U-tube Steam Generator Fault Detection Using Fuzzy Model

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***Abstract*— In safety critical system like power plant system, the problem of detecting the occurrence of faults is of paramount importance due to their disastrous consequences. To allow efficient performance under different operating conditions, a power plant system requires the integration of many subsystems. This results in a complex system which will inevitably be subjected to faults caused by actuators, sensors or subsystems faults during operation. One of the major subsystems, in power plant is U-tube Steam Generator (UTSG). This paper is concerned with Fault Detection and Isolation (FDI) of UTSG system using fuzzy model. These methods aims at checking the consistency between observed and predicted behaviour by residuals. When an inconsistency is detected between the measured and predicted behaviours obtained using a faultless system model, a fault can be indicated. Simulation results presented in the final part of the paper confirm the effectiveness of this approach.**

***Index Terms*— Fault detection; Fuzzy model; PWR Power Plant; Steam generator**

I. Introduction

SINCE no system in the real world can work perfectly at all time under all conditions, it is crucial to be able to detect and identify the possible faults in the system as early as possible so that measures can be taken to prevent significant performance degradation or damages to the system. This is particularly true in safety critical applications, such as power plants.

Power plants generate electricity by driving the armature coupled to a steam turbine using the heat produced from continuous fission of fuel. As shown in Fig.1, for a PWR power plant to perform the function of generating electricity, there are approximately one hundred support systems. In addition, for emergencies, there are dedicated systems to mitigate the consequences of accidents. This results in a complex system which will inevitably be subjected to faults caused by actuators, sensors or systems faults during operation. If faults occur, it is very difficult for a human operator to perform routine tasks, such as distinguishing normal from abnormal conditions and predicting future states, etc. A minor and often benign fault could potentially develop into catastrophic events if left unattended for or incorrectly responded to. Therefore proper and timely fault diagnosis is of premier importance to guarantee the safe and reliable operation.

In PWR power plants, the design of a single system to detect and isolate all faults would be difficult due to the size of the Fault Detection and Isolation (FDI) problem. To overcome this problem, a modular FDI architecture can be designed for individual PWR systems. Each system of the PWR with measurable inputs and outputs can be isolated from the rest of the plant and can be diagnosed separately. This allows the problem of FDI to be broken down into the more controllable tasks. One of the major subsystems, in PWR power plant is U-tube Steam Generator (UTSG). This paper is concerned with fault detection of UTSG system using fuzzy model.

A fault is defined as the unpermitted deviations of at least one characteristic property or parameter (feature) of the system from the acceptable, usual, standard condition. The goal of fault detection (Ding, 2008; Isermann, 2006), is the determination of faults present in a system and their instant of detection. Model-based fault detection methods rely on the concept of analytical redundancy. The simplest analytical redundancy scheme consists in the comparison of system output measurements with the corresponding analytically computed values, obtained from measurements of other variables and/or from previous measurements of the same variable by means of a model. In the general case, different estimations of a same variable, measured or not, can be compared. The resultant differences are called *residuals*, which are indicative of faults in the system. Under ideal conditions, residuals are zero in the absence of faults and non-zero when a fault is present. In this paper, the fault detection problem for UTSG nonlinear systems is addressed.

The remainder of this paper is organized as follows: in *Section 2*, UTSG dynamic is reviewed. Fuzzy model applied to Fault Detection is recalled in *Section 3*. Result are shown in *Section 4*. Finally, the major conclusions are drawn in *Section 5*.

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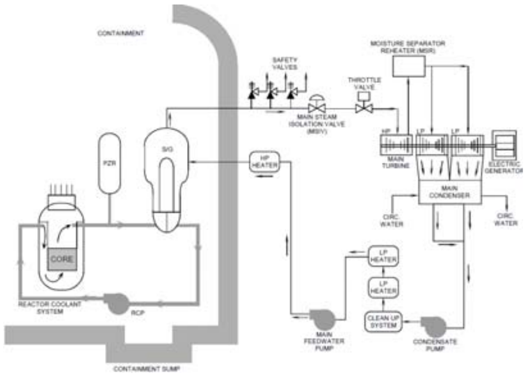

Fig.1:A schematic of the PWR and main steam subsystems.

