Fault Modeling, Detection and Classification using Fuzzy Logic, Kalman Filter and Genetic Neuro-Fuzzy Systems

Haris M. Khalid and Muhammad Akram

Abstract—**In this paper, an efficient scheme has been proposed to model, detect and classify the fault. The modeling of fault has been proposed with the fuzzy logic using membership function. Fault detection of the unprecedented changes in system reliability and find the failed component state by classifying the faults is proposed using kalman filter and hybrid neuro-fuzzy computing techniques respectively. A fault is detected whenever the moving average of the Kalman filter residual exceeds a threshold value. The fault classification has been made effective by implementing a hybrid genetic neuro-fuzzy Inference system (GANFIS). By doing so, the critical information about the presence or absence of a fault is gained in the shortest possible time, with not only confirmation of the findings but also an accurate unfolding-in-time of the finer details of the fault, thus completing the overall fault diagnosis picture of the system under test. The proposed scheme is evaluated extensively on a two-tank process used in industry exemplified by a benchmarked laboratory scale coupled-tank system.**

Keyword: Kalman filter; hybrid neuro-fuzzy; soft computing; ANN; genetic algorithm; ANFIS; GANFIS; fault detection; fault classification; benchmarked laboratory scale two-tank system.

I. Introduction

In recent times, the advancements in fault diagnosis systems are facing a heavy challenge of design problems. The main reason behind this issue is that the classical analytical techniques often cannot provide a feasible and acceptable solution to tasks and problems which are difficult and other than the textbook this affecting the efficiency of system operation and reduces economic benefit to the industry. This promotes the reason of using soft computing techniques such as fuzzy logic, neural networks and evolutionary algorithm which are more robust in tackling real time industrial applications of fault diagnosis. The main objective of fault detection and isolation (FDI) is to provide early warnings to operators, such that appropriate actions can be taken to prevent the break down of the system after the occurrence of faults. By using the soft computing patterns, an improvement can be made in the reliability and safety of the system, and avoid unnecessary and costly stoppages. Complete reliance on human operators to monitor the conditions of the systems is often difficult, especially as engineering systems are becoming more complex.

For example, in chemical process control industry, several kinds of failures may compromise safety and productivity. A chemical or process control engineer has to tackle and monitor various critical issues of faults which, if worsen can prove fatal and lead to swear accident, for example, temperature run-away with injuries to personnel, environmental pollution, equipments damage. Major failures to be considered in chemical processes are: actuator failures (e.g., electric-power failures, pump failures, valves failures), process failures (e.g., abrupt variations of some process parameters, side reactions due to impurities in the raw materials) and sensor failures. To tackle these difficulties, FDI techniques are developed.

The model-based approach is popular for developing FDI techniques ([1];[2]). It mainly consists of two stages [3]. The first one is to generate residuals by computing the difference between the measured output and the estimated output obtained from the model of the system [3]. Any departure from zero of the residuals indicates a fault has likely occurred [4]. However, these methods are developed mainly for linear systems assuming that a precise mathematical model of the system is available which is not always the case in industries [5]; [6]. R. Doraiswami ([7]; [8]) has done considerable work in the detection and identification of faults and tuning parameters. M.A.Rahim [39] has done a work of integration of industrial system techniques with the development of model-based adaptive control charts for quality monitoring.

To overcome these problems of fault diagnosis, soft computing is considered as an emerging approach, which parallels the remarkable ability of the human mind to reason and learn in circumstances characterized by uncertainty and imprecision.

The paper is organized as follows: in Section II the related work is presented and Fault Diagnosis problem statement is considered in Section III. Section IV discusses the implementation and simulation results. Finally some conclusions are given Section V.

