# A PC-BASED SIGNAL VALIDATION SYSTEM FOR NUCLEAR POWER PLANTS

Ali S. ERBAY and Belle R. UPADHYAYA
The University of Tennessee,
Knoxville, U.S.A.

Serhat SEKER
Istanbul Technical University
Istanbul, Turkey

## Abstract

In order to achieve the desired operating configuration in any process, the system conditions must be measured accurately. Examples of measurements are temperature, pressure, flow, level, motor current, vibration, etc. However, in order to operate within desired limits, it is important to know the reliability of plant measurements. Signal validation (SV) deals with this issue, and is defined as the detection, isolation and characterization of faulty signals. Also referred to as fault detection, signal validation checks inconsistencies among redundant measurements and estimates their expected values using other measurements and system models. The benefits of SV are both economic and safety related. Catastrophic signal failure can result in plant shutdown and lost revenue. Pre-catastrophic failure detection would therefore minimize plant downtime and increase plant availability. The control action taken depends primarily upon the information provided by the plant instruments. Thus, increased plant productivity and increased reliability of operator actions, would result from the implementation of such a system. The purpose of this study is to investigate some of the existing signal validation methods by incremental improvements and to develop new modules. Each of the SV modules performs a specific task. The architecture consists of four modules, an information base and a system executive integrated with a graphical user interface (GUI). All the modules are used for validation during both steady-state and transient operating conditions. The entire system was developed in the PC-framework under Microsoft Windows™. Some improvements were made in the structure of static data-driven models by incorporating one and two-step regression. Kalman filtering is based on the use of a physical model of plant components and was implemented for a steam generator system in a nuclear power plant. This is applicable to both steady-state and transient operations. The system executive performs several tasks: sequencing of module operation, requisition of additional data, evaluating SV information from the various modules, and displaying instrument or system status to the operator. The decision-making within the system executive was developed using a robust fuzzy logic approach. The computer display was performed by GUI objects compatible with Microsoft Windows.

## INTRODUCTION

In order to achieve the desired operating configuration in any process, the system conditions must be measured accurately. Examples of measurements are temperature, pressure, flow, level, motor current, vibration, etc. However, in order to operate within desired limits, it is important to know the reliability of plant measurements. Signal validation (SV) deals with this issue, and is defined as the detection, isolation and characterization of faulty signals. Also referred to as fault detection, signal validation checks inconsistencies among redundant measurements and estimates their expected values using other measurements and system models.

The benefits of SV are both economic and safety related. Catastrophic signal failure can result in plant shutdown and lost revenue. Pre-catastrophic failure detection would therefore minimize plant downtime and increase plant availability. The control action taken depends primarily upon the information provided by the plant instruments. Thus, increased plant productivity and increased reliability of operator actions, would result from the implementation of such a system.

The purpose of this study is to investigate some of the existing signal validation methods by incremental improvements and to develop new modules. Each of the SV modules performs a specific task. The architecture consists of four modules, an information base and a system executive integrated with a graphical user interface (GUI). The following four modules were integrated in the new PC-based system (See Fig. 1).

- Generalized Consistency Checking (GCC) and Sequential Probability Ratio Test (SPRT),
- Process Empirical Modeling (PEM),
- Artificial Neural Network (ANN) prediction, and
- Kalman Filtering Technique (KFT).

All the modules are used for validation during both steady-state and transient operating conditions. The entire system was developed in the PC-framework under Microsoft Windows™. Some improvements were made in the structure of static data-driven models by incorporating one and two-step regression. Kalman filtering is based on the use of a physical model of plant components and was implemented for a steam generator system in a nuclear power plant. This is applicable to both steady-state and transient operations.

The system executive performs several tasks: sequencing of module operation, requisition of additional data, evaluating SV information from the various modules, and displaying instrument or system status to the operator. The decision-making within the system executive was developed using a robust fuzzy logic approach. The computer display was performed by GUI objects compatible with Microsoft Windows™.

## SIGNAL VALIDATION MODULES

The primary advantage of using different SV algorithms is to compensate for prediction errors during transient operating conditions, in which some SV modules may not give good estimations of the measured variables. Another potential benefit is to have software redundancy, so that false alarms may be reduced. These modules operate in parallel and the system architecture is flexible for adding or removing an SV module. Operational data from two pressurized water reactors (PWRs) were used to develop these modules.

### Generalized Consistency Checking (GCC) and Sequential Probability Ratio Test (SPRT)

The GCC and SPRT techniques were developed previously at The University of Tennessee and applied to a signal validation system.[1,2,3] GCC is a method for the systematic cross comparison of signals from redundant sensors measuring the same process variable. The algorithm provides information about measurement inconsistencies at each sampling instant. After excluding the signals with maximum inconsistency indices, the best estimate at any time is computed as a weighted average of the remaining signals. The procedure is then repeated for subsequent sampling instants. The algorithm does not make comparisons between sets of measurements at different times. Any two redundant measurements are defined to be inconsistent if the difference between their values is greater than a specified threshold value. This threshold value depends on the selected signal pair and is based on sensor tolerances and technical specifications. The inconsistency indices of the individual measurements and the best estimate for the given process variable are determined as functions of sampling time instants.

The SPRT has the ability to check and record sensor degradation. The SPRT makes decisions on the basis of cumulative information provided by the measurement history. Unlike the GCC method, the SPRT does not make inter-signal comparison or consistency checking among the signals. The SPRT is an optimal decision-making (DM) procedure and requires a minimum number of samples from a sensor to make decisions based on specified missed- and false-alarm probabilities. These quantities provide a measure of confidence for the decision. The SPRT is applied to the difference between the sensor output and the estimated value of the process variable. The estimate is obtained from the GCC algorithm. The SPRT uses recursive calculations of the logarithm of the likelihood ratio (LLR) function representing the degradation information of a sensor based on samples.

The SPRT is performed for bias and noise degradations after the GCC analysis of the module is completed. The two algorithms are combined as one module and produce several outputs that are used in DM:

- Estimate of the process variable,
- LLR for each signal,
- Inconsistency index for each signal, and
- Indication if the signal is excluded from calculations.

Figures 2 and 3 show results of this SV algorithm using operational data from a four-loop PWR power plant. The LLR value of -10 in Fig. 3 indicated that sensors 1 and 2 were normal while the +20 value of LLR indicated possible anomaly in sensor 3.

### Process Empirical Modeling (PEM)

The PEM module was developed and used previously at The University of Tennessee for signal validation applications.[1,2,3] The PEM establishes multiple-input single-output (MISO) models. The measured sensor output is then compared against a predicted output based on the PEM. The module provides an independent estimation of a process variable. Monitoring sensor degradation or drift by on-line monitoring of the sensor output is possible using the estimates of the PEM module.

The PEM creates an optimal nonlinear MISO model from a given data set. This data set has a similar function as the training data set used in artificial neural networks. The form of the data-driven predictive model is

$$y = c_0 + \sum_{i=1}^{m} c_i \Phi_i(\underline{x}) \tag{1}$$

where

$y$ = estimate of the process variable at time instant $t$,
$\underline{x}$ = vector of input signals at time instant $t$,
$m$ = number of terms in the model,
$\Phi_i$ = nonlinear function of input signals, and
$c_i$ = constant coefficient.