II. UTSG DYNAMICS

A. *UTSG nonlinear model*

In UTSG operation, high pressure liquid from the power plant primary loop flows in and out of primary side (also called the tube side). The primary side liquid flow path is up from the hot leg inlet, to a semicircular turnaround and then down to the cold leg exit Fig.1. Feedwater enters the UTSG from the steam plant. At this junction, the feed-water mixes with the liquid being discharged from the liquid-vapor separation devices. The liquid mixture flows downward through the annular *downcomer* region. After a turn at the bottom of the downcomer, the liquid is heated during an upward passage outside the U-tubes in the *tube bundle region*. The heat transferred across the tube bundles causes evaporation of some of the liquid and a two-phase mixture exits from the tube bundle entering the *riser*. The liquid and vapor are partially separated by swirl vanes at the top of the riser and more separation occurs near the top of the UTSG. The vapor that results from this is saturated with a quality of about 99.75%. This vapor is then fed to the turbine units and other auxiliary equipment.

UTSG is a highly nonlinear, unstable and multivariable thermal-hydraulic process system. The three outputs of a UTSG which are usually measured are the water level $y = L_w$, the cold-leg temperature T_{cl}, and the secondary steam pressure P_{sat}. The five disturbances acting upon the system are the hot-leg temperature T_{hl}, the primary pressure P_{pr}, the primary mass flow rate q_{pr} (always a constant within small random variations), the feedwater temperature T_{fw}, and steam flow rate $v = q_{st}$. There is only one manipulated control input which is the feedwater flow rate $u = q_{fw}$. Changes in the power demand are translated to changes in the UTSG steam flow rate and this signal provides the persistent excitation needed for effective system identification. The hot-leg temperature and the feedwater temperature are usually expressed as functions of the operating power, and given the current operating power level they can all be calculated in a straightforward manner.

A UTSG simulator developed by Strohmayer (1982) and modified by Choi (1987) is adopted for the purpose of this work. The simulator was developed using lumped parameter, mass, momentum, and energy conservation equations. An integrated secondary recirculation-loop momentum equation has been incorporated into simulator to calculate the water level. There are seven control volumes in the model spatial domain: four on the secondary side, the steam dome-downcomer (SDD) region, the tube bundle region and the riser region, which is divided into a saturated volume and a subcooled volume. The three control volumes on the primary side are the inlet plenum, the outlet plenum, and the fluid volume within the tube bundle region.

B. *Fault scenarios*

From the continuous-time non-linear equations described in previous section, a simulator has been implemented in Matlab/Simulink. In the simulations, three different cases of faults in the steam generator have been diagnosed. The proposed faults are: the closure of main steam isolation valve [f_1], the main feedwater valve opening increase[f_2], and the main feedwater valve opening decrease [f_3]. Faults are inserted in the UTSG simulator. The simulation is run for 600 s. Faults create changes in several residuals obtained by using dynamic NF models of the process under examination. Both normal and faulty operation data were generated using the UTSG simulator.

III. FAULT DETECTION USING FUZZY MODEL

The model-based technique proposed in (Mendonça et al. 2009) uses a fuzzy model for the process running in normal operation, and one model for each of the faults to be detected. Suppose that a process is running, and *n* possible faults can be detected. The fault detection and isolation system for these *n* faults is depicted in Fig. 2. The multidimensional input of the system, *u*, enters both the process and a model (observer) in normal operation. The vector of residuals *e* is defined as

$$e = y - \hat{y}$$

where y is the output of the system and $\hat{y}$ is the output of the model in normal operation. When any component of *e* is bigger than a certain threshold, the system detects a fault.

A. *Fault isolation using fuzzy model*

In the FDI architecture (see Fig. 2), fault isolation is obtained by residual evaluation of each of the *n* models, one for each fault. At each time instant *k*, a residual e_i is computed for each fault

$$e_i(k) = y_i - \hat{y}_i$$

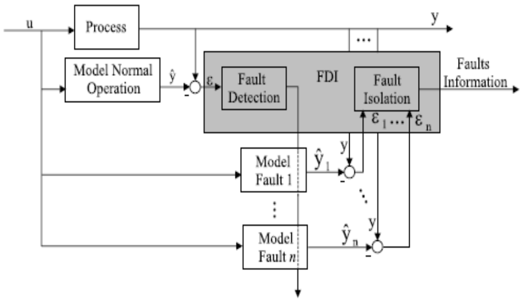

Fig. 2. Fault detection and isolation scheme.

where $\hat{y}_i$ is the output of the observer for the fault i, with $i=1,2,...,n$. the residual e_i is a vector with dimension m, which is equal to the number of outputs. Each scalar residual can be noted as

$$e_{ij}(k) = y_{ij} - \hat{y}_{ij}$$

where $\hat{y}_{ij}$ is the output of the observer for the fault i, and output j, with $j=1,...,m$.

