Fault Diagnosis of Helical Coil Steam Generator Systems of an Integral Pressurized Water Reactor Using Optimal Sensor Selection

Fan Li, Belle R. Upadhyaya, *Life Senior Member, IEEE*, and Sergio R. P. Perillo

***Abstract*—Fault diagnosis is an important area in nuclear power industry for effective and continuous operation of power plants. Fault diagnosis approaches depend critically on the sensors that measure important process variables. Allocation of these sensors determines the effectiveness of fault diagnostic methods. However, the emphasis of most approaches is primarily on the procedure to perform fault detection and isolation (FDI) given a set of sensors. Little attention has been given to actual allocation of the sensors for achieving efficient FDI performance. This paper presents a graph-based approach as a solution for optimization of sensor selection to ensure fault observability, as well as fault resolution to a maximum possible extent. Principal component analysis (PCA), a multivariate data-driven technique, is used to capture the relationships among the measurements and to characterize by a data hyper-plane. Fault directions for the different fault scenarios are obtained using singular value decomposition of the prediction errors, and fault isolation is then accomplished from new projections on these fault directions. Results of the helical coil steam generator (HCSG) system of the International Reactor Innovative and Secure (IRIS) nuclear reactor demonstrate the proposed FDI approach with optimized sensor selection, and its future application to large industrial systems.**

***Index Terms*—Fault diagnosis, helical coil steam generator, optimum sensor selection, principal component analysis.**

I. Introduction

FAULT detection and isolation (FDI) has long been considered as an important design feature of the advanced instrumentation and control (I&C) systems of nuclear power plants. The main objectives of FDI are to observe incipient faults and to determine their root causes, which is crucial for safe operation and condition-based maintenance planning of any large industrial process. It can result in significant reduction in plant downtime and considerable amount of maintenance cost savings.

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Many modern FDI approaches are based on analytical redundancy. Functional relationships among process variables governed by the fundamental conservation laws such as mass, momentum, and energy balance, can replace hardware redundancy for plant measurements [1]. However, it is generally very difficult to build physics-based models for fault diagnosis purposes due to the complexity of a nuclear power plant. Thus, so-called soft computing methods, such as artificial neural networks (ANN) [2], principal component analysis (PCA) [3], fuzzy logic [4], group method of data handling (GMDH) [5], and many other data-based empirical modeling techniques, have shown great capabilities of capturing the relationships among various process measurements.

PCA, as one of the most popular data-based methods for extracting information from process data, has been widely used throughout the process industry. In general, PCA is a decomposition method which is used to reduce the dimensionality of the data. A major challenge in applying the PCA technique to fault diagnosis of nuclear power plants is that there are so many monitored process measurements, thanks in part to recent expansion of the digital I&C technologies into the nuclear power industry. Process information is continuously stored in plant historical databases at discrete time intervals. Therefore, we must find a systematic means of choosing proper variables used in the PCA-based fault diagnostic system for feature extraction. In our previous work [6], a graph-based optimum sensor selection scheme was presented from a fault diagnostics perspective. Issues of fault detectability and discriminability were discussed to ensure that selected sensor networks were capable of observing every postulated fault in the process, meanwhile obtaining a maximum possible fault resolution. Directed graph (DG) was employed to describe propagation of fault effects and was used as a basis for sensor selection.

This paper further proposes a PCA-based fault diagnostic system with optimized sensor selection to overcome the above limitations. A schematic of the proposed system is shown in Fig. 1. In this approach, optimum sensor selection is carried out from the fault diagnostics perspective for a nuclear power system. And simulation data of the selected sensors are generated based on the well-developed physics models of the system. The PCA models are constructed upon the simulation data to obtain the fault residuals that signify the mismatch between the model predictions and the actual data. Because different anomalies cause the violation of different relationships among the process variables, patterns of the fault residuals can be classified for fault identification. Here we introduce the notion of fault

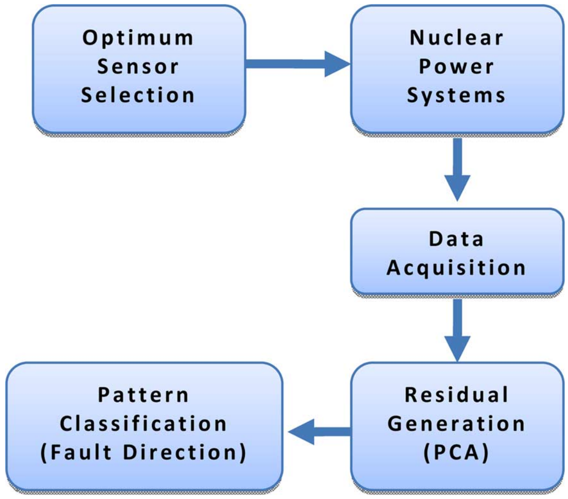

Fig. 1. An integrated architecture of a fault diagnostic system.