This equation can also be interpreted in the following form:

$$y = f(\underline{x}(t)) \tag{2}$$

As a new contribution of this research, the static model given in Equation (2) is extended also for dynamic systems in which system variables can change significantly over time. A system may be modeled with a first order or a second order differential equation in the form:

$$\frac{dy}{dt} = f(\underline{x}) \tag{3}$$

or

$$\frac{dy}{dt} = f\left(\frac{d\underline{x}}{dt}, \underline{x}\right) \tag{4}$$

or

$$y = f\left(\frac{d\underline{x}}{dt}, \underline{x}\right) \tag{5}$$

Using finite-difference numerical technique, the first derivative is approximated as

$$\frac{dy}{dt} = \frac{y(t) - y(t-1)}{\Delta t} \tag{6}$$

where $t$ denotes the discrete sampling time and $\Delta t$ denotes the sampling time interval. Then Equation (3) may be converted from continuous time domain to discrete time domain as:

$$y(t) = f(\underline{x}(t), y(t-1)) \tag{7}$$

Equations (4) becomes

$$y(t) = f\left(\underline{x}(t), \underline{x}(t-1), \underline{y}(t-1)\right) \tag{8}$$

and Equation (5) becomes

$$y(t) = f(\underline{x}(t), \underline{x}(t-1)) \tag{9}$$

Both forms of discrete representations (Equations (7) and (9)) were incorporated in the PEM module. The previous values of input and output vectors are treated as an additional input to the regular PEM model given in Equation (1). Thus, the algorithm remains the same for all forms of the model equation.

PEM was performed for two variables: steam generator wide range water level and steam generator pressure. Table I shows the functional forms of the PEM module for these two different data sets with the following input signals.

$x(1)$ = steam generator feedwater flow rate,
$x(2)$ = steam generator wide-range water level at previous time instant,
$x(3)$ = reactor coolant system (RCS) flow rate,
$x(4)$ = steam generator steam flow rate,
$x(5)$ = steam generator steam pressure at previous time instant,
$x(6)$ = hot leg temperature, and
$x(7)$ = cold leg temperature.

The models were created using 100 training patterns, which were sampled at regular intervals over the entire data interval. The PEM models were incorporated into the PC-based signal validation system. As seen in Table I, dynamic models improved the accuracy of the estimated variable. However, in some type of sensors, a static model is accurate enough to predict the estimated state variable.

## Artificial Neural Networks (ANNs)

ANNs are parallel computational models for mapping one set of data with another set. In this study, an SV module was developed using a hetero-associative backpropagation ANN. During ANN modeling, two types of models were taken into consideration: One incorporating Equation (2) and the other incorporating Equations (7) and (9). The hyperbolic tangent was chosen as the transfer function for the processing element. Figure 4 shows a backpropagation ANN for dynamic systems such as transient and semi-transient behaviors in Nuclear Power Plants.

The ANN module was developed with NeuralWare's NeuralWorks software with a fast-backpropagation algorithm.[4] The software produced a C subroutine which was incorporated into the PC-based signal validation system as an SV module. Results obtained from this SV module were similar in behavior to those obtained from PEM, provided that both the algorithms were executed with the same training data. Table II shows the signals used to estimate the steam generator wide-range water level and steam generator pressure.

## Kalman Filtering Technique (KFT)

The Kalman filtering technique (KFT) is an optimal state estimation algorithm for general stochastic systems.[5] It requires the knowledge of a dynamic system model and is applicable to both stationary and nonstationary processes. The KFT has been studied and developed thoroughly in several areas.

The Kalman filter can be thought of as an optimal estimator that produces three types of outputs,[6] given a noisy measurement sequence and the associated models (Fig. 5). It can be thought of as a state estimator or a reconstructor, that is, it reconstructs estimates of the state $x(t)$ from noisy measurements $y(t)$. In this respect, it is almost an implicit solution of equations: since the state is not available directly, the models used can be considered as the means to implicitly extract $x(t)$ from $y(t)$. Second, the Kalman estimator may be thought of as a measurement filter. It accepts a noisy measurement sequence $y(t)$, and produces a filtered measurement sequence $\hat{y}(t|t)$ as the output. Finally, the estimator serves as a whitening filter that accepts noisy correlated measurements $y(t)$ and produces uncorrelated or white random process $e(t)$, called the innovations sequence. The notation $(t|t\text{-}1)$ denotes an estimation for time instant $t$ with measurements given up to time $t$-1.

A process may be modeled by a set of stochastic linear vector difference equations in the state-space form as

$$x(t) = Ax(t-1) + Bw(t-1) \tag{10}$$

where $x$ is the state vector with Gaussian noise sequence $\{w\}$ and noise covariance $Q$. The corresponding measurement model is given by

$$y(t) = Cx(t) + v(t) \tag{11}$$

where $y$ is the measurement vector with Gaussian noise sequence $\{v\}$ and noise covariance $R$. Coefficient matrices $A$, $B$ and $C$ are determined using the parameters of the physical model. The equations that describe the state estimation are called the Kalman filter equations. The optimal filtered estimate $\hat{x}(t|t)$ is then computed recursively as[6]

$$\hat{x}(t|t) = \hat{x}(t|t-1) + G(t)e(t) \tag{12}$$

where

$\hat{x}(t|t-1) = A\hat{x}(t-1|t-1)$ = one-step state prediction,

$G(t)$ = Kalman gain, and

$e(t) = y(t) - C\hat{x}(t|t-1)$ = innovation sequence, information gained from a subsequent measurement.

The recursive algorithm of the KFT is illustrated in Fig. 6. The recursive algorithm is initiated with $P(0|0) = P(0)$, which is the initial error covariance matrix of the initial state estimation $\hat{x}(0|0)$. The algorithm is executed for each measurement sample, and a filtered estimate is calculated.

### Extension to State Estimation of Nonlinear Systems

The primary assumption made, in the development of the Kalman filter equations was that the system to be modeled should be linear. However, most of the real-world modeling includes nonlinear equations, so that a modification to the standard Kalman filtering algorithm is needed. For example the U-tube steam generator (UTSG) model of a PWR is described by nonlinear equations and is used in this study for the application of KFT.

The modification to the standard Kalman filter begins by modeling the system using nonlinear difference equations in the state-space form as

$$x(t) = f(x(t-1)) + w(t-1) \tag{13}$$

and the corresponding measurement model

$$y(t) = h(x(t)) + v(t) \tag{14}$$

where

*x(t)* = state vector with Gaussian noise sequence $\{w\}$ and noise variance $Q$,
*y(t)* = measurement vector with Gaussian noise sequence $\{v\}$ and noise variance $R$, and
*f(x(t)), h(x(t))* = nonlinear functions of the state vector.