1) Membership functions based on the residuals

A membership function μ_{eij} is derived for each residual e_{ij}. The membership functions are trapezoidal, as this type revealed to be the most appropriate to describe the residuals in a simple and effective way. The spread of these membership functions is chosen based on the maximum and minimum variations of the residuals, which can be obtained experimentally. The core of each membership function indicates the possible isolation of a fault, i.e., if e_{ij} is zero, then the value of the membership function μ_{eij} should be one. To accommodate process noise, disturbances and model-plant mismatches, the core is a small interval around zero. The size of this interval is again determined based on experimental data.

The m membership functions $\mu_{i1},...,\mu_{im}$ must be aggregated using a conjunction operator, which assures that a fault is isolated only when all the residuals e_{ij} are close to zero. The aggregation can be given by

$$\gamma_i = t(\mu_{i1},\ldots,\mu_{im})$$

where t is a triangular norm, which is in this paper the minimum operator. Other t-norms could be used, but the min is used for the sake of simplicity. The function γ_i resulting from aggregating the membership functions μ_{eij} will be used to isolate the faults.

2) Fuzzy decision factors

At each time instant the outputs $y_i(k)$ are read from a sensor. The outputs of each faulty fuzzy model $\hat{y}_i(k)$ are computed, as well as the residuals $e_{ij}(k)$. Note that these computations are simple and fast (multiplications and additions). This characteristic can be very important for real-time implementations. Further, at each time instant the value of each function γ_i can also be computed in an easy and fast way. Let $d_i(k) \in [0,1]$ be the value of γ_i at time instant k. We called $d_i(k)$ a fuzzy decision factor. A fuzzy decision factor $d_i(k)$ is high only if all the residuals are close to zero.

To isolate a fault i, the value of $d_i(k)$ must be higher than a threshold T, which must be close to one. The threshold is obtained experimentally and defines the regions of fault and no fault. In practice, the definition of this value revealed to be relatively easy, and a value around $T=0.7$ isolate the faults properly. This value can suffer a slight change in others processes. Note that several $d_i(k)$ can be above the threshold at a certain time k. Therefore, a fault i is isolated only when the remaining faults are below T. However, if only one fault is above the threshold at a certain time instant, it can occur due to noise or model errors. Therefore, this approach considers that a fault is isolated when d_i is above the threshold T and the remaining d_l decision factors are below the same threshold for t_k consecutive time instants.

B. Fuzzy modeling

The Takagi-Sugeno-Kang (TSK) fuzzy models are suitable to model a large class of nonlinear systems, they can describe complex and highly nonlinear models only with a small number of rules see (Takagi T., 1985), (Sugeno M., 1993). TSK fuzzy model consists of if-then rules with fuzzy antecedents and mathematical functions in the consequent part. The antecedent fuzzy sets divide the input space into a number of fuzzy regions, while the consequent functions describe the system's behavior in these regions. Assume that data from an unknown system $y=F(x)$ is observed. The aim is to use this data to construct a deterministic function $y=f(x)$ that can approximate $F(x)$. The function f is represented as a collection of fuzzy if–then rules.

Fuzzy modeling and identification from measured data are effective tools for approximation of uncertain nonlinear systems. Such a modeling technique is applied successfully to a large class of single-input, single-output (SISO), as well as multi-input, single-output (MISO) nonlinear dynamic systems. The simplest and most widely used approach for modeling nonlinear dynamics using TSK fuzzy model is extending the ARX Auto Regressive with EXogenous inputs model to form the so called Nonlinear Auto Regressive with EXogenous inputs (NARX) model, The TSK fuzzy model consists of a set of rules with the following structure:

$$R_i : \text{if } x_1 \text{ is } A_{i1} \text{ and } \cdots \text{ and } x_{in} \text{ is } A_{in} \text{ then } y_i = a_i x + b_i$$

with $i=1,...,K$. Here, R_i is the ith rule, $A_{i1},..., A_{in}$ are fuzzy sets defined in the antecedent space, x$=[x_1,..., x_n]^T$ is the antecedent vector, $\boldsymbol{a}_i=[a_{i1},...,a_{in}]^T$ and b_i are model parameters to be determined, and y_i is the rule output variable. K denotes the number of rules in the rule base, and the aggregated output of the model, $\hat{y}$, is calculated by taking the weighted average of the rule consequents:

$$\hat{y} = \frac{\sum_{i=1}^{K} \beta_i y_i}{\sum_{i=1}^{K} \beta_i}$$

where β_i is the degree of activation of the i[th] rule:

$\beta_i = \prod_{j=1}^{n} \mu_{A_{ij}}$, $i=1,...,K$ and μ_{Aij} is the membership function of the fuzzy set A_{ij} in the antecedent of R_i. The nonlinear identification problem is solved in two steps: structure identification, and parameter estimation.

