated for each of the 5 variables: AAKR, kernel regression and linear regression, respectively. The final models were compared and chosen based upon their Mean Absolute Percent Error (MAPE), defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\text{Actual}(i) - \text{Predicted}(i)}{\text{Actual}(i)}\right| \tag{9}$$

Where:

n is the number of fitted points.

i corresponds to the i-th value

For the purpose of this paper, only results from steam flow rate and steam temperature are analyzed, since they are the ones investigated for fault detection in this research. Also, only half of the 60-hour power demand profile is shown.

In Figs. 8 and 9 the model predictions obtained show good agreement with the data, and the difference between predictions and the query data are relatively small.

7. FAULT DETECTION AND RESULTS

Two variables were chosen to show how inferential models along with SPRT can be used to detect faults. The artificial fault added to the feed water flow rate is a 1% step of the current value at a given time for 60 seconds during transient, i.e., as power demand transitioned from 100% to 70%. Same applies to the feed water temperature, but a 0.4% step is applied in this case instead. Fig. 10 shows the artificial fault introduced in the feed water flow rate.
The data containing the faults for each of the variables was passed to each related SPRT to see if it would screen out such faults. The SPRT function implemented in the Process and

Equipment Monitoring (PEM) Matlab® toolbox [19,20] uses a multivariate normal distribution based on the training data provided to detect anomalies and has a logic implemented in which the user can choose to set the logic to trigger the alarm and tag that data as having a high likelihood of being faulty. The results are shown in Figs. 11 and 12. In the upper part of each figure it shows the original distribution mean (in red) and how the new data mean deviates from that mean. In the lower part the SPRT logic triggers whenever the new data deviates from the original distribution with "True" meaning the new data does belong to the original distribution, and "False" otherwise. The logic in both cases is 3 out of 4, i.e., it is needed 3 consecutive flags to trigger the false alarm and signal the new data as not belonging to the original distribution.

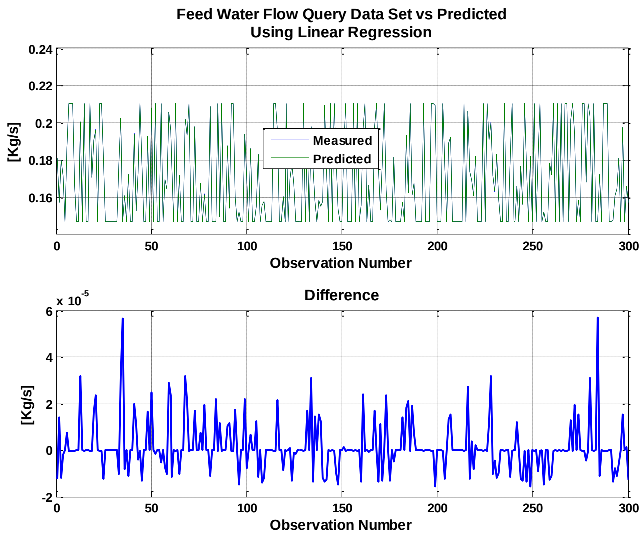

Figure 8: Feed water flow model results.

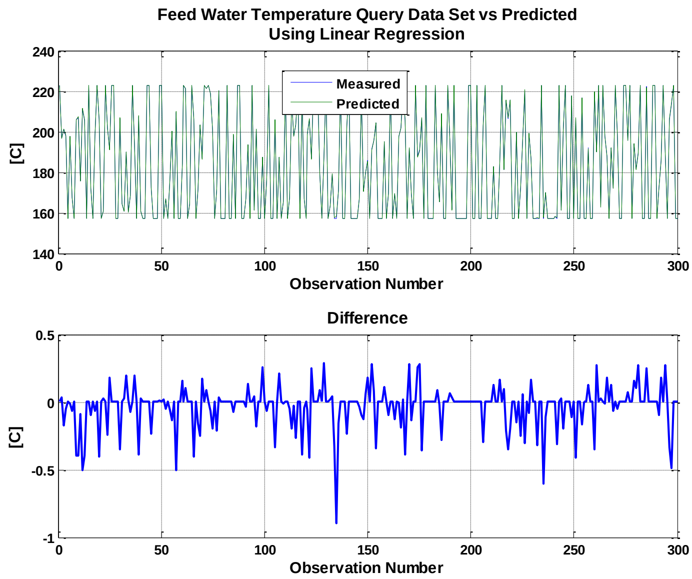

Figure 9: Feed water temperature model results.

