Robust Techniques for Monitoring and Fault Diagnosis of IRIS Helical Coil Steam Generators

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A robust approach to thermal performance monitoring and fault diagnosis, for a IRIS Helical Coil Steam Generator (HCSG), has been developed. Traditional fault detection and isolation methods suffer from high false alarm rates, missed detection rates, and misdiagnosis due to the mismatch between the models and the actual plant due to unknown disturbances. A subspace identification technique is used to build dynamic models for the HCSG system, and are more appropriate for robust fault detection and isolation (FDI) design than physical models. The parity space approach for FDI, is then applied to design residual generators that are robust to initial operation conditions and process disturbances. In the design stage, both steady state and transient thermal-hydraulic models have been developed to simulate the HCSG behavior. The steady state analysis demonstrates that primary coolant temperature profile provides a feasible solution to monitor the fluid level in the helical coil tubes, which is important for monitoring the thermal performance and the control of the HCSG system. The dynamic analysis is performed to generate a database for the development of subspace models. Simulation results show that the developed FDI method is capable of detecting and isolating the related sensor and actuator faults even with the influence of process disturbances and measurement disturbances.

KEYWORDS: Fault detection and isolation, helical coil steam generator, robust technique, thermal-hydraulic model, data-driven model.

I. Introduction

Incipient fault detection and isolation and fault tolerant control are considered as essential features of next generation nuclear power plants in order to achieve significant improvements in operation performance and plant safety 1). The major difficulty of implementing an FDI system is to avoid the misdiagnosis and the subsequent incorrect control system reconfiguration. However, models developed for design simulation or other applications always contain uncertainties due to a variety of unknown disturbance sources. The mismatch between the models and the actual plant may generate erroneous characteristics for diagnosis. Therefore, robustness to model uncertainties is an important FDI issue in engineering applications.

Many robust FDI techniques have been developed over the past two decades 2). However, all these techniques assume that the system models are available in simple structures with low uncertainty. This assumption is not true for the helical coil steam generators in International Reactor Innovative and Secure (IRIS) reactor, partly because it is very difficult to obtain accurate physical models for the system and partly because the physical models are too complicated for robust FDI design. In particular, the heterogeneous nature in heat transfer requires that many nodes be used and consequently the resulting high dimensional state space representation may cause significant uncertainties. In this paper, data-based models are developed for the HCSG system based on the simulation data using a subspace identification technique 3). The identified model can automatically capture the dominant system dynamics and ignore the insignificant disturbances. The identified linear state space model has a much simpler structure than traditional system identification methods such as MARMAX and stochastic empirical models 4). In addition, all the dynamic modes of the system are compressed into a single system matrix whether they come from the real system or the disturbances. The nonlinear system behavior is represented by recursively updating the model to implement local linearization.

Robust parity space approach is applied to the identified HCSG models for fault detection and isolation. This approach is based on the parity relations inherent in the system, which are able to represent the temporal redundancy and predict the future system outputs using the past process states and the past inputs. These parity relations are used as...
residual generators for fault detection. Robust residuals are designed such that they are statistically significant if and only if there are faults involved in the system. Fault isolation is achieved by designing a structured residual set in which residuals are sensitive to all faults but one. In this way, each residual generator is dedicated to isolate an individual fault. In order to trade off the sensitivity to all the other faults and the insensitivity to the disturbances and the dedicated fault, robust residual generators are designed through optimization.

Effective fault monitoring of the HCSG is a critical issue in IRIS reactor due to its location inside the reactor vessel. In the IRIS design concept, the eight steam generators are separated into four groups. A schematic of the steam generator connection is shown in Figure 1. Each group shares the same feed water line and the steam line. The grouping design feature deprives the capability of individual steam generator monitoring. Any performance degradation of either steam generator in the same group might be compensated by the other steam generator. In order to achieve individual HCSG monitoring, the steam generator level is identified as an independent process variable to evaluate the heat transfer performance, and a new approach has been developed to measure it based on the principle that the heat transfer in the saturated boiling region is much more efficient than that in the single-phase superheated steam region. Because the new method takes advantage of the inherent heat transfer features, it provides a practical solution to the individual steam generator monitoring.