II. Related Works

In recent years, a prominent related work has been done in the field of fault diagnosis and isolation using soft computing techniques. Among these techniques, neural networks are used for their capability of approximating nonlinear functions and their learning ability [9] and also to generate residuals for fault detection [10]. However, due to their black box nature, it is very difficult to employ them for isolating the faults. Moreover, it is also required that fault diagnostic system should be able to incorporate the experience of the operators [11] and provide fuzzy reasoning while considering their experience [12]. An up-to-date presentation of motor fault detection and diagnosis methods was recently published in a special section in [13]. The literature review is being subdivided into three sections comprising of fault diagnosis using expert systems, fuzzy logic, neural network and Genetic Algorithm.

In recent years, the application of fuzzy logic to model-based fault diagnosis approaches has gained increasing attention in both fundamental research and application. Initial attempts at

Manuscript **Ajest-KFUPM-Haris-Soft-Computing.tex**

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the application of expert systems for fault diagnosis can be found in the work of Henley [14] and Niida [15]. Structuring the knowledge-base through hierarchical classification can be found in [16]. Ideas on knowledge-based diagnostic systems based on the task framework can be found in [17]. A rule-based expert system for fault diagnosis in a cracker unit is described in [18]. More work on expert systems in chemical process fault diagnosis can be found in [19] and [20]. Wo et al. [21] presented an expert fault diagnostic system that uses rules with certainty factors. Leung and Romagnoli [22] presented a probabilistic model-based expert system for fault diagnosis. An expert system approach for fault diagnosis in batch processes was discussed in Scenna [23].

There is also great work done while considering the application of ANN in the area of fault diagnosis. A number of papers address the problem of fault diagnosis using back-propagation neural networks. In chemical engineering, Watanabe et al. [24], Venkatasubramanian and Chan [25], Ungar et al. [26] and Hoskins et al. [27] were among the first researchers to demonstrate the usefulness of neural networks for fault diagnosis. A detailed and thorough analysis of neural networks for fault diagnosis in steady-state processes was presented by Venkatasubramanian et al. [28]. This work was later extended to utilize dynamic process data by Vaidyanathan and Venkatasubramanian [29]. A hierarchical neural network architecture for the detection of multiple faults was proposed by Watanabe et al. [30]. Most of the work on improvement of performance of standard back-propagation neural networks for fault diagnosis is based on the idea of explicit feature presentation to the neural networks by Fan et al. [31], Farell and Roat [32], Tsai and Chang [33], and Maki and Loparo [34]. Modifications to the selection of basis functions have also been suggested to the standard back-propagation network. For example, Leonard and Kramer [35] suggested the use of radial basis function networks for fault diagnosis applications.

Genetic Algorithms (GAs) are a special type of *evolutionary algorithms,* algorithms that simulate biological processes to solve search and optimization problems. GAs have been implemented for a wide variety of problems, both real-world (e.g. Fault diagnosis, fault tolerant) and abstract (e.g. solving NP-complete problems [36]. The bulk of the GA literature is concerned with practical applications. For a very complete bibliography, see [36], which contains a comprehensive survey. Fault Diagnosis with the perspective of reliability issues, and implementation of neural networks with genetic algorithm can also seen in ([37]-[38]).

In this paper, a fault diagnosis problem using hybrid neuro-fuzzy computing techniques is proposed to meet the requirements for a quick and reliable fault detection and isolation scheme. The proposed scheme has been evaluated on a laboratory scaled based two-tank system. It is the most used prototype applied in the wastewater treatment plant, the petro-chemical plant, and the oil/gas systems. The main contribution of the paper is the implementation of genetic neuro-fuzzy systems on fault diagnosis problem for accuracy and reliability of Fault Detection and Isolation.

III. The Fault Diagnosis Problem Statement

In process control industry, fault is a harsh and unaffordable factor. It merely hits the efficiency of system and this reducing all the growth and production capacities. The early detection and diagnosis of faults in mission critical systems becomes highly crucial for preventing failure of equipment, loss of productivity and profits, management of assets, reduction of shutdowns.

To have an effective fault diagnosis of highly non-linear systems, hybrid techniques have been introduced here by showing the genetic neuro-fuzzy Based- FDI.