direction as a pattern classification technique. Fault direction is referred to as a prediction error direction which corresponds to a particular type of anomaly. The particular anomaly may be isolated as the one with maximum projection on the enumerated set of fault directions. It is worth noting that the fault diagnosis procedure developed in this work requires that faults are postulated, thus enabling generation of fault residual sub-spaces.

It is shown in this paper that if sensors are suitably selected based on the knowledge of fault propagation manner within the process, the obtained sensor set will have already partially guaranteed the basic properties such as fault detectability and discriminability before PCA is employed for fault diagnosis. In this paper, the optimized sensor selection integrated with the PCA-based FDI algorithm is demonstrated to have a satisfactory fault diagnosis performance on a pair of helical coil steam generators (HCSG) found in the International Reactor Innovative & Secure (IRIS) system. The procedure developed in this work provides a selection of the process measurements that optimizes the FDI task, thus avoiding the arbitrary choice of measurements for PCA modeling.

II. Principal Component Analysis Algorithm

PCA is a statistical algorithm of dimension reduction by projecting data on to a lower dimensional space such that the major variation of the original data can be preserved. Given a normalized data matrix $X(m \times n)$ composed of m observations with n measured variables. PCA decomposes X into two components, a predicted value $\hat{X}$ and an error value E, which determine two orthogonal subspaces, i.e., the principal component (PC) subspace and the residual component (RC) subspace, respectively

$$\begin{aligned} X &= \hat{X} + E \\ \hat{X} &= TP^T \\ E &= T_E P_E^T. \end{aligned} \tag{1}$$

In (1), P is the orthogonal loading matrix and T is the score matrix. The scores T in the PC subspace explain the dominant variation of the measured variables, and the scores T_E in the RC subspace represent the insignificant variation due to model reduction error. The column vectors of principal component loadings $P(n \times l)$ are the eigenvectors corresponding to the l largest eigenvalues of the covariance matrix $(X^T X)/m$ and the columns of P_E are the eigenvectors corresponding to the smallest $n - l$ eigenvalues.

A new sample x can be projected on the PCA model, represented by the loading matrix P, to obtain the new scores $t = xP$.

And, the residuals of the new sample are generated as follows.

$$e = x - tP^T = x - xPP^T = x(I - PP^T). \tag{2}$$

The residuals e obtained above can be combined into a squared prediction error (SPE) statistic Q as

$$Q = ee^T. \tag{3}$$

The proposed fault isolation scheme is based on the Q statistic, and described as follows [7].

Let $F = [f_1\ f_2\ f_3\ \ldots\ f_R]$, where $f_1\ f_2\ f_3\ \ldots\ f_R$ are column vectors, denote the fault directions for R postulated scenarios. These fault directions can be extracted from the historical data using clustering techniques [8]. The fault direction f_i in the fault matrix F represents the direction in the residual space for the i_{th} fault such that the samples corresponding to the fault have the maximum projection on the fault direction f_i. In other words, if e_i denotes the residuals for samples corresponding to the i_{th} fault, the optimization problem is

$$J = \max_{f_i} f_i^T e_i^T e_i f_i \tag{4}$$

subject to the constraint

$$f_i^T f_i = 1. \tag{5}$$

Using the Lagranian multiplier and differentiating J with respect to f_i and setting the derivative to zero for maximization, we get

$$e_i^T e_i f_i = \sigma f_i. \tag{6}$$

The fault direction f_i is thus obtained as the first eigenvector of $e_i^T e_i$.

Once the fault matrix F is properly defined, fault isolation can be accomplished by calculating the projections onto F and through identifying the fault as the one with the maximum projection norm. The fault isolation index for the i_{th} fault is defined as [7]

$$FI_i = 1 - Q_i/Q \tag{7}$$

where

$$Q_i = e\left(I - f_i f_i^T\right)\left(I - f_i f_i^T\right)e^T.$$

In the above equations, Q is already defined in (3) as a squared error. It usually can be deemed as the distance of the samples from the origin, while Q_i signifies the distance of the samples from the origin after subtracting the projection of the residuals on the specific fault direction f_i. It represents the sum of squares of residuals remaining after removing the contribution from the $i_{\rm th}$ fault direction.