In this paper, both a steady state model and a dynamic model are developed for the HCSG system in Section 2. The steady state analysis results demonstrate that the shell side fluid temperature profile can be used to measure the steam generator level in the coiled tubes. The dynamic model is based on conservation laws with distributed parameter description of the system. In Section 3, a subspace identification technique is introduced to extract data-based models from the data generated by the model. The identified models are able to successfully predict the measured system outputs. The robust sensor and actuator fault detection and isolation based on the identified models is presented in Section 4. Some concluding remarks and future recommendations are given in Section 5.

II. HCSG System

1. System Description

The helical coil steam generator is a major contributor to the safety and the cost of IRIS reactor design. The steam generator size can be reduced through the helical coil design. The heat transfer of the coiled configuration is much more efficient than straight tubes because of the larger heat transfer area per unit volume and the secondary flow induced by the coil geometry. The superheated steam also avoids the need to install a steam-water separator in the steam generator. The possibility of tube rupture is reduced because the secondary fluid flows inside the SG tubes and thus the tubes experience compression force from the outside.

![Figure 1. HCSG grouping layout in IRIS design.](image)

In the HCSG, the primary fluid flows downward from the top to the bottom on the shell side. The primary side heat transfer is sub-cooled forced convection along the entire steam generator length and the secondary fluid flows upward inside the coiled tubes from the bottom to the top of the steam generator. The feed water flows into the sub-cooled region of the steam generator. In the sub-cooled 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. In the HCSG system, the length of liquid film heat transfer is short since the flow velocity is high. Saturated boiling ends when the critical heat flux is reached and the liquid film disappears. Because of the large mass flow rate, the critical heat flux occurs at relatively high steam quality. When the steam quality becomes one, the liquid evaporation ceases and the steam becomes superheated. In addition, the steam outlet temperature cannot be greater than the inlet temperature of the primary fluid.

A schematic of the HCSG control system is shown in Figure 2. The overall control objective is to supply adequate steam with appropriate thermal energy. As the
power demand changes, the throttle valve setting changes to maintain the turbine header pressure at the set point value. Meanwhile, in order to prevent the carryover of water to the turbine system or dry-out of the steam generator tubes, a feed forward controller is used to suppress a possible large mismatch between the feed water flow rate and the steam flow rate. A feedback controller is then used to fine tune the feed water control valve such that the steam superheat is maintained at the set point value. Because the steam superheat is related to both the steam temperature and the steam pressure, the superheated length and the steam pressure can be indirectly controlled during power transients.

![Schematic of the HCSG control system.](image)

The fault detection and isolation of the helical coil steam generator is based on the dynamic model related to the open loop system although the system is operating under closed loop configuration. The measured turbine header pressure and the steam generator superheat are used to generate the required control action of the turbine control valve and the feed water control valve. Because the input to the turbine control valve and the feed water control valve can be measured or obtained from the microprocessor if digital control is implemented, it is then only necessary to build a model representing the open-loop system regardless of whether the system is operating in closed-loop configuration or not. Figure 2 also shows the related input and output variables of a HCSG model. The inputs to the system model include hot leg temperature, primary flow rate, feed water temperature, steam flow rate, and feed water flow rate. The system outputs include steam outlet temperature, steam generator pressure, and cold leg temperature. It is worthwhile to mention that controller outputs need to be used as the model inputs in order to diagnose actuator faults.

2. Principle of Steam Generator Level Measurement

The traditional level measurement of a recirculation U-tube steam generator is based on the pressure difference between the reference leg connected to the steam phase and the measurement leg connected to the bottom of the steam generator. For both wet reference leg and dry reference leg detectors, the indicated level is not consistent with the actual level when the steam generator temperature changes. In the case of HCSG, because two steam generators are grouped into one steam collector, and because the generated steam has high superheat, the level measurement based on the pressure difference becomes unreliable.