The optimal filter estimate is calculated using the following equations

$$\hat{x}(t|t) = \hat{x}(t|t-1) + G(t)e(t) \tag{15}$$

$$\hat{x}(t|t-1) = f(\hat{x}(t-1|t-1)) \tag{16}$$

In the extended Kalman filter, the Kalman gain *G(t)* has partial differentiations of the nonlinear functions of the state vector. The overall algorithmic procedure for the extended Kalman filter in calculating the optimal estimates is similar to the one given in Fig. 6.

The PC-based signal validation system has a KFT module which is based on the extended Kalman filter, and uses a nonlinear model of the UTSG. This model was previously developed at The University of Tennessee for a four-loop PWR.[7] The model consists of 19 state variables for the steam generator and 4 state variables for the controller, for a total of 23 state variables. The measurement vector includes

- steam generator wide-range water level,
- steam generator pressure,
- steam generator main feedwater flow,
- steam generator steam flow,
- reactor coolant system (RCS) flow,
- hot leg temperature, and
- cold leg temperature.

The UTSG model equations were discretized in the form of Equation (16). The discretized model equations were used in calculating the state estimates and their partial differentials were used in calculating the Kalman gain. The results obtained from this technique indicate that the estimations from the KFT module were very close to the actual *good* measurements. The use of measurements provides high accuracy in estimating these variables.

## SIGNAL VALIDATION SYSTEM INTEGRATION

The system executive controls input-output among various devices and the programs. One important task of the system executive is to receive live data from an operational nuclear power plant. This is accomplished by using a local area network (LAN) and gathering information from a data acquisition computer. Figure 7 shows the schematic of acquiring live data for the PC-based signal validation program, whereas Fig. 1 shows a general overview of the integration of the individual SV modules

## Fuzzy Logic Decision Making

The decision-making (DM) algorithm consists of three steps:

1. Construction of fuzzy sets from primary events. These are errors between measurements and SV module estimations or other indices such as inconsistency indices from general consistency checking.
2. Propagation of fuzzy sets through the fault-tree (fuzzy OR gate).[8]
3. Comparison of the resultant fuzzy set with prototype fuzzy sets (*very bad, bad, medium, good* or *very good*) using dissemble index calculations.

In the first step, the SV modules produce an estimate. The absolute difference between the estimated and measured value is used to construct a fuzzy set in the truthness domain. For another module, like the GCC module, the inconsistency index may be used to construct this fuzzy set. A graphical representation of converting from crisp error to fuzzy truthness is given in Fig. 8a. Suppose the difference between the measured and estimated steam generator pressure is 30 psi. From Fig. 8a, this yields with 70% belief, the sensor is faulty (If the error is more than 40 psi, it is definite that the sensor is faulty). The truth 0.7 is then taken as the basis for the maximum of the membership function and a triangular membership function in the *Truth* domain *[0,1]* is constructed as shown in Fig. 8b. Here *Truth* is an indication of the truthness of the sensor being faulty. The relationship between the confidence and the error is different for each state variable and for each module. If the signal validation module produces estimates closer to the measurements, then the relationship between the error and confidence will be on a much tighter scale (e.g. 30 psi will mark a 100% confidence, rather than 30 psi marking 70% confidence of the sensor being faulty).

In the second step, every primary event (in this study the error between the measured and estimated state) of the fault-tree is considered as fuzzy and a membership function, $\mu_{PE}(x) \rightarrow [0,1]$, describing the degree of membership to a particular set, is constructed. The AND, OR, and NOT gates composing the fault-tree are treated linguistically, and their dyadic operation on the fuzzy sets constituting the primary events is computed through the extension principle.[9] For example, the OR gate is modeled using the extension principle as:

$$\mu_{R_1 \cup R_2}(x,y) = \max_{x \cup y}\left(\min\left(\mu_{R_1}(x), \mu_{R_2}(y)\right)\right) \tag{17}$$

where $\cup$ denotes the maximum of two crisp values. The fault-tree, used in DM for the PC-based SV system, is shown in Fig. 9.

In the final step of DM, the outcome of the logical operations is a new fuzzy set defined in the range *[0,1]*. The top event is also considered as a fuzzy variable that takes five fuzzy values, namely, *safe, no fault, fault warning, fault, severe fault.* This value can also be interpreted as a sensor quality index such as *very good, good, medium, bad* and *very bad.* The five fuzzy values are algebraically depicted in the range *[0,1]* with five membership functions that compose a library of prototypes. Generally, the result of the logical operations on the membership functions defining the primary events will be somewhat different from the prototype membership functions defining the linguistic values of the top event. The prototype library is shown in Fig. 10.

In order to draw a conclusion concerning the type of top event, the distance between the computed membership function and the prototype membership functions is calculated. This distance is also referred to as the dissemblence index and the minimum dissemblence index value is used to define the output of the fault-tree as *safe, no fault, fault warning, fault* or *severe fault.* An overall schematic of the DM is given in Fig. 11.

## Graphical User Interface

Another important task of the system executive is to display processed and measured data to the user. This task is accomplished in a user-friendly environment in which the user is able to navigate through the information space easily. Hypertext links and Microsoft Windows™ standards enable the design of graphical user interface (GUI) objects. These GUI objects are designed with virtual reality techniques so that the user can recognize them by relating them with every-day objects. Navigation through this information space is managed by point-and-click operations of the mouse interface of a standard PC. This simplifies the use of key sequences to accomplish a certain action.

The GUI of the PC-based signal validation system has different ways of displaying information. Instant measurements are displayed in digital and analog forms. The analog displays, as shown in Fig. 12, are simulated using graphical objects. However, digital presentations of the measurements are always important for plant engineering systems. Also, an historical trend plot of the measured and estimated values is of importance, to conclude a final decision about the system. The graphical plots are created with Visual Basic's extended custom control objects. Navigating to these plots are established by hypertext buttons, located at the border of each corresponding information window.

The results of the DM module are also displayed by means of modern techniques. If the sampling time is in the order of a minute or less, it may be difficult for the user to read out the final outcome of the fuzzy logic fault-tree in terms of linguistic values, such as *safe*, *no fault*, *fault warning*, *fault* and *severe fault*. Instead, icon representations of such values are used as shown in Fig. 12. The icon "smiley" is used to indicate the final outcome of the DM module.

The information displayed in the windows shown in Fig. 12 are instantaneous displays of measured values, results of SV module estimates and fuzzy logic based DM results. An historical plot can be obtained by pressing the plot button on the bottom of each instantaneous display window. In addition, an historical plot of the quality index is also shown as a function of time. The quality index has the following meaning.

*0 = safe,*
*1 = no fault,*
*2 = fault warning,*
*3 = fault,*
*4 = severe fault.*

An example of historical plot of the SV modules are shown in Fig. 13. Note that since steam generator wide range water level measurements consist of only one sensor channel, GCC algorithm is not applied for this measurement. If the measurement has more than one sensor channel, then the plot window incorporates buttons for each related sensor at the bottom of each historical trend plot window. The user may click these buttons to view the related information.

The system executive also provides some hypertext buttons, which provide links to product information and on-line help. The on-line help was developed with Microsoft Word and compiled with Microsoft Help Compiler.