Thus, the fault isolation index FI_i quantifies the fraction of Q that is due to the fault direction f_i. When the $i_{\rm th}$ fault occurs, FI_i is expected to be the highest among all the fault directions, which results in the isolation of the $i_{\rm th}$ fault from the other fault scenarios.

As discussed in the previous section, a caveat with PCA or any other data-based empirical modeling methods is that they are not able to efficiently solve process monitoring and fault diagnosis problems as a whole unless other process information is utilized. Historically, the emphasis of most PCA-based research has been more on monitoring algorithms given a set of sensors and less on the actual selection of sensors for efficient detection and isolation of process malfunctions. Fortunately, many researchers from other fields have resorted to sensor network design based on the graph theory [9]–[11]. The graph-based optimum sensor selection strategy is presented from a fault diagnostics perspective in the next section, and more details in this topic can be found in [6].

III. Optimum Sensor Selection Algorithms

Sensor selection has been treated as an optimization problem in most of the earlier work. The first attempt to present a technique to optimally locate sensors was made by Lambert [12], where he used probabilistic importance of events in fault trees to decide optimal sensor locations. Vaclavek and Loucka [13] described the problem of sensor network design and employed graph theory to ensure the observability of a specified set of important variables in a multi-component flow network. Ali and Narasimhan [14] addressed the concept of reliability of state variable estimation and developed graph-theoretic algorithms for maximizing the reliability. The reliability of the process was defined as the smallest reliability among all of the variables. Unlike the approaches based on graph theory and linear algebra, Bagajewicz [15] proposed a Mixed Integer Non-Linear Programming (MINLP) problem to obtain cost-optimal structures subject to the desired level of precision, residual precision, and error detectability. An alternative Mixed Integer Linear Programming (MILP) formulation which was useful for both small-and medium-size problems was presented by Bagajewicz and Cabrera [16]. Sen *et al.* [17] presented a genetic algorithm based approach that can be applied to the design of non-redundant sensor networks using different objective functions.

The solution to the problem of optimum sensor selection in this work is broadly broken down into two tasks: (1) fault modeling or prediction of cause-effect behavior of the system, generating a set of variables that are affected whenever a fault occurs, and (2) use of the generated sets to identify sensors based on various design criteria, such as fault observability, fault resolution, etc.

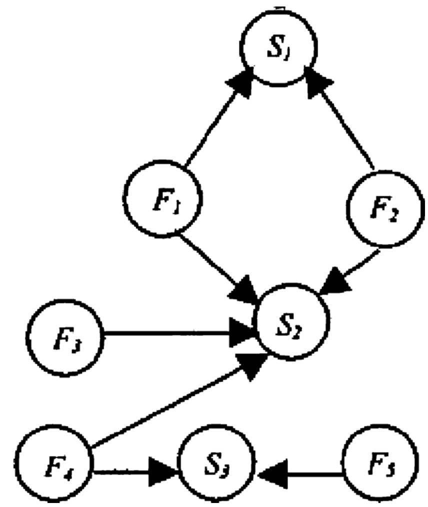

Fig. 2. Directed graph of a hypothetical process.

A. Directed Graph Method

Fault propagation or cause-effect behavior can be derived on a basis of qualitative models that are used to represent the process. Directed graph (DG) is such a qualitative model that can be used to infer cause-effect behavior in a system. It normally consists of a set of nodes and directed branches. The nodes represent the process variables and the branches represent the causal influences between the nodes. Arrows of a branch reflect direction of the effects between variables, and fault propagation patterns can thus be inferred graphically.

The DG modeling is a convenient approach because it clearly illustrates interactions among the important process variables, and can be easily developed from the empirical relationships or engineering fundamental principles. Fig. 2 shows a DG diagram of a hypothetical process with the connections from fault nodes to potential sensor locations. In this figure, each fault node F connects through a branch to a sensor node S, thus indicating that the fault affects the reading of the corresponding sensor.