1) Structure identification

The structure of the model must be determined first. To identify the fuzzy model, the regression matrix X and an output vector y are constructed from the available data:

$$X = [\mathrm{x}_1, \ldots, \mathrm{x}_N]^T, \quad Y = [y_1, \ldots, y_N]^T$$

Thus, the matrix to be clustered is given by $Z=[X,Y]^T$. The parameter $N»n$ is the number of samples used for identification. In this step, the significant inputs are chosen. A decision tree search approach have been proposed for input selection in fuzzy modeling (Mendonça, Vieira, & Sousa, 2007). That paper proposed two different approaches of decision tree search algorithms: bottom–up and top–down. The branching decision at each node of the tree is made based on the accuracy of the model available at the node. The bottom–up approach starts with only one input, and increases the number of inputs until a given performance criterion does not improve. This method leads to simple and accurate fuzzy models, as desired in model based FDI applications. Note that the smaller the vector x, the faster the model. Moreover, the fuzzy models for FDI must be both simple and accurate models to detect the faults as fast as possible. Therefore, the fuzzy modeling approach used in this paper uses the bottom–up approach.

2) Parameter estimation

The antecedent fuzzy sets, A_{ij}, and the consequent parameters, $\boldsymbol{a}_i$, b_i, are determined in this step. The Gustafson–Kessel fuzzy clustering algorithm computes a fuzzy partition matrix $\boldsymbol{U}$, whose ik^{th} element $u_{ik} \in [0\ 1]$ is the membership degree of the data object $\mathbf{z}_k$ in cluster i.

The fuzzy sets in the antecedent of the rules are obtained from the partition matrix $\boldsymbol{U}$. One-dimensional fuzzy sets A_{ij} are obtained from the multidimensional fuzzy sets defined point-wise in the i^{th} row of the partition matrix by projections onto the space of the input variables.

The point-wise defined fuzzy sets A_{ij} are approximated by suitable parametric functions to compute $\mu_{Aij}(x_j)$ for any value of xj (Babuška, 1998). The consequent parameters for each rule are obtained as a weighted ordinary least-square estimate. More details of this fuzzy identification method can be found in (Babuška 1998).

IV. Simulation Results

A. Faultless scenario

This scenario is used to test the fuzzy model in faultless situation. The fuzzy model identified using the fault free data gathered from the simulator can be used for residual generation. The residual signals are calculated as difference between estimated outputs given by the fuzzy model and the actual value of the outputs. The responses of the proposed fuzzy models and the responses of the real system are shown in Figs. 3–4. A similar comparison between the responses of the proposed models with the outputs of the simulator shows the effectiveness and feasibility of the developed models in terms of more accurate and less deviation between the responses of the models and the real outputs. This validates the accuracy of the proposed models over the operating ranges. It should be emphasized that the models could accurately describe the behavior of the steam generator for specific operating conditions. Thus, they are not global and could not be considered as reliable models outside that range. Nevertheless, it is possible to achieve some limited numbers of models over a full range of input–output data to cover the wide range of operation. A nuclear plant usually operates at 100% full power, and this is the power level of interest for fault diagnosis. The simulated data belongs to the normal operation of the steam generator with full power of the plant. The proposed models are merely valid for these conditions. Thus, conditions such as the start up, or the cases when the plant is working with very low power, requires different models, with the same and/or different modeling approaches.

B. faulty Scenario

The UTSG simulator was run with the fault free and then all faulty scenarios appearing one by one over the operating ranges. The generated residuals for the closure of main steam isolation valve are presented in Figs. 5–6. The residuals are close to zero before fault inception at 100 s. Subsequently, residuals deviate from zero in different manners. A large set of data was generated for the fuzzy decision factors. The fuzzy decision factors has been computed using this data set as explained in section 3. In all the simulation experiments faults were detected timely using this FDI method.