## CONCLUSIONS

In general, the results obtained from the studies have shown the feasibility of implementing a PC-based signal validation system for nuclear power plants. The UTSG in a nuclear power plant was the focus of study in this research. Steam generator water level and steam generator pressure signals from a UTSG were used to illustrate the performance of the four signal validation modules.

The PC-based signal validation system was tested using off-line data obtained from two PWR's. The sampling interval for PWR-1 data was 15 minutes, whereas the sampling interval for PWR-2 data was 30 seconds. It was noticed in this study, that the sampling time of data is important to obtain an accurate model for the PEM and ANN modules. For example, if fluctuating water levels are measured at very short sampling intervals, the model to be fit to the data may confuse the training phase of constructing these models. Therefore, longer sampling time intervals are more suitable for steam generator water level (e.g. in the order of minutes).

While, the incorporation of the GCC module in the PC-based signal validation system was straightforward, the development of the PEM and ANN modules required several variations in input signal selection. Static models were found to be sufficient to validate the steam generator pressure. The steam generator wide-range water level signal was modeled successfully with dynamic structures such as incorporating past measurements of the input variables. The use of such models is very common in the ANN literature, whereas the same technique was applied to the PEM module for the first time to construct a model of the steam generator wide range water level.

Another important observation that was made during this study was the similarity between ANNs and PEM: for the same number and type of training patterns (100 training patterns over the entire transient and steady-state operating conditions) both models behaved similarly in predicting the signals to be validated.

Since the KFT requires an analytical model of the system to be validated, previously developed models of the UTSG were used.[7] This model performed very well when used in conjunction with measurements from another similar plant in the KFT calculations. The measurement of several signals is crucial in obtaining a good KFT estimate. Since the KFT module and the UTSG model make several assumptions, the state estimation has some error, compared with the state measurement. Excellent results can be obtained by including state measurements in correcting the KFT estimate.

The use of SPRT in fault detection can be made sensitive to small changes in signal levels by the proper choice of false-alarm and missed-alarm probabilities. Thus the incipient changes in instrument calibration can be detected with as low as 0.5% changes in the signal levels.

The fault-tree methodology provided a useful tool in developing a procedure for sensor status determination. To reach a final conclusion, a fuzzy logic was used for fault-tree computations. The results were displayed in a user-friendly manner by means of icons, so that the results of the DM could be recognized easily, even at short sampling time intervals and at a high screen information update rate.

As the DM plots indicate, deviations were detected in the steam generator wide range level for some time instants. These might have occurred due to the level fluctuations inside the UTSG during process transients. The DM algorithm of the system executive detected very few anomalies (in spikes) in the steam generator pressure sensors.

The development of the signal validation system in the Microsoft Windows™ environment enabled the use of effective GUIs. Since this is a common operating system, this validation technology can be easily ported to compatible PCs in nuclear power plants.

## ACKNOWLEDGMENTS

This research was sponsored by a grant to The University of Tennessee by the Tennessee Valley Authority (TVA) Resource Group, Research and Development. The authors appreciate the constructive remarks by the reviewers.

## REFERENCES

1. B. R. Upadhyaya, T. W. Kerlin, K. E. holbert, O. Glocker, V. M. Morgenstern, and Z. Frey, "Signal Validation in Nuclear Power Plants," Annual Report prepared for the U.S. Department of Energy by The University of Tennessee, DOE/NE/37959-24 (September 1988).
2. K. E. Holbert, "Comprehensive Signal Validation for Nuclear Power Plants," Ph.D. Dissertation, The University of Tennessee, nuclear Engineering (August 1989).
3. B. R. Upadhyaya, T. W. Kerlin, K. E. holbert, O. Glocker, V. M. Morgenstern, Z. Frey and J. Olvera, "Development and Testing of an Integrated Signal Validation System for Nuclear Power Plants," Volume 1, 2, 3, Research report prepared for the U.S. Department of Energy, DOE/NE/37959 34, 35, 36 (September 1989).
4. NeuralWare, "Neural Computing," Technical Publications Group, NeuralWare Inc. (1993).
5. R. E. Kalman, "A New Approach to Linear Filtering and Prediction Problems," Journal of Basic Engineering, Volume 82 (1960).
6. R. G. Brown, "Introduction to Random Signals and Applied Kalman Filtering," John Wiley, New York (1992).
7. E. Eryürek, "A Parallel, Fault-Tolerant control and Diagnostics System for Nuclear Power Plants," Ph.D. Dissertation, The University of Tennessee, Nuclear Engineering (1994).
8. A. S. Erbay and A. Ikonomopoulos, "A Fuzzy Logic Methodology for Fault-Tree Analysis in Critical Safety Systems," Transactions of the American Nuclear Society, Volume 68, Part A, pp. 134 -135, San Diego California (June 1993).
9. D. Dubois and H. Prade, "Fuzzy Sets and Systems: Theory and Applications," Academic Press, Boston, Massachusetts (1980).