B. Fault Observability and Resolution Criteria

Fault observability refers to the situation where every fault defined for the process has to be observed by at least one sensor. Given a process DG model, the fault observability problem becomes one of finding the minimum number of sensors that would cover all the faults in the process. This is commonly known as the "minimum set-covering problem" [18], in which the sets to be covered are the sets of sensors affected by each fault. Fault resolution refers to the identification of the exact fault that occurs. The maximum resolution that can be attained is restricted by the topology of the DG and the position of the fault nodes in the DG. Hence, given the constraints on measurement points, the fault resolution problem is about selecting sensor locations so that every fault is resolved to the maximum extent possible. This condition is referred to as the "highest fault resolution". For fault resolution problems, a set of "virtual" faults are formed to distinguish the faults in the process. Thus, the resolution problem reduces to finding a cover for these new virtual fault sets, as well as the original sets affected by each fault. For instance, let A_i and A_j denote the sets of sensors connected to a pair of faults i and j, respectively. A virtual fault set, $B_{ij} = (A_i \cup A_j) - (A_i \cap A_j)$, is generated for fault i and fault j. Note that the set B_{ij} represents the symmetric difference of sets A_i and A_j. As discussed by Raghuraj *et al.* [19], any fault resolution problem (single fault, multiple fault, etc.) can be converted to a suitable fault observability problem, thus can be further solved as a set-covering problem.

Minimum set-covering is a classical problem in computer science and complexity theory. It is one of the most important discrete optimization problems because it serves as a model for real world problems, which include facility location problem, airline crew scheduling, nurse scheduling problem, resource allocation, assembly line balancing, vehicle routing, etc. Minimum set-covering is a problem of covering the columns of an $m \times n$ binary matrix with a subset of rows at minimal cost [20]. Set-covering problems can be formulated as follows:

$$\text{minimize} \left[\sum_{i=1}^{m} c_i x_i\right] \tag{8}$$

subject to

$$\sum_{i=1}^{m} D_{ij} x_i \geq 1, \quad j = 1, \ldots, n \tag{9}$$

$$x_i \in \{0, 1\}, \quad i = 1, \ldots, m. \tag{10}$$

Equation (8) is the objective function of a set-covering problem, where $c_i (i = 1, \ldots, m)$ is referred to as the weight or cost, and x_i is the decision variable. Equation (9) is a constraint to ensure that each column is covered by at least one row, and D_{ij} is the constraint coefficient matrix of $m \times n$ whose elements comprise of either “1” or “0”. A column $j (j = 1, \ldots, n)$ is covered by a row $i (i = 1, \ldots, m)$ if $D_{ij} = 1$. Set-covering problems call for a minimum cost subset S, such that each column $j (j = 1, \ldots, n)$ is covered by at least one row, $i \in S$. Finally, (10) is the integrality constraint in which the value is represented as in (11)

$$x_i = \begin{cases} 1 & \text{if } i \in S, \\ 0 & \text{otherwise.} \end{cases} \tag{11}$$

Minimum set-covering problems can be solved exactly by enumeration, but with an increasing number of fault nodes and potential sensor locations, it may not be computationally feasible to solve the problem in that fashion. In many instances, one may only be interested in a “good enough” solution rather than an exact solution, where heuristics often offer a quick and reasonably approximate solution. A greedy search algorithm has been developed for solving fault observability and resolution problems [21]. This search algorithm is summarized below.

Firstly, we need to build a bipartite graph, which consists of a causal set including all the fault nodes and the observability set including the sensor nodes with only input arcs in a DG model. A graph is bipartite if a vertex set can be partitioned into two sets in such a way that no two vertices from the same set are adjacent. These two sets constitute a bipartition of the original vertex set [22]. Whenever there is a directed branch from a fault node to a sensor node, a path from that fault node to the sensor node is drawn in the bipartite graph.

Once the bipartite graph is constructed, the sensor node that has the maximum number of paths connected to it is chosen. We need to check if all the fault nodes are covered by the chosen sensors. If they are covered, this gives the minimum number of sensors for observability. If some of the fault nodes are not covered, then all the paths from the covered fault nodes to other sensors are deleted. Once again, the sensor with the maximum number of paths connected to it is chosen. At this time, a check is made again to see if all the fault nodes are covered. This procedure is continued until all the fault nodes are covered.

Although it has been found that in many cases some faults are still indistinguishable using the optimal sensor set obtained through the sensor selection scheme, the selected sensors can aid in the proposed PCA-based fault diagnostic system when the process information is utilized. Therefore, the overall method as described in the preceding sections consists of the following steps:

i) Define the faults of interest in a nuclear power system (including process fault and sensor fault) based on the operation history records and available system knowledge, then build DG models of the system, which can be implemented by using empirical relationships or fundamental mathematical models of the system.

ii) Solve the formulated minimum set-covering problem to select the optimal set of sensors. The obtained sensor set partially guarantees detection and isolation of all the faults defined in the first step.

iii) Highlight those faults that cannot be isolated by the information provided by the DG model and the sensor set obtained in the steps (i) and (ii). They will be left to the PCA fault diagnostic system for further detection and isolation.