A. System Description

The Benchmarked laboratory-scale process control system has been used to collect data. The data has been collected at a sampling time of 50 milli second. The different data sets have been generated for PI Control based water level control. Different fault scenarios have also been considered for the generation of the data sets.

The proposed scheme has been evaluated on the above- cited process control system. The scheme is carried out by jointly interpreting model outputs. The implementation plan for the proposed scheme is shown in the Fig 1. It should be noted that hybrid genetic neuro-fuzzy technique is applied to the fault diagnosis of the system.

B. Experimental Setup

Process Data has been generated through an experimental setup as shown in Fig. 2. A two tank system has been used in order to collect the data with the introduction of actuator, and sensor faults through the system as can be seen in the labview circuit window. An amplified voltage of 18 volts has been used to handle the controller effectively for the changes/fluctuation produced in the system. So, the fault diagnosis was done over here in a closed loop identification where in the same time, the controller is suppressing the faults.

C. Process Data Collection and Description

The process data has been collected at 50 milli-seconds sampling time. The main objective of the benchmarked dual-tank system is to reach a reference height of 200 ml of the second tank. During this process, several faults have been introduced such as the leakage faults, sensor faults and actuator faults. Leakage faults have been introduced through the pipe clogs of the system, knobs between the first and the second tank etc. Sensor faults have been introduced by introducing a gain in the circuit as if there is a fault in the level sensor of the tank. Actuator faults have been introduced by introducing a gain in the setup for the actuator that comprises of the motor and pump. A PI controller has been employed in order to reach the desired reference height. Due to the inclusion of faults, the controller was finding it difficult to reach the desired level. For this reason, the power of the motor has been increased from 5 volts to 18 volts in order to provide it the maximum throttle to reach the desired level. In doing so, the actuator performed well in achieving its desired level but it also suppressed the faults of the system. So, it made the task of detecting the faults. After the

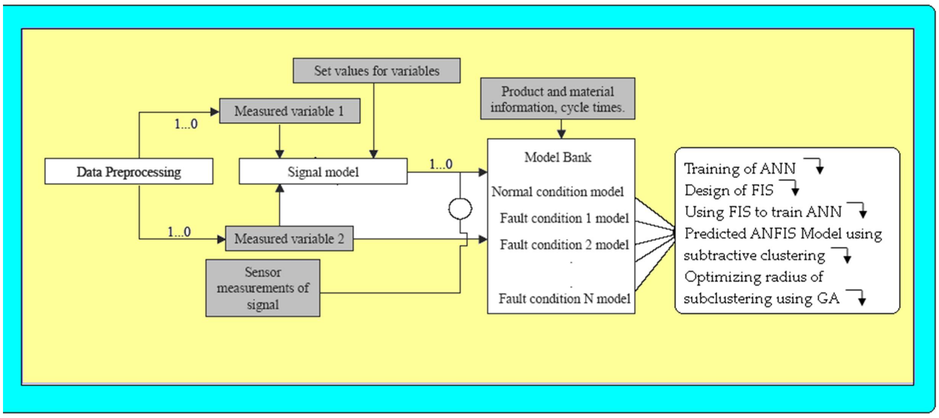

Fig. 1. Implementation plan for the evaluation of the proposed scheme

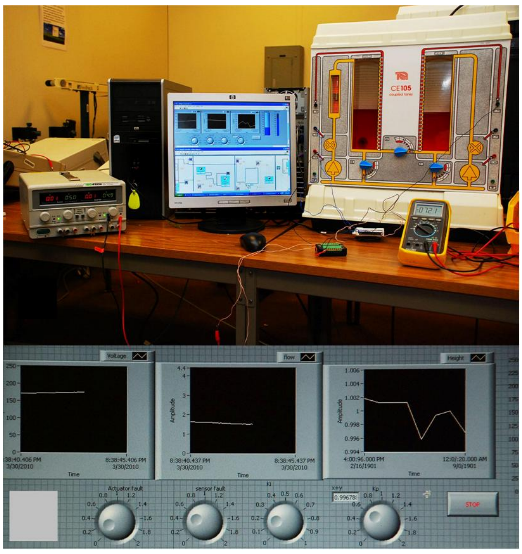

Fig. 2. A – The two tank system interfaced with the Labview through a DAQ and the amplifier for the magnified voltage , B – The labview setup of the apparatus including the ciruit window and the block diagram of the experiment.

collection of data, techniques such as settling time, steady state value, and coherence spectra can help us to give an insight of the fault.