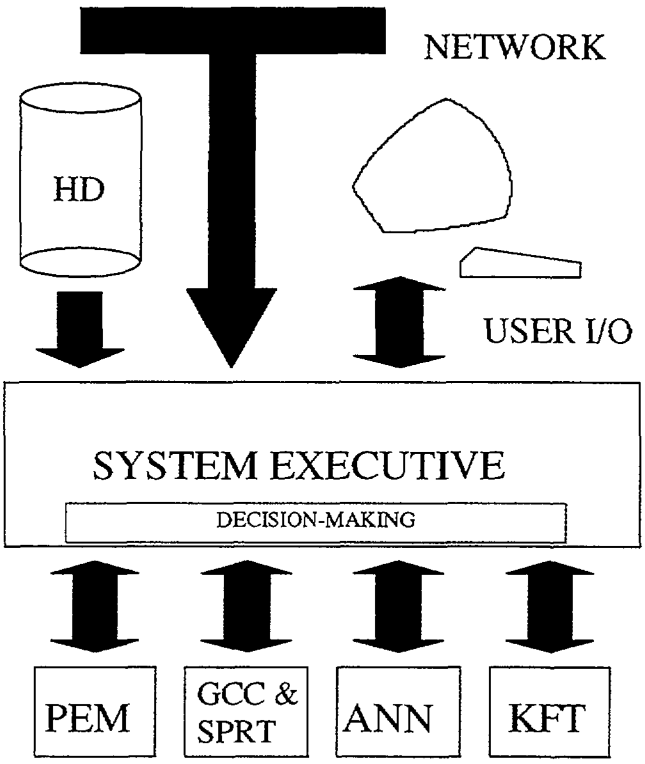


**Figure 1:** Integration of SV modules with system executive.

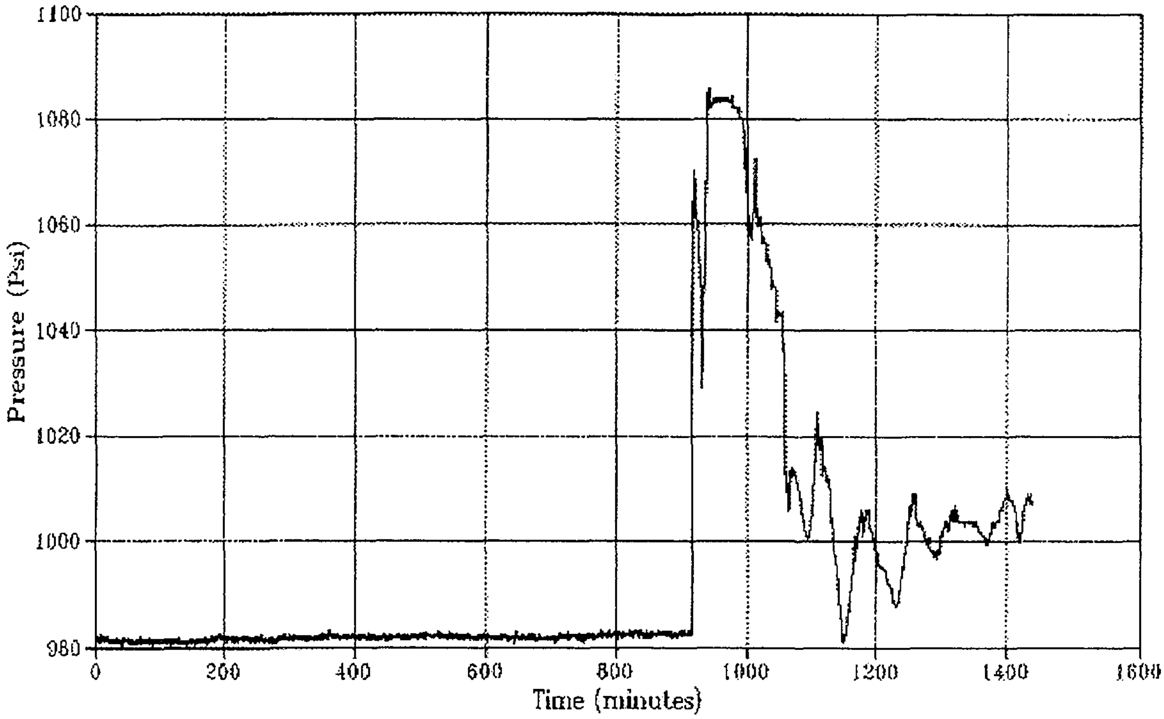


**Figure 2:** GCC estimate of the steam generator pressure.

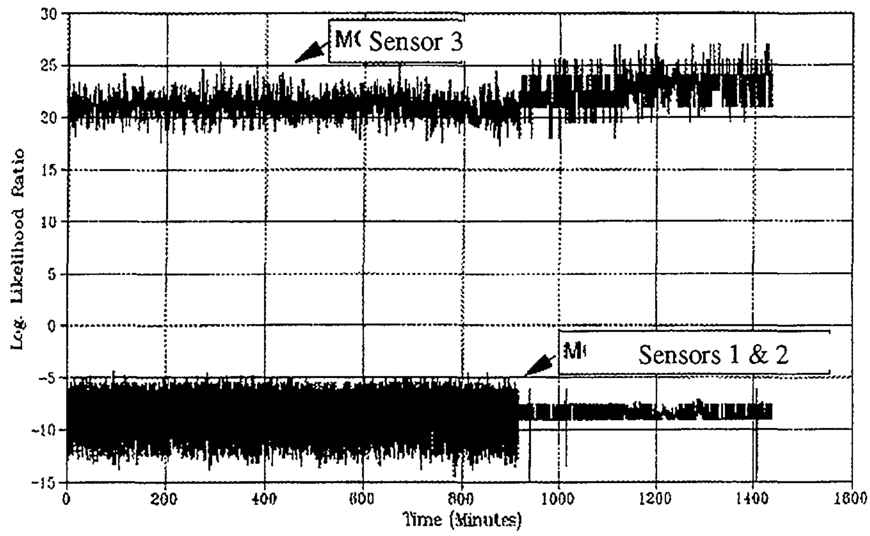


**Figure 3:** LLR computed by SPRT of the steam generator pressure.

**Table I:** Process empirical models.

| Modeled State Variable | Model | Constants | Modeling Error |
|---|---|---|---|
| Steam Generator Water Level | $c_1x(3)^2 + c_2x(7) + c_3x(7)^2 + c_4x(6) + c_5x(6)^2 + c_6$ *(Static model)* | $c_1 = -0.003$ $c_2 = 59.869$ $c_3 = -0.054$ $c_4 = -16.315$ $c_5 = 0.014$ $c_6 = -1176.855$ | 4.13% |
| Steam Generator Pressure | $c_1x(7) + c_2x(4) + c_3x(6) + c_4x(1) + c_5$ *(Static model)* | $c_1 = 8.311$ $c_2 = -13.888$ $c_3 = 0.121$ $c_4 = -0.016$ $c_5 = -3633.133$ | 0.31% |
| Steam Generator Water Level | $c_1x(2) + c_2x(7) + c_3x(6) + c_4x(1) + c_5x(4) + c_6$ *(Dynamic model)* | $c_1 = 0.993$ $c_2 = -.040$ $c_3 = 0.041$ $c_4 = 0.001$ $c_5 = -2.266$ $c_6 = .331$ | 0.47% |
| Steam Generator Pressure | $c_1x(5) + c_2x(7) + c_3x(6) + c_4x(1) + c_5x(4) + c_6$ *(Dynamic model)* | $c_1 = 1.019$ $c_2 = 0.190$ $c_3 = -0.368$ $c_4 = 0.003$ $c_5 = 4.348$ $c_6 = 78.404$ | 0.09% |

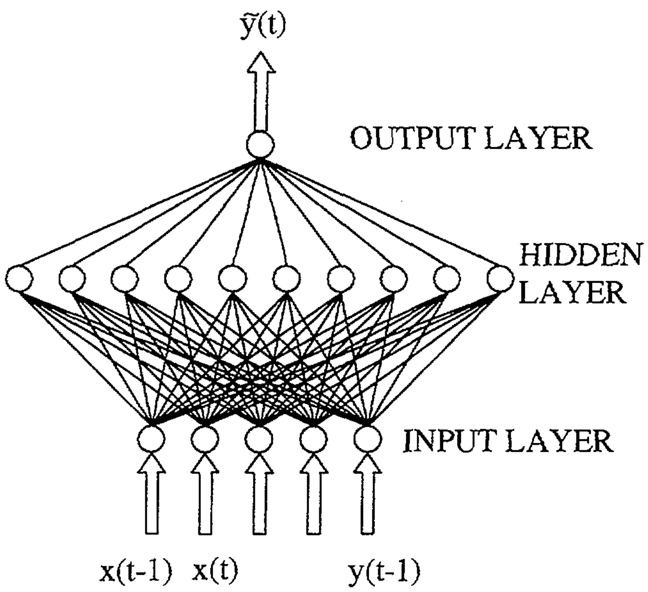


**Figure 4:** Backpropagation ANN for dynamic systems.

**Table II:** Inputs used in ANN modeling.

| Estimated Variable | Steam Generator Main Feedwater Flow | RCS Flow | Steam Generator Steam Flow | Hot Leg Temperature | Cold Leg Temperature | Steam Generator Water Level | Steam Generator Pressure |
|---|---|---|---|---|---|---|---|
| Steam Generator Water Level or Pressure (Static Modeling) | t | t | t | t | t | N/A | N/A |
| Steam Generator Water Level (Dynamic Modeling) | t | t | t | t | t | t-1 | N/A |
| Steam Generator Pressure for (Dynamic Modeling) | t | t | t | t | t | N/A | t-1 |
| Steam Generator Water Level or Pressure (Dynamic Modeling) | t, t-1 | t, t-1 | t, t-1 | t, t-1 | t, t-1 | N/A | N/A |