IV. Application to Helical Coil Steam Generator Systems

A. System Description

The International Reactor Innovative & Secure (IRIS) is one of the next generation nuclear reactor designs developed by an international team of industry, national laboratory, and university partners led by Westinghouse Electric Company [23]. The IRIS is a member of the integral primary system reactor class of designs which houses all functions of the primary coolant system inside a single reactor pressure vessel, as shown in Fig. 3. Eight spool-type primary coolant pumps, eight steam generators, and control rod drives are fully integrated into the reactor vessel.

Eight helical coil steam generators (HCSG) are installed in four pairs in the annular space between the core barrel and the reactor vessel wall. In the HCSG system, 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 height and the secondary fluid flows upward inside the coiled tubes from the bottom to the top. 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. The saturated region begins when the bulk fluid becomes saturated.

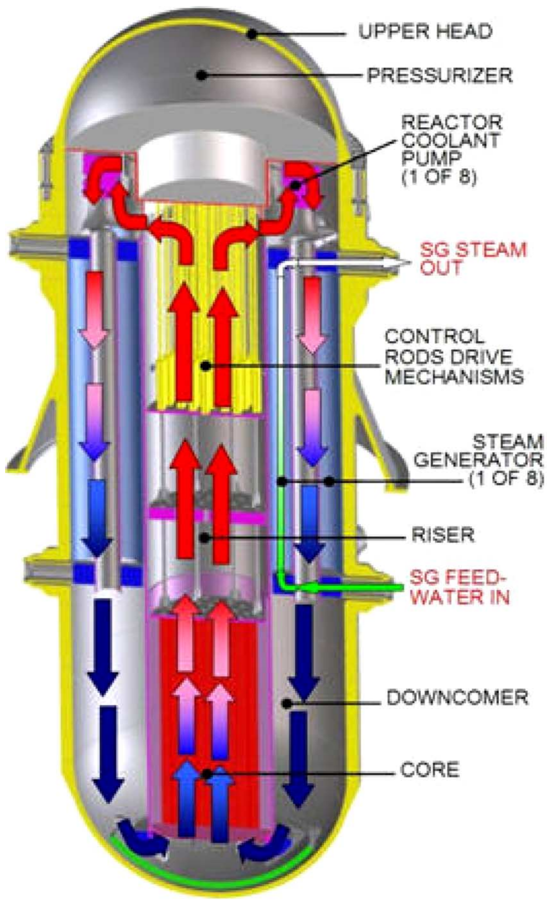

Fig. 3. IRIS primary system layout [23].

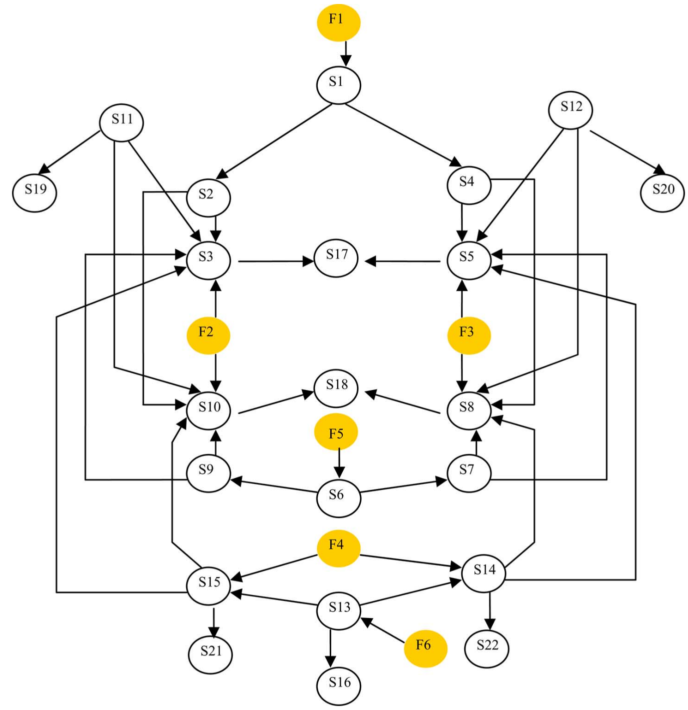

Fig. 4. Directed graph of one pair of HCSGs.

The heat transfer in the saturated boiling region is dominated by nucleate boiling, which is much more efficient than single-phase heat transfer. When the steam quality becomes one, the liquid evaporation ceases and the steam becomes superheated.