D. Model of the Coupled Tank System

The physical system under evaluation is formed of two tanks connected by a pipe. The leakage is simulated in the tank by opening the drain valve. A DC motor-driven pump supplies the fluid to the first tank and a PI controller is used to control the fluid level in the second tank by maintaining the level at a specified level, as shown in Fig 3.

A step input is applied to the dc motor- pump system to

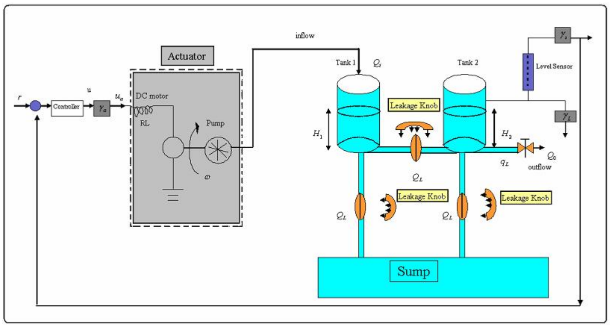

Fig. 3. Process control system: A Lab-scale two-tank system

fill the first tank. The opening of the drainage valve introduces a leakage in the tank. Various types of leakage faults are introduced and the liquid height in the second tank, H_2, and the inflow rate, Q_i, are both measured. The National Instruments LABVIEW package is employed to collect these data.

A benchmark model of a cascade connection of a dc motor and a pump relating the input to the motor, *u,* and the flow, Q_i, is a first-order system:

$$\dot{Q}_i = -a_m Q_i + b_m \phi(u) \tag{1}$$

where a_m and b_m are the parameters of the motor-pump system and $\phi(u)$ is a dead-band and saturation type of nonlinearity. It is assumed that the leakage Q_ℓ occurs in tank 1 and is given by:

$$Q_\ell = C_{d\ell}\sqrt{2gH_1} \tag{2}$$

With the inclusion of the leakage, the liquid level system is modeled by:

$$A_1 \frac{dH_1}{dt} = Q_i - C_{12}\varphi(H_1 - H_2) - C_\ell \varphi(H_1) \quad (3)$$
$$A_2 \frac{dH_2}{dt} = C_{12}\varphi(H_1 - H_2) - C_0 \varphi(H_2) \quad (4)$$

where $\varphi(.) = sign(.)\sqrt{2g(.)}$,$Q_\ell = C_\ell \varphi(H_1)$is the leakage flow rate, $Q_0 = C_0\varphi(H_2)$is the output flow rate, H_1 is the height of the liquid in tank 1, $H_2$is the height of the liquid in tank 2, A_1 and A_2 are the cross-sectional areas of the 2 tanks, g=980$cm/\sec^2$ is the gravitational constant, C_{12} and C_o are the discharge coefficient of the inter-tank and output valves, respectively.