Based on the principle that the heat transfer coefficient in water is much larger than the heat transfer coefficient in steam, many types of multiple-point level detectors have been developed 

![Figure 2. Schematic of the HCSG control system.](image)

3. Development of the Steady State Model

A detailed steady state model was developed to demonstrate the approach to the level measurement in the coiled tubes based on the fluid temperature profile on the primary side. The analysis is based on a single straight channel analysis and the helical features are represented implicitly by some correction factors with respect to friction factor and heat transfer coefficient. Different empirical correlations associated with the sub-cooled region, the saturated boiling region, and superheated region. Because the heat transfer coefficient in the tubes decreases significantly from the saturated boiling region to the superheated region, a sharp breakpoint of the shell side fluid temperature profile can be observed and used to measure the water level in the coiled tubes. As is evident, the physical principle of the proposed HCSG level measurement is the same as that of the multiple-point level detector. In the case of the HCSG, the heat transfer mechanism is inherent in the system, so it provides an efficient solution to individual steam generator level monitoring.
(1) Initialize the cell-averaged pressure and enthalpy with the outlet values of the previous cell.
(2) Iterate over the heat transfer rate and the pressure drop until convergence.
    • Calculate the heat transfer coefficients and the friction factors using the cell averaged thermal properties.
    • Calculate the heat transfer rate from the primary side to the secondary side and the pressure loss within the cell.
    • Calculate the values of the outlet enthalpy and the outlet pressure.
    • Update the cell averaged pressure and enthalpy of the cell.
(3) End the iteration.

In the above algorithm, Dittus-Boelter correlation and Colebrook equation are used to calculate the heat transfer coefficient and the pressure drop, respectively, for the single-phase region \(^{10}\). Thom’s correlation and Chen’s correlation \(^{11}\) are used to calculate the two-phase heat transfer coefficient and the pressure drop, respectively, in the saturated boiling region. In order to take into account the effect of secondary flow introduced by the coil geometry, a ratio of the coil to the straight tube is used for the heat transfer coefficient and the friction factor, and is given by \(^{12}\):

\[
\frac{f_c}{f_s} = (\text{Re}(\frac{R_o}{R_C})) \frac{1}{20}
\]

The symbols \(f_c\), \(f_s\) represent friction factors for tube coil and straight tube, respectively, \(R_o\) represents the outer tube radius, and \(R_C\) represents the coil radius.

This model has been applied to the preliminary design data for the IRIS reactor. The calculated temperature profiles of the primary fluid and the secondary fluid are shown in Figure 3. The calculated lengths of the sub-cooled region, the saturated boiling region and the superheated region are 4.5 m, 21.5 m, and 6.0 m, respectively. The calculated steam outlet temperature is 317 °C and the primary inlet fluid temperature is 328 °C. The calculated results are within 0.5% of the results obtained from a more sophisticated code (RELAP). Figure 3 clearly shows the break point of the primary fluid temperature when the saturated boiling heat transfer transits to the superheated heat transfer at the tube length 26 meters. This break point can be directly used as an indicator of the steam generator level and the primary fluid temperature profile indeed provides a practical solution for measuring the steam generator level in the coiled tubes.

4. Development of the Dynamic Model

In order to generate data to characterize the dynamic relationship among the measured variables, a nodal model has been developed using Simulink. Figure 4 shows the nodalization scheme. In each heat transfer regime, two lumps with equal volume are used to consider the axial temperature changes. Correspondingly, six metal nodes are used to describe the heat transfer from the primary side to the secondary side.

This development of the dynamic model is based on the following assumptions \(^{13}\):

![Figure 3. Fluid temperature versus tube length at 100% power.](image)

![Figure 4. Schematic of the nodalization for a helical coil steam generator.](image)
(1) A single pressure is used to characterize the superheated region.
(2) The superheated steam satisfies the ideal gas law modified by an expansion coefficient.
(3) The fluid temperatures of the two nodes in the saturated region on the secondary side are equal to the saturated temperature.
(4) The pressure distribution in each region does not change during small perturbations.
(5) The steam quality in the boiling region can be assumed to be a linear function of the axial coordinate, so the density in the boiling region can be approximated as a function of the steam pressure.
(6) The steam generation rate is assumed to be equal to the boiling rate.
(7) The heat transfer coefficients for the superheated region, the saturated region, and the sub-cooled region are assumed to be constant.