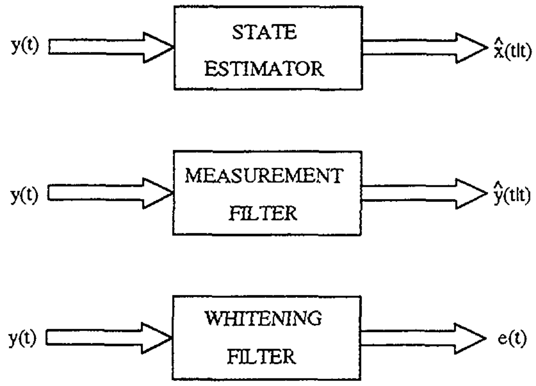


**Figure 5:** Various representations of the Kalman filter estimator.

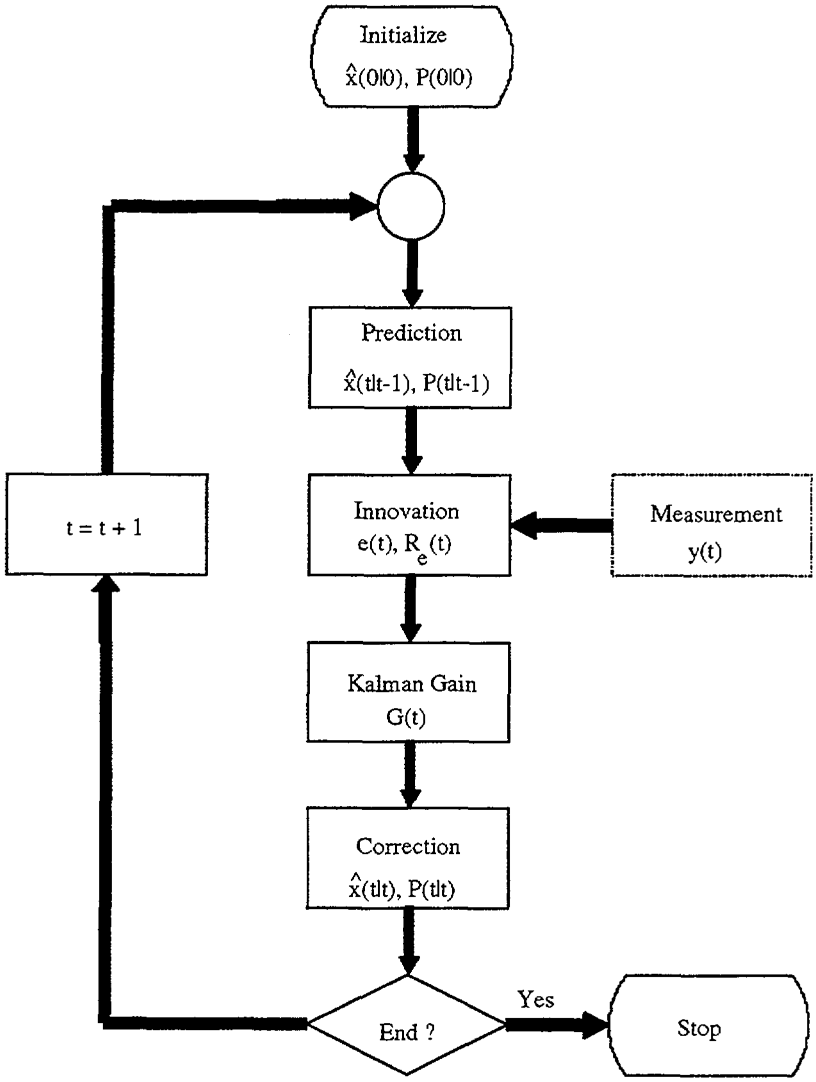


**Figure 6:** Kalman filter calculations.

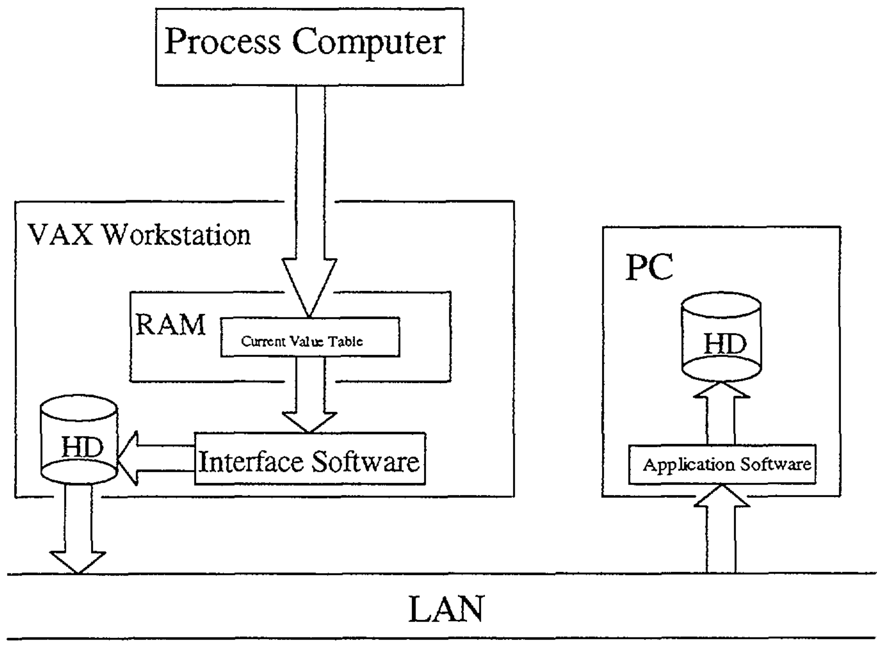


**Figure 7:** Information flow from process computer to the PC-based signal validation system.

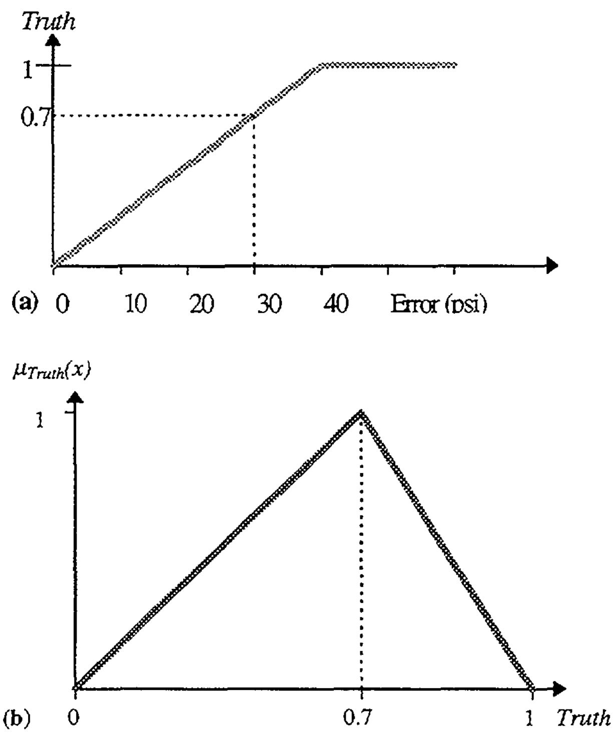