An IRIS simulation model developed previously at the University of Tennessee is used for this work, which includes reactor core, HCSGs, and balance-of-plant (BOP) systems [24]. The IRIS simulation is developed in MATLAB/SIMULINK environment. The six-group point reactor kinetics equations along with the Mann's nodal model are used to develop the reactor core heat transfer model [25]. The HCSG equations can be found in [26].

For one pair of HCSGs, the DG model is constructed based on the steady state mass and heat balance equations [26]. A total of 22 available sensors (S nodes in Fig. 4) are listed in Table I. And six F nodes in Fig. 4 represent the postulated faults in the system, as described in Table II. Both process faults and sensor faults are considered in the HCSG fault diagnosis. Three sensor faults considered are sensor drifts; and the thermal degradation of SG-A and SG-B, as well as the secondary flow distribution anomaly, are process faults considered for the HCSG system. The DG model clearly illustrates the cause-effect relationships among the involved variables and the propagation pathways from the fault nodes to the other nodes.

TABLE I
AVAILABLE SENSORS FOR A PAIR OF HCSGS

Sensor Nodes	*Description*	*Sensor Nodes*	*Description*
S_1	T_{hot} of SG-A&B	S_{12}	Primary coolant inlet flow to SG-B
S_2	T_{hot} of SG-A	S_{13}	Total feed flow
S_3	T_{cold} of SG-A	S_{14}	Feed flow to SG-B
S_4	T_{hot} of SG-B	S_{15}	Feed flow to SG-A
S_5	T_{cold} of SG-B	S_{16}	Total steam flow
S_6	T_{feed} of SG-A&B	S_{17}	T_{cold} of SG-A&B
S_7	T_{feed} of SG-B	S_{18}	T_{steam} of SG-A&B
S_8	T_{steam} of SG-B	S_{19}	Primary coolant outlet flow from SG-A
S_9	T_{feed} of SG-A	S_{20}	Primary coolant outlet flow from SG-B
S_{10}	T_{steam} of SG-A	S_{21}	Steam flow from SG-A
S_{11}	Primary coolant inlet flow to SG-A	S_{22}	Steam flow from SG-B

TABLE II
FAULT NODES FOR A PAIR OF HCSGS

Fault	*Description*	*Fault Direction #*
F_1	Hot leg temperature sensor fault	1
F_2	SG-A heat transfer degradation	2
F_3	SG-B heat transfer degradation	3
F_4	Secondary flow distribution anomaly	4
F_5	Feedwater temperature sensor fault	5
F_6	Feedwater flow sensor fault	6

B. Results of Optimal Sensor Selection

Firstly, the greedy search heuristic is used to find the minimum set of sensors required to observe all the six faults listed in Table II for one pair of HCSGs. This is a minimum set-covering problem that has been discussed in the previous section. This optimization problem can be formulated as follows:

$$\text{minimize} \left[\sum_{i=1}^{22} x_i\right] \tag{12}$$

subject to

$$\sum_{i=1}^{22} D_{ij} x_i \geq 1, \quad j = 1, \ldots, 6 \tag{13}$$

$$x_i \in \{0, 1\}, \quad i = 1, \ldots, 22. \tag{14}$$

Equation (12) is the objective function of the set-covering problem, where x_i is the decision variable. Equation (13) is a constraint to ensure that each fault is covered by at least one sensor, where D_{ij} is the $(i, j)_{\text{th}}$ entry of the constraint coefficient matrix whose elements comprise of either "1" or "0." Finally, (14) allows the decision variable x_i to only take binary numbers.

Solving the set-covering problem gives nodes $[S_3, S_5]$ as the sensor set. Even though all the faults can be detected, not every one of them can be distinguished from one another.

To obtain the set of sensors that gives maximum resolution under single-fault assumption, additional virtual faults must be created as discussed in the previous section. This involves generating $C_6^2 = 15$ virtual faults. Therefore, the HCSG system now has 21 faults (6 original faults plus 15 virtual faults). The new optimization problem can be modified as follows:

$$\text{minimize} \left[\sum_{i=1}^{22} x_i\right] \tag{15}$$

subject to

$$\sum_{i=1}^{22} D_{ij} x_i \geq 1, \quad j = 1, \ldots, 21 \tag{16}$$

$$x_i \in \{0, 1\}, \quad i = 1, \ldots, 22. \tag{17}$$

The greedy search heuristic for fault diagnostic observability is applied to the new problem, which generates $[S_3, S_5, S_8, S_{10}, S_{13}, S_{16}]$ as the minimum sensor set for full isolation of the six postulated faults. The advantage of using this optimized sensor set is that fault propagation information about the HCSG system is utilized, and some basic properties such as fault detectability and identifiability are already taken into account before PCA is employed to monitor system behavior.