In order to build a reduced order data-based model of the HCSG system, the dynamic response of the system is obtained by exciting the system inputs with white Gaussian noise of 1% power. The perturbed system inputs include hot leg temperature, primary water flow rate, feed water temperature, and steam flow rate. The dynamic response analysis is also useful to determine the flow rate, feed water temperature, and steam flow rate.

III. Subspace Model Identification
A subspace model is developed to characterize the dynamic relationship among the measured variables in the HCSG using a subspace identification technique. Because of the data driven nature, the technique allows for on-line implementation and accurate models can be achieved through adaptively updating the models using the most recent data.

1. Subspace Identification Algorithm
Subspace identification is based on state estimation of a dynamic system rather than input-output error. The identification first determines the Kalman states directly from system inputs and outputs based on geometrical projection. The system matrices are then recovered based on the prediction error using the estimated states. Subspace identification method obtains a reduced order of model by directly extracting a reduced order of estimated state sequences, while traditional identification methods derive reduced order of models after higher order of models have been obtained.

The model structure of subspace identification is given as follows:

\[ x_{k+1} = Ax_k + Bu_k + w_k \]
\[ y_k = Cx_k + Du_k + v_k \]

where
\[ u_k \] = input signals.
\[ y_k \] = output signals.
\[ w_k \] = unobserved process noise.
\[ v_k \] = unobserved measurement noise.

\[ A, B, C, D \] = system matrices.

The process noise and the measurement noise are assumed to be zero-mean, white noise sequences with the following covariance structure:

\[ E[\begin{bmatrix} w_i \\ v_j \end{bmatrix}] = (Q, S) \]

The pair \( \{A, C\} \) and the pair \( \{A, [B, Q^{1/2}]\} \) are assumed to be observable and controllable, respectively.

Subspace identification algorithm represents the future output as a linear combination of the past input and output as well as the future input \( i \). For a given length of time widow \( j \), the past input and the future input at the time instant \( i \) is contained in the matrices \( U_p \) and \( U_f \), respectively:

\[ U_p = U_{i, i+1} = \begin{bmatrix} u_i & u_{i+1} & \cdots & u_{i+4} \\ u_i & u_{i+2} & \cdots & u_{i+j} \\ \vdots & \vdots & \ddots & \vdots \\ u_i & u_{i+j-2} & \cdots & u_{i+j-4} \end{bmatrix} \]
\[ U_f = U_{i, i+1} = \begin{bmatrix} u_i & u_{i+1} & \cdots & u_{i+j-1} \\ u_i & u_{i+2} & \cdots & u_{i+j} \\ \vdots & \vdots & \ddots & \vdots \\ u_i & u_{i+j-2} & \cdots & u_{i+j-3} \end{bmatrix} \]

The past output matrix \( Y_p \) and the future output matrix \( Y_f \) are defined similarly. The past information, including both the input and the output, is contained in the matrix \( W_p \), and is given by:

\[ W_p = \begin{bmatrix} Y_p \\ U_p \end{bmatrix} \]

The past state vector \( X_p \) and the future state vector \( X_f \) are defined as follows:

\[ X_p = (x_0, x_1, \ldots, x_{i-1}) \]
\[ X_f = (x_f, x_{i+1}, \ldots, x_{i+j-1}) \]

The state estimate \( \hat{X}_f \) and the extended observability matrix \( \Gamma_i \) can be determined by projecting the future output onto the row space of \( W_p \) along the row space of \( U_f \), and is given by:

\[ Z = Y_f / U_f \]
\[ W_p = \Gamma_i \hat{X}_f \]

where \( \Gamma_i \) is defined as follows:

\[ \Gamma_i = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{i-1} \end{bmatrix} \]
Because only \( n \) dimensional row space of \( Z \) is sufficient to estimate \( \tilde{X}_f \) and \( \Gamma_i \) for an \( n \)th order system. The basis vectors can be extracted from singular value decomposition of the matrix \( Z \), and is given by:

\[
Z \approx U_1 S_1 V_1^T
\]

(4)

Only \( n \) significant singular values are retained in the matrix \( S_1 \).