**Figure 8:** Construction of fuzzy sets from crisp errors between measurements and estimates.

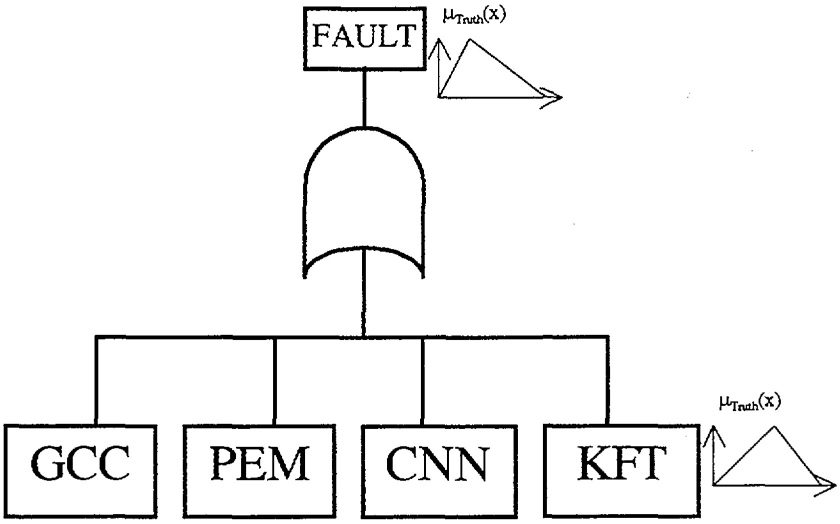


**Figure 9:** Fault-tree leading to sensor fault.

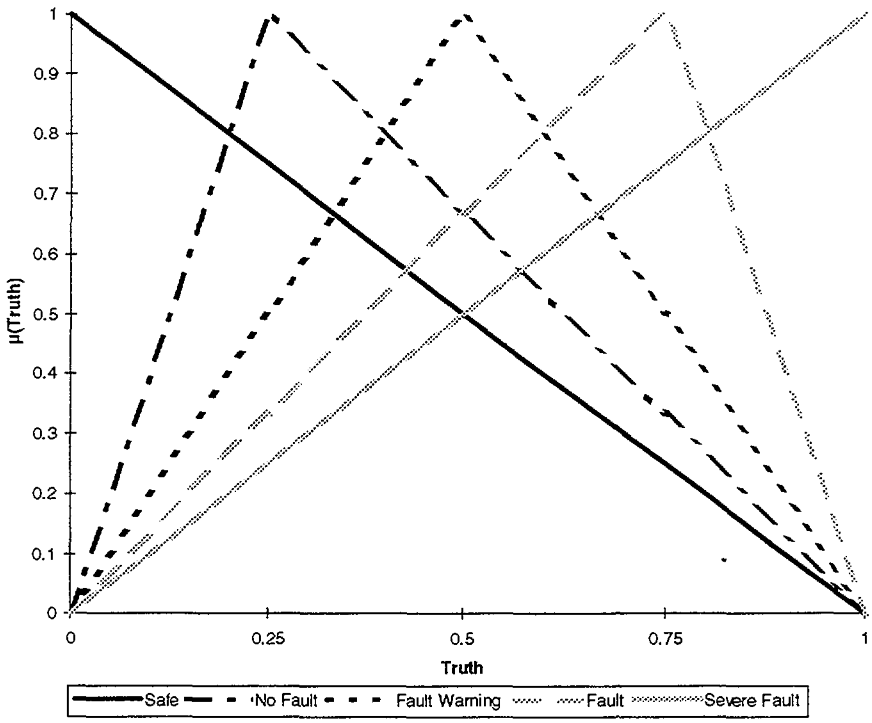


**Figure 10:** Library of prototype fuzzy sets.

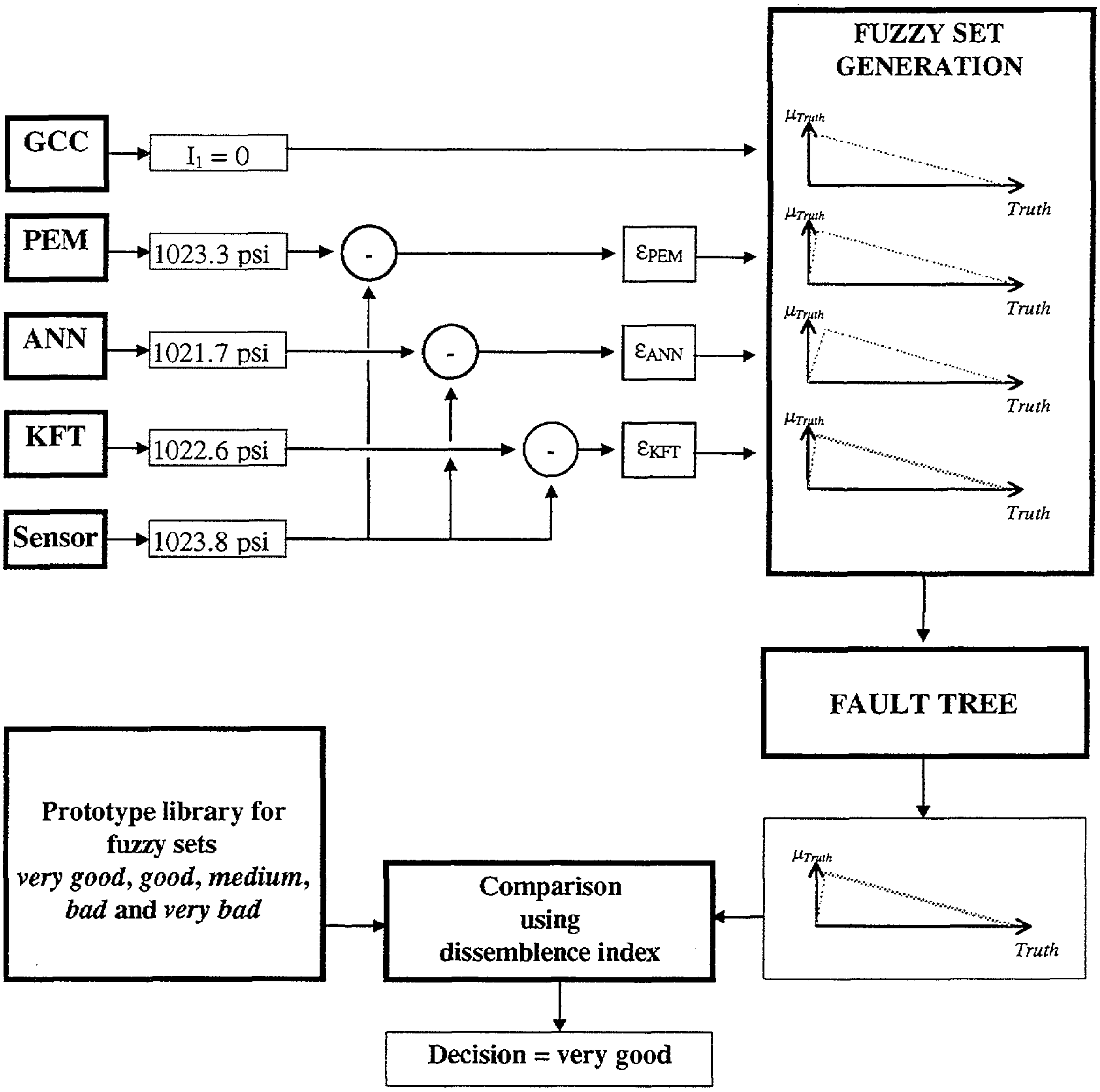