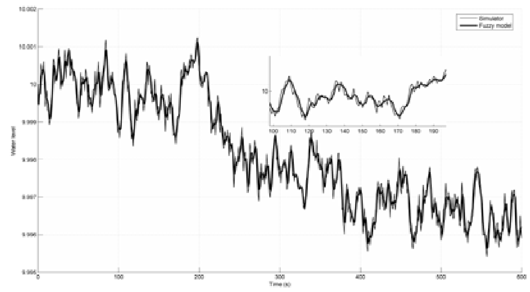

Fig.3: Fuzzy model performance for steam generator water level.

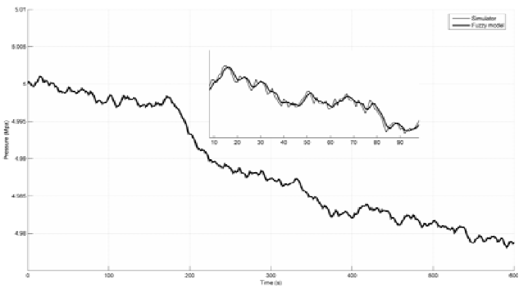

Fig.4: Fuzzy model performance for steam generator secondary steam pressure.

V. Conclusions

The accurate and timely fault diagnosis of safety critical systems is important because it can decrease the probability of catastrophic failures, increase the life of the plant, and reduce maintenance costs. In this paper, a multiple-model FDI scheme has been presented for a steam generator. Fuzzy techniques have been applied for both residual generation and fault isolation. In the first step of FDI, the use of fuzzy model is considered as an important extension to the traditional model-based approach for residual generation. Simulation results show the effectiveness of the used approach. The fault detection results obtained using the proposed approach show good performance in the considered scenarios. Future research will consider the extension of the proposed FDI scheme to a larger number of faults.

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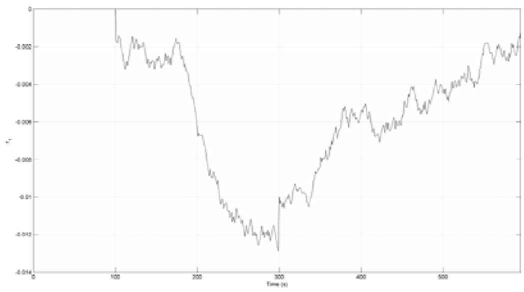

Fig.5: Generated residual of steam generator water level for f1.

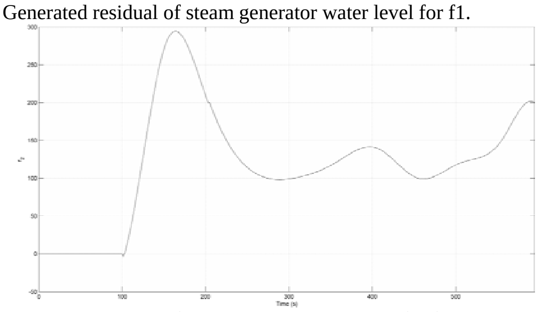

Fig.6: Generated residual of secondary steam pressure for f_1.

References

[1] Babuska, R., 1998. Fuzzy modeling for control. Boston, MA: Kluwer Academic Publishers.

[2] Choi, J.I., 1987. Nonlinear digital computer control for the steam generator system in a pressurized water reactor plant. Ph.D. dissertation. Massachusetts Inst. Technol., Cambridge.

[3] Ding S., 2008. Model-based fault diagnosis techniques: design schemes, algorithms, and tools. Springer Verlag.

[4] Isermann R., 2006. Fault-diagnosis systems: an introduction from fault detection to fault tolerance. Springer Verlag.

[5] Mendonça L.F. , J.M.C. Sousa, J.M.G. Sa´ da Costa, 2009. “An architecture for fault detection and isolation based on fuzzy methods” , *Expert Systems with Applications* 36 (2009) 1092–1104.

[6] Mendonça, L. F., Vieira, S. M., & Sousa, J. M. C. (2007). Decision tree search methods in fuzzy modeling and classification. *International Journal of Approximate Reasoning*, 44(2), 106–123.

[7] Takagi, T., & Sugeno, M., 1985. Fuzzy identification of systems and its applications to modelling and control. *IEEE Transactions on Systems Man and Cybernetics*, 15(1), 116–132.

[8] Sugeno, M., & Yasukawa, T., 1993. A fuzzy-logic-based approach to qualitative modeling. IEEE *Transactions on Fuzzy Systems*, 1(1), 7–31.

[9] Strohmayer,W.H., 1982. “Dynamic modeling of vertical U-tube steam generators for operational safety systems”. Ph.D. dissertation. MIT, Cambridge, MA.

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