Because \( \Gamma_i \) is of full column rank and \( \tilde{X}_f \) is of full row rank, a comparison of Equations (3) and (4) results in the computational method for \( \tilde{X}_f \) and \( \Gamma_i \) without knowing the system matrices \( A, B, C \) and \( D \), as follows:

\[
\Gamma_i = U_1 S_1^{1/2}
\]

(5)

\[
\tilde{X}_f = \Gamma_i Z
\]

The system matrices \( A, B, C \) and \( D \) can be recovered based on two consecutive estimated state sequences. From Equation (5), two consecutive estimated state sequences are computed as follows:

\[
\tilde{X}_i = (\tilde{x}_i, \tilde{x}_{i+1}, \ldots, \tilde{x}_{i+n-1}) = \Gamma_i^* Z_i
\]

\[
\tilde{X}_{i+1} = (\tilde{x}_{i+1}, \tilde{x}_{i+2}, \ldots, \tilde{x}_{i+n}) = \Gamma_{i+1}^* Z_{i+1}
\]

where \( Z_{i+1} \) is calculated based on the projection of \( Y_f \) with the border between the past and the future shifted one row block downward.

The two consecutive state sequences are related by the following matrix equations:

\[
\tilde{X}_{i+1} = A\tilde{X}_i + BU_{ij} + \rho_w
\]

\[
Y_{ij} = C\tilde{X}_i + DU_{ij} + \rho_v
\]

(6)

From Equation (6), the system matrices and the noise characteristic matrices can then be recovered using classical least-squares method.

2. Subspace Model of HCSG

A Multiple-Input Multiple-Output (MIMO) state space model is developed to characterize the dynamic relationship among the measured variables of the helical coil steam generator using subspace identification technique. The system is excited with Gaussian noise inputs. The appropriate choice of the excitation inputs plays a significant role in the quality of the identified model. If too much power is included in the input signals, some nonlinear mode of the system will be excited. However, if the included power is too small, the identified model cannot capture enough system dynamics. The obtained linear model using inputs with 1% noise power is able to give good performance in predicting the dynamic behavior of the cold leg temperature, the steam outlet temperature, and the steam generator pressure.

Figure 6 shows the singular values of the weighted oblique projection matrix.

The number of states is chosen as six. If too many state variables are chosen, the resulting model loses the capability of generalization because some of the degree of freedom is used to model system noise. If too few state variables are used, the resulting model may not be able to explain some significant dynamics of the system. In general, the number of state variables should be chosen such that no significant information can be included if the number of state variables is further increased.

In order to test the generalization capability of the identified model, a validation data set is generated with reactor power at 80% full power and the excitation power of inputs at 1%. Figure 7 shows the comparison of results between the actual cold leg temperature and the steam outlet temperature obtained from the Simulink model and the corresponding predicted values based on the identified model. The prediction errors are indeed very small. The prediction error index \( \gamma \) may be defined as follows:

\[
\gamma = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (y_k - \hat{y}_k)^2}
\]

where

\( N \) = the number of validation data points.

\( y_k \) = the actual value of the kth data points.

\( \hat{y}_k \) = the predicted value of the kth data points.

The prediction error indices are 17%, 8.8%, 8.8%, 10.6%, 10.6% and 8.3% for the cold leg temperature, the steam generator pressure, the steam outlet temperature, the subcooled length and the saturated boiling length, respectively.
These indices show that the identified model is able to give better prediction for the other output than the cold leg temperature.

![Figure 7. Model prediction of cold leg temperature.](image)

**IV. Robust Parity Space FDI Algorithm**

In general, under fault circumstances, the dynamic behavior of a MIMO linear system with \( n \) state variables, \( l \) system outputs, and \( m \) system inputs can be represented by

\[
x(k+1) = Ax(k) + Bu(k) + E_1 d(k) + R_1 f(k)
\]

\[
y(k) = Cx(k) + Du(k) + E_2 d(k) + R_2 f(k)
\]

where \( f \) = additive sensor, actuator, or process faults. In the above equation, the matrices \( E_1 \in R^{nxp} \) and \( E_2 \in R^{nxq} \) are disturbance distribution matrices for \( p \) disturbance sources. The structure of \( R_1 \in R^{nxq} \) and \( R_2 \in R^{nxq} \) depends on the types of the \( q \) considered faults.