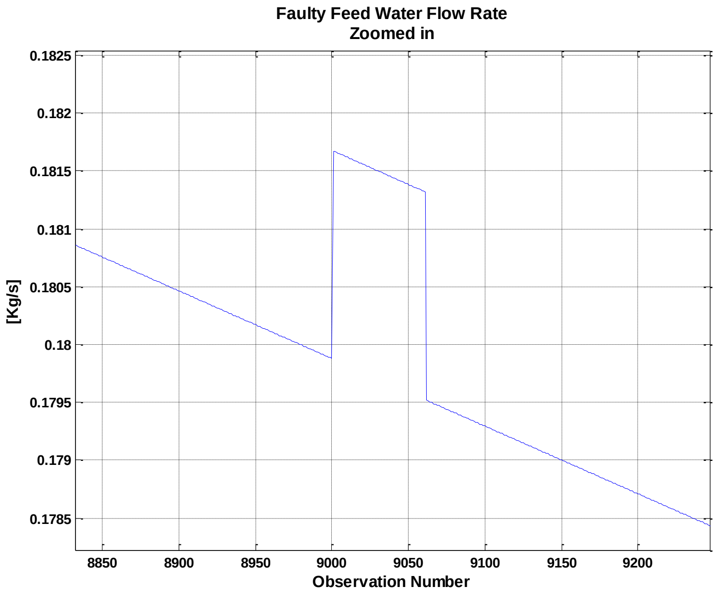

Figure 10: Fault introduced in feed water flow.

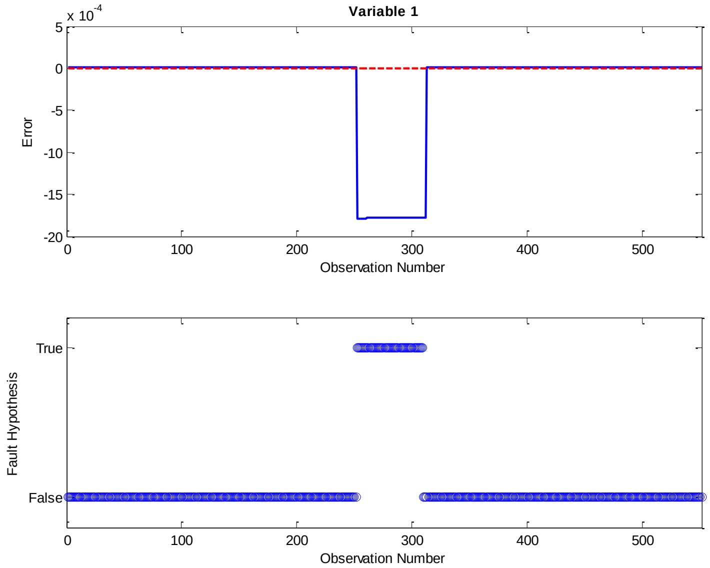

Figure 11: SPRT feed water flow fault detection.

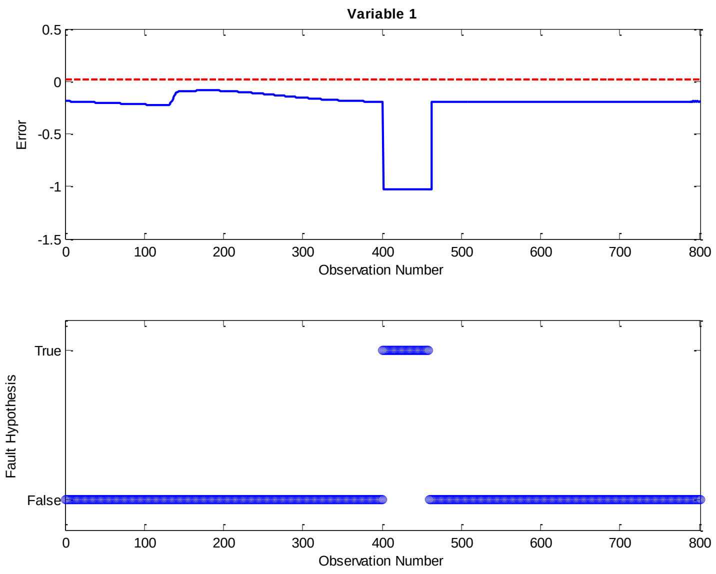

Figure 12: SPRT feed water temperature fault detection.

8. CONCLUSIONS

In this research an IRIS plant Simulink model used to supply the necessary data to obtain five different data-based models. Such models showed good agreement with the data they originate from and, along with SPRT, were used to detect anomalies artificially added to feed water flow and feed water temperature data. Results demonstrate data-based models can be successfully applied in detecting anomalies in data, with feasibility to be used in real-world systems to identify faulty readings from sensors and equipment.

ACKNOWLEDGMENTS

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