The model of the two-tank fluid control system, shown above in Fig. 3, is of a second order and is nonlinear with a smooth square-root type of nonlinearity. For design purposes, a linearized model of the fluid system is required and is given below in (5) and (6):

$$\frac{dh_1}{dt} = b_1 q_i - (a_1 + \alpha) h_1 + a_1 h_2 \quad (5)$$
$$\frac{dh_2}{dt} = a_2 h_1 - (a_2 - \beta) h_2 \quad (6)$$

where h_1 and h_2 are the increments in the nominal (leakage-free) heights H_1^0 and H_2^0:

$$b_1 = \frac{1}{A_1}, \quad a_1 = \frac{C_{db}}{2\sqrt{2g(H_1^0 - H_2^0)}}, \quad \beta = \frac{C_0}{2\sqrt{2gH_2^0}},$$
$$a_2 = a_1 + \frac{C_{do}}{2\sqrt{2gH_2^0}} \quad \alpha = \frac{C_{d\ell}}{2\sqrt{2gH_1^0}}$$

and the parameter α indicates the amount of leakage.

A PI controller, with gains $k_p$and k_I, is used to maintain the level of the Tank 2 at the desired reference input r as:

$$\begin{aligned} \dot{x}_3 &= e = r - h_2 \\ u &= k_p e + k_I x_3 \end{aligned} \quad (7)$$

The linearized model of the entire system formed by the motor, pump, and the tanks is given by:

$$\dot{x} = Ax + Br \quad y = Cx \quad (8)$$

where

$$x = \begin{bmatrix} h_1 \\ h_2 \\ x_3 \\ q_i \end{bmatrix}, \ A = \begin{bmatrix} -a_1 - \alpha & a_1 & 0 & b_1 \\ a_2 & -a_2 - \beta & 0 & 0 \\ -1 & 0 & 0 & 0 \\ -b_m k_p & 0 & b_m k_I & -a_m \end{bmatrix},$$
$$B = \begin{bmatrix} 0 & 0 & 1 & b_m k_p \end{bmatrix}^T, \ C = [1 \quad 0 \quad 0 \quad 0]$$

where q_i, q_ℓ, q_0, h_1 and h_2 are the increments in Q_i, Q_ℓ, Q_0, H_1^0 and H_2^0, respectively, the parameters a_1 and a_2 are associated with linearization whereas the parameters α and β are respectively associated with the leakage and the output flow rate, i.e. $q_\ell = \alpha h_1$, $q_o = \beta h_2$.

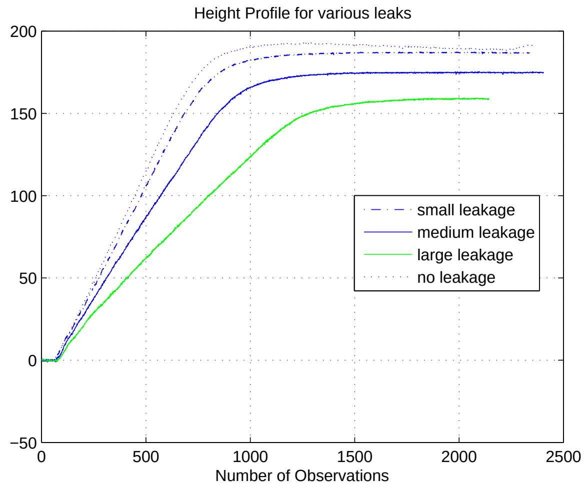

Fig. 4. Various Height Profile Scenarios

IV. Implementation and Simulation Results

A. *Modeling of Fuzzy Logic-Based Fault Diagnosis*

Model of fuzzy Logic-Based Fault Diagnosis is being made by considering the dynamics and behavior of the physical system. As mentioned earlier, various types of leakage faults were introduced by opening the drainage valve and the liquid height profiles in the second tank were subsequently analyzed.

Rules of the input has been defined as per by expert analysis. The type of membership functions used are the tr-bel-s, triangular and *gbelf* as it was matching the dynamics of the scenario. On the Universe of Discourse, the height profile and flow profile, being the input of the system defined with considering the variation of the steady state values of the profile. The profiles are being categorized as per their variation in the height as well as the steady state values. On Basis of the conditions mentioned above, the Fuzzy Logic is modeled on Matlab on both Sugeno and Mamdani-Based Functions as shown in the Fig. (4-11). Various height profiles are shown in Fig. 4. Then flow profile input and height profile input for different fault scenarios defined with membership functions are shown in Fig. 5 and Fig. 6 respectively. Rules defined for different scenarios are shown in Fig. 7. Flow and height profile with *g-belf* function is shown in Fig. 8 and Fig. 9 respectively. Based on Sugeno type and Mamdani type, rules vewers can be seen in Fig. 10 and Fig. 11 respectively.