**Figure 11:** An example of making a decision for pressure sensor status using fault-tree methodology.

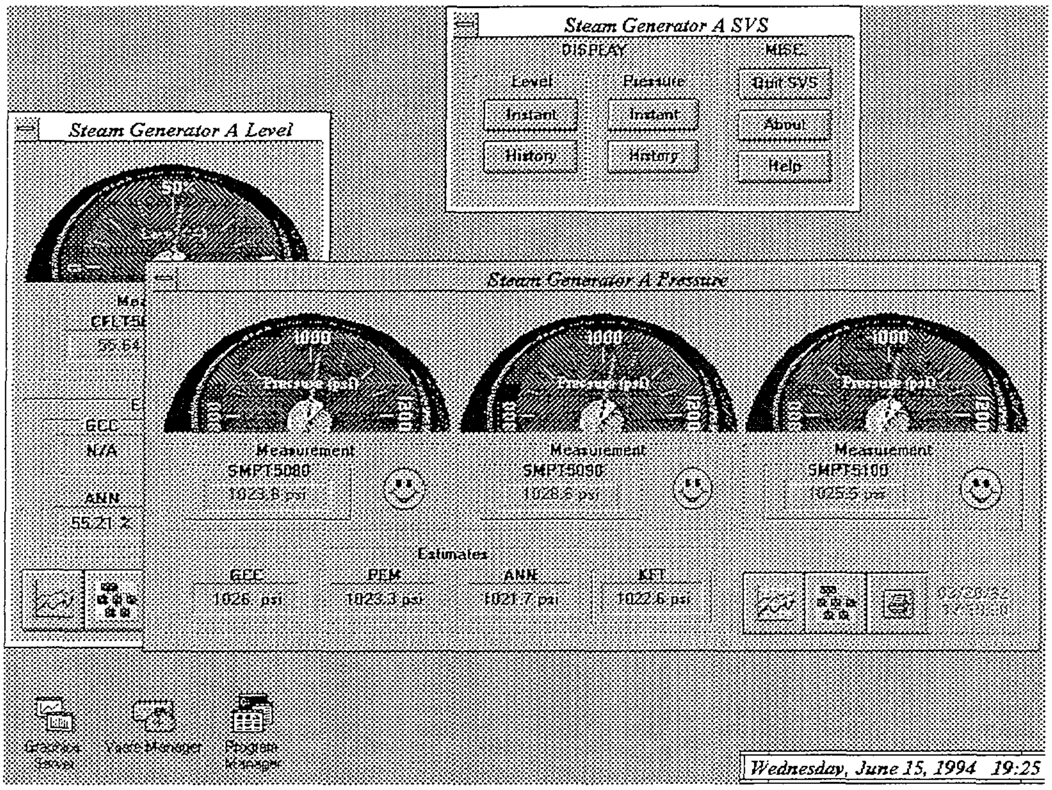


**Figure 12:** Initial GUI of the PC-based signal validation system.

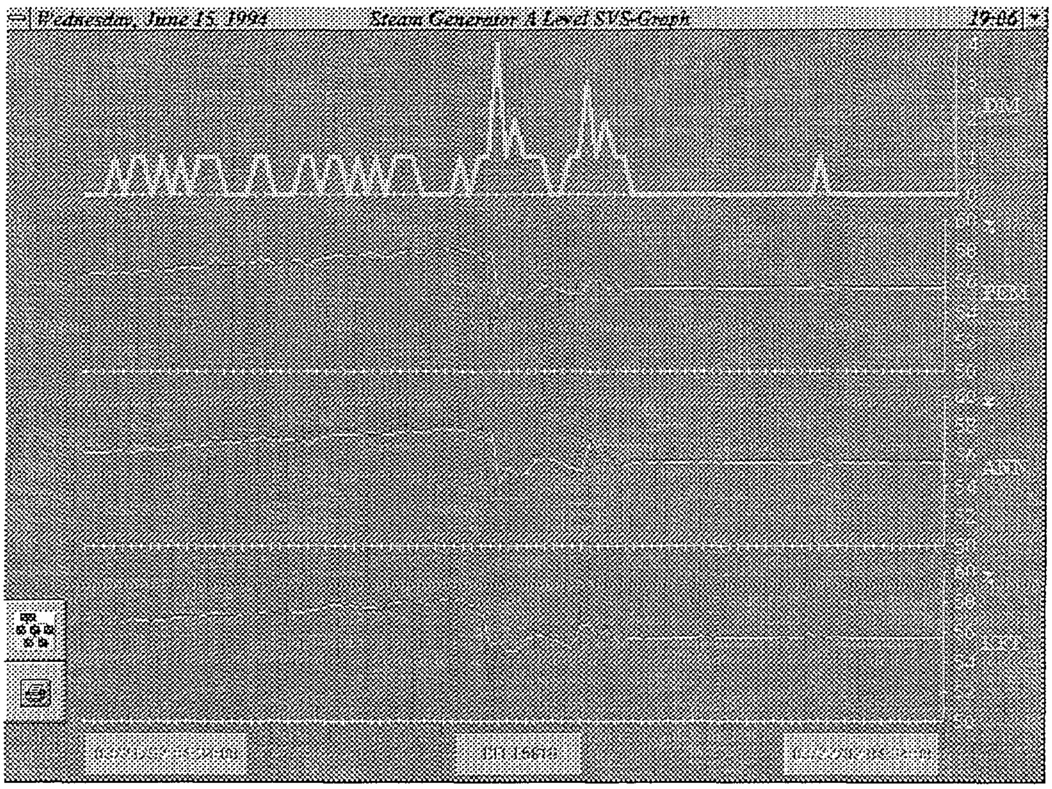


**Figure 13:** Information window displaying the historical trend of steam generator wide range water level and SV module estimates and DM results.