**1. Robust Residual Design**

The ultimate goal of fault detection and isolation is to generate a fault signal that is statistically significant if and only if there are faults involved in the studied system \(^{16}\). The fault signal \( r(t) \) satisfies the following property:

\[
r(t) \neq 0 \text{ iff } f(t) \neq 0.
\]

The fault signal can be generated using the parity relation approach. It is assumed in the approach that a dynamic model can be used to predict the future system outputs based on the past process states and the past inputs; therefore, the temporal redundancy can be used for residual generator design \(^{16}\).

**2. Fault Detection**

A good fault detector should avoid unacceptable false alarm rate and missed detection rate. However, because the developed models inevitably have uncertainty due to some unmeasured inputs or unknown disturbances, they may act on the system outputs resulting in false alarms. If a large residual threshold is used to avoid false alarms, some fault effects may be masked and thus cause missing detection. Therefore, an optimization scheme must be designed to accomplish a tradeoff between false alarm rate and missing detection rate.

Considering a time window of length \((s+1)\), the following time redundancy relations in matrix form can be derived \(^2\):

\[
Y(k) = [\Gamma(k), H(k), L(k)] \begin{bmatrix} U(k) \\ d(k) \end{bmatrix} + M(k) f(k)
\]

The \( H(k) \in R^{[(s+1)l][(s+1)m]}, L(k) \in R^{[(s+1)l][(s+1)p]}, \) and \( M(k) \in R^{[(s+1)l][(s+1)q]} \) matrices are Toeplitz block Hankel matrices, relating system inputs, disturbances and faults to system outputs, respectively. For example, \( H(k) \)

is defined as follows:

\[
H(k) = \begin{bmatrix} D & 0 & \star & 0 \\ CB & D & 0 & \star \\ \star & \star & \star & 0 \\ CA^{-1}B & CA^{-2}B & \star & D \end{bmatrix}
\]

Using the information within the time window, one residual vector corresponding to the number of system outputs can be generated as follows:

\[
r(k) = V^T [Y(k) - HU(k)]
\]

and

\[
r(k) = V^T [\Gamma(k), L(k)] \begin{bmatrix} x(k-s) \\ d(k) \end{bmatrix} + V^T M(k) f(k)
\]

where \( V^T \in R^{[(s+1)l]} \).

Equations (9) and (10) represent the computational form of the residual and the internal form from system physics, respectively. In order to make the generated residual insensitive to the disturbance, the following conditions should be satisfied:

\[
V^T [\Gamma(k), L(k)] = 0
\]

When this condition is satisfied, the internal form of the residual takes the following simplified form:

\[
r(k) = V^T M(k) f(k)
\]

This residual is then only dependent on the fault occurrence and independent of the disturbance, so such a residual generator has perfect property for fault detection. However, a perfect residual generator usually does not exist.
for most applications because a transformation row vector \( V^T \), which is orthogonal to all the column vectors of the matrices \( \Gamma(k) \) and \( L(k) \) exists only if it lies in the null space of \([\Gamma(k), L(k)]\). This requires that the matrix \([\Gamma(k), L(k)]\) must be column rank deficient. Moreover, even if such a column vector can be defined, there is still no guarantee that the residual generated using the obtained row vector \( V^T \) is sensitive to all the considered faults. In this situation, it is more reasonable to obtain an optimal solution minimizing the objective function \( J \) defined as follows 2):

\[
J = \frac{(V^T Z)(V^T Z)^T}{(V^T Q)(V^T Q)^T}
\]

where
\[
Z(k) = M(k)
\]
\[
Q(k) = [\Gamma(k), L(k)]
\]

The optimization can be solved as a standard generalized eigenvalue problem defined as follows:

\[
ZZ^T v_i = \lambda_i QQ^T v_i
\]

The optimal solution of \( V^T \) is the eigenvector \( v_i^T \) corresponding to the minimum eigenvalue.

3. Fault Isolation

Structured residual set provides a simple and systematic approach to fault isolation. The residual set is obtained by computing the residuals of a set of models. If the models are chosen such that each model is only sensitive to a subset of the considered faults, the residual structure can then be used for fault isolation because each fault has different fault signature in terms of the residual vector.