Case-I: Model of Fuzzy Logic using triangular-Shaped, Generalized Bell-shaped and S-Shaped Membership Functions:

Mathematical Representation:

Equation (9) is representing the triangular membership function which is used for designing the transition state of the height profile as shown in the Fig. 4.

$$f(x_v, a_{tf}, b_{Pt}, c_{tf}) = \left\{ \begin{array}{c} 0, x_v \le a_{tf} \\ \frac{x_v - a_{tf}}{b_{Pt} - a_{tf}}, a_{tf} \le x_v \le b_{Pt} \\ \frac{c_{tf} - x_v}{c_{tf} - b_{Pt}}, b_{Pt} \le x_v \le c_{tf} \\ 0, c_{tf} \le x_v \end{array} \right\} \quad (9)$$

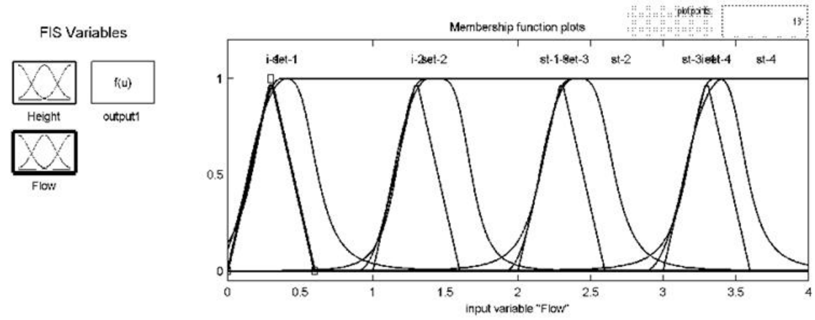

Fig. 5. Flow Profile Input: Different Scenarios defined with membership function plots using tri-gbel-s mf on a universe of discourse

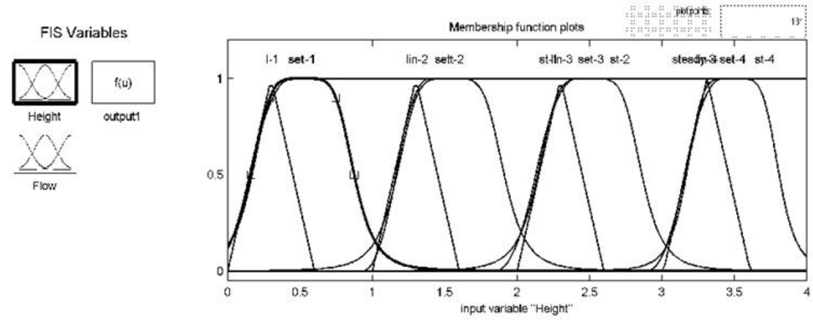

Fig. 6. Height Profile Input: Different Scenarios defined with membership function plots using tri-gbel-s mf on a universe of discourse

where v stands for vector, Pt stands for transition-feet, tf stands for transition-feet.

Equation (10) is representing the generalized bell function which is used for designing the settling state of the height profile as shown in the Fig. 4.

$$f(x_v, a_{ps}, b_{scc}, c_{ps}) = \frac{1}{1 + \left| \frac{x_v - c_{ps}}{a_{ps}} \right|^{2b_{scc}}} \tag{10}$$

where v stands for vector, ps stands for parameter-settling, scc stands for settling curve center.