C. PCA-Based Fault Diagnostic Results

A simulation database without any faults is created for the pair of helical coil steam generators (HCSG), SG-A and SG-B, under the different power levels ranging from 40% to 100% plant capacity. The six postulated fault cases are simulated and the faulty data are generated as well. Included in the simulation are the six sensors identified by using the aforementioned greedy search algorithm:

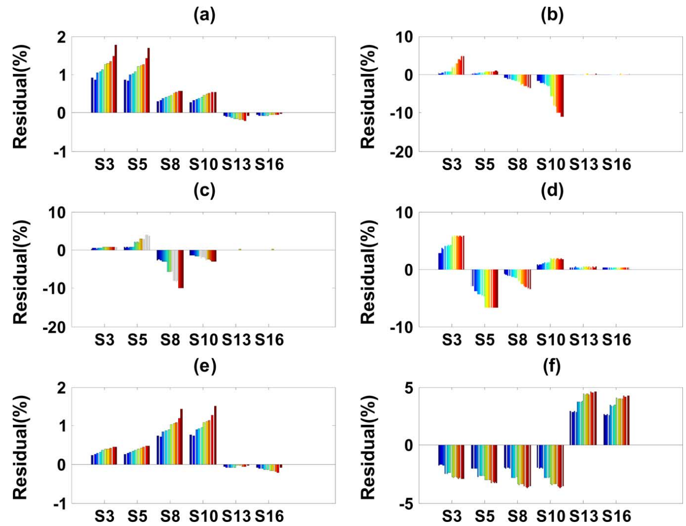

Fig. 5. Residual patterns for six HCSG faults. (a) Fault #1, (b) Fault #2, (c) Fault #3, (d) Fault #4, (e) Fault #5, (f) Fault #6.

S_3: cold leg temperature of SG-A;

S_5: cold leg temperature of SG-B;

S_8: steam temperature leaving the secondary side of SG-B;

S_{10}: steam temperature leaving the secondary side of SG-A;

S_{13}: feed water flow going into the secondary side of SG-A and SG-B;

S_{16}: steam flow leaving the secondary side of SG-A and SG-B.

A PCA model is developed based on the simulated data for normal operation. The principal component loadings P and the scores T in the PC subspace are obtained in a way that is described in (1) previously. It is assumed that small residuals are generated and limited to a certain range if there are no faults in the process. However, the causal relations among the process variables are to be violated if one of the six faults occurs. As a result, the mapping of fault residuals from residual generators or system models increases in a specific direction. In this study, the residuals are calculated as described in (2), using the developed PCA model along with faulty simulation data. And they are illustrated in Fig. 5 for all the six postulated faults.

As an example to understand the fault residual patterns, the secondary flow distribution anomaly (Fault #4) is discussed here. The secondary flow distribution anomaly is a process fault in the HCSG system. When this fault occurs, the flows going into the secondary side of each steam generator will be different. However, because the secondary fluid flows inside the helical coil tubes, it is unrealistic to directly measure the flow rate into each steam generator and the fault effects cannot be directly observed based on the flow rates. For this reason, the fault needs to be monitored from the other measured variables such as the primary outlet temperatures and the steam outlet temperatures.

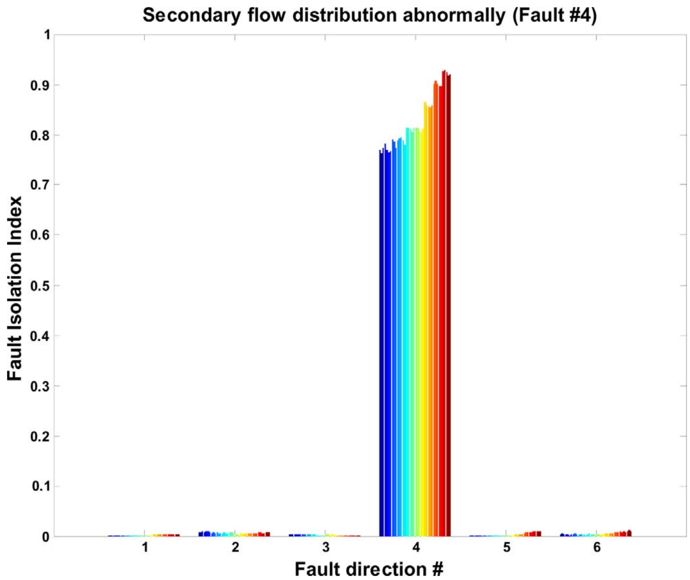

Fig. 6. Fault isolation index for secondary flow distribution anomaly.