Although it is possible to design numerous residual structures for fault isolation with different isolation properties, a generalized residual set is a simple design scheme for fault isolation. In this scheme, each residual is sensitive to all but one fault. In particular, the residual structure dedicated to isolate the \( i^{th} \) fault is given as follows 17):

\[
r_i(t) = 0 \quad \text{for the } i^{th} \text{ fault.}
\]
\[
r_i(t) \neq 0 \quad \text{for the other faults.}
\]

For example, the residual generator insensitive to the \( i^{th} \) sensor fault can be designed as if it is a disturbance. The fault response equation of the system is reformulated as follows 2):

\[
x(k+1) = Ax(k) + Bu(k) + [E_i, R_i] \begin{bmatrix} d(k) \\ f_i(k) \end{bmatrix} d(k) + \bar{R}_i f_i(k)
\]
\[
y(k) = Cx(k) + Du(k) + [E_i, R_i] \begin{bmatrix} d(k) \\ f_i(k) \end{bmatrix} d(k) + \bar{R}_i f_i(k)
\]

where
\[
R_1 = [R_{ij}, \bar{R}_{ij}]
\]
\[
R_2 = [R_{2ij}, \bar{R}_{2ij}]
\]
\[
f = [f_i, f_i]
\]

The residual generator then takes the following form:

\[
r_i(k) = V_i^T M_i(k) \tilde{f}_i(k)
\]

This is sensitive to all but the \( i^{th} \) fault.

4. HCSG Fault Detection and Isolation

Figure 8 shows the residual sequence generated from a robust residual generator for HCSG during fault free conditions. The residual generator is built based on a model identified at 100% power level and the inputs are white Gaussian noise with 2% power. Although the new data is collected at a different power level (80%) and different input signals with some process disturbance introduced, the residuals are still small. This shows that the residual generator is robust to initial operation conditions and input signals, as well as process disturbances. Therefore, such a residual generator will not cause significant false alarm rate.

Figure 9 shows the residual of steam outlet temperature sensor bias fault with a fault magnitude of 0.5 °C at the 200th sample. The residual generator can respond very quickly and is sensitive to a small fault. This shows that the fault detection scheme is able to detect an incipient fault.

Figure 10 shows the residual of cold leg temperature sensor bias fault with a fault magnitude of 1.0 °C at the 200th sample. In the upper subplot, the residual responds sensitively and quickly for fault detection. The lower subplot shows the residual generated by the residual generator dedicated to isolate cold leg temperature sensor fault. As can be seen, the residual is close to zero. Therefore, this fault can be correctly isolated.

Similar results are also obtained for the primary flow rate fault with a fault magnitude of 0.5% nominal value and feed water flow meter sensor fault with a fault magnitude of 0.5% nominal value. Because the dedicated residual generators generate zero-mean residual sequence, these faults can therefore be correctly isolated. If it is assumed that the primary flow measurement is healthy, the primary flow rate fault can be considered as an actuation fault. If the feed water controller input to the feed water control valve is used as the model input instead of feed water flow rate, feed water control valve actuation fault can be detected and isolated in the same manner as a feed water flow meter sensor fault.

V. Concluding Remarks and Future Work

In this paper, both a physics model and an empirical model are developed for the fault monitoring of IRIS helical coil steam generator. The physics model is based on basic conservation laws with distributed parameter description to simulate the system behavior. The steady state analysis demonstrates that the shell side fluid temperature profile can be used as a measurement of the fluid level in the coiled
tubes, which is important for inventory control and for operation performance monitoring. Using the data generated from the dynamic model, a sixth order state space model is developed for the helical coil steam generator at full power operation conditions using a subspace identification technique. The identified model is able to predict the steam generator pressure, the cold leg temperature, the steam outlet temperature, the sub-cooled length, and the saturated boiling length with acceptable accuracy. The developed robust parity space FDI approach is able to successfully detect and isolate the sensor and actuator faults of the system created on the developed simulator.

Future work includes developing a global strategy of system identification and robust fault detection, and isolation applicable for the entire operating regime of the system.

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Figure 8. Residual sequence for fault free condition with process disturbance.

Figure 9. Fault detection of steam outlet temperature sensor fault.

Figure 10. Fault isolation of cold leg temperature sensor fault.
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