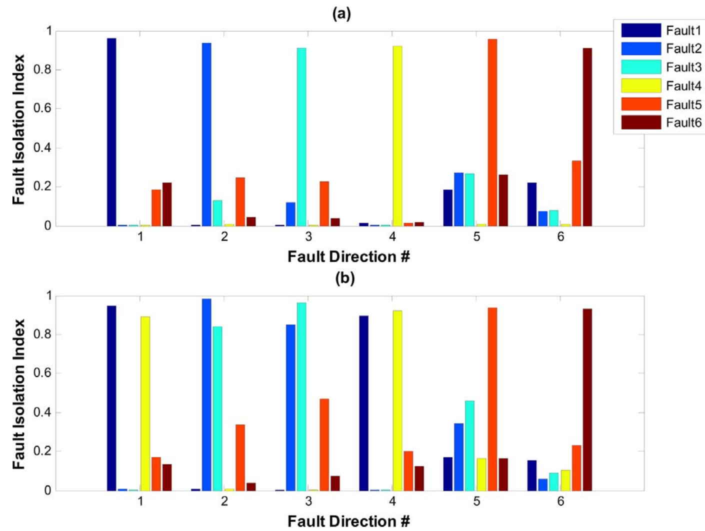

Fig. 7. Fault isolation index for a pair of HCSGs. (a) Optimized Sensor Set, (b) Reduced Sensor Set.

As shown in Fig. 5(d), the cold leg temperature (S_3) and steam outlet temperature (S_{10}) of SG-A have positive components, indicating an increase in both measurements when the secondary flow rate into the SG-A decreases; and the cold leg temperature (S_5) and steam outlet temperature (S_8) of SG-B have negative components, indicating a decrease in them when the secondary flow rate into the SG-B increases. Note that this fault case has been simulated under different power levels (40% to 100%), thus the fault residuals are shown in different colors in the figure.

Characterized in the (3)–(7), the PCA-based fault isolation scheme is implemented on those fault residuals. Six fault directions correspond to the six fault cases. Fig. 6 illustrates the secondary flow distribution anomaly isolation. It can be seen that the fault isolation index on fault direction #4 is close to unity, while the fault isolation indices on the other five fault directions are extremely small. Thus, satisfactory isolation of Fault #4 is achieved.

For the sake of comparison, we remove two temperature sensors, both in SG-B (S_5 and S_8), from the optimized sensor set. The four remaining sensors $[S_3, S_{10}, S_{13}, S_{16}]$, therefore, constitute the “reduced sensor set”. New PCA models are then built upon this set of sensors for the HCSG fault diagnosis. The fault isolation index is calculated for each fault scenario. Fig. 7(a) shows fault isolation of the HCSG system using the 6-sensor optimized set. It is found that all the six postulated faults are diagnosed correctly as the maximum isolation index for each of them shows up on the corresponding fault direction. Fig. 7(b) illustrates the fault isolation indices when the reduced sensor set is used. It is seen that when the hot leg temperature sensor is under degradation (Fault #1), the isolation index values on both fault direction #1 and fault direction #4 are high, which is difficult for fault isolation. Same problems arise for the isolation of Faults #2, #3, and #4. Thus, the reduced sensor set $[S_3, S_{10}, S_{13}, S_{16}]$ appears to be insufficient for fault diagnosis purposes. These comparison plots illustrate the effectiveness of the proposed optimal sensor selection scheme.

V. Concluding Remarks

A design framework, based on detection and isolation of faults in sensors, devices, and the plant process, is developed for determining optimum sensor selection. The algorithms use the directed graph approach that characterizes cause-effect propagation among various process variables. The greedy search heuristic is applied to solve the formulated optimization problems. The results show the effectiveness of the sensor selection approach in automating the choice of sensors for the objective of fault detection and isolation.

A data characterization using the PCA algorithm is introduced to generate fault signatures of the postulated faults in the HCSG system. The fault isolation index provides a convenient means of isolating faults using projections of the residuals on the various fault directions. The continuation of research includes sensor selection design for the diagnosis of multiple faults that may occur simultaneously, and the application to a nuclear desalination plant. The use of optimal sensor selection also provides a systematic approach to signal selection for effective fault monitoring.

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