Equation (11) is representing the S-shaped function which is used for designing the steady state of the height profile as shown in the Fig. 4.

$$f(x_v, a_{ssp}, b_{ssp}) = \left\{ \begin{array}{c} 0, x_{vector} \leq a_{ssp} \\ 2\left(\frac{x_v - a_{ssp}}{b_{ssp} - a_{ssp}}\right)^2, a_{ssp} \leq x_v \leq \frac{a_{ssp}+b_{ssp}}{2} \\ 1 - 2\left(\frac{x_v - b_{ssp}}{b_{ssp} - a_{ssp}}\right)^2, \frac{a_{ssp}+b_{ssp}}{2} \leq x_v \leq b_{ssp} \\ 1, x_v \geq b_{ssp} \end{array} \right\} \tag{11}$$

where v stands for vector, ssp stands for steady state parameter.

Equation (12) is representing the final combination of the three function in order to transform the complete state of height profile as shown in the Fig. 4.

$$f(x_v, a_{cum.}, b_{cum.}, c_{cum.}) = \max \left[\begin{array}{c} \left(\min\left(\frac{x_v - a_{tf}}{b_{Pt} - a_{tf}}, \frac{c_{tf} - x_v}{c_{tf} - b_{Pt}}\right), 0\right) \\ \left(\min\left(\frac{1}{1 + \left|\frac{x_v - c_{ps}}{a_{ps}}\right|^{2b_{scc}}}\right), 0\right) \\ \left(\min\left(2\left(\frac{x_v - a_{ssp}}{b_{ssp} - a_{ssp}}\right)^2, 1 - 2\left(\frac{x_v - b_{ssp}}{b_{ssp} - a_{ssp}}\right)^2, 0\right)\right) \end{array} \right] \tag{12}$$

where v stands for vector, $cum.$ stands for cumulative, tf stands for transition-feet, pt stands for peak-transition, ssp stands for steady state paramter, ps stands for parameter settling.

The tasks of our fault diagnosis scheme, GANFIS system as shown in Fig. 12 are executed with an increasing precision accompanied with a more detailed fault picture. Firstly, the data collected from the plant has been initialized and the parameters are being optimized which comprises of the pre-processing and normalization of the data. Then, the optimal cluster centering has been done through ANFIS using the subtractive clustering technique. Then, the genetic optimization of the sensitive pa-

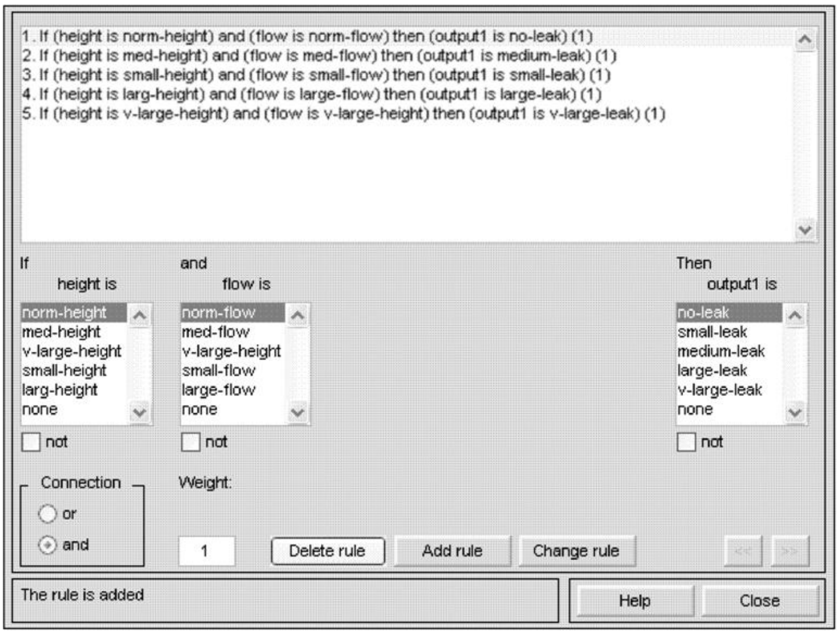

Fig. 7. Rules defined for different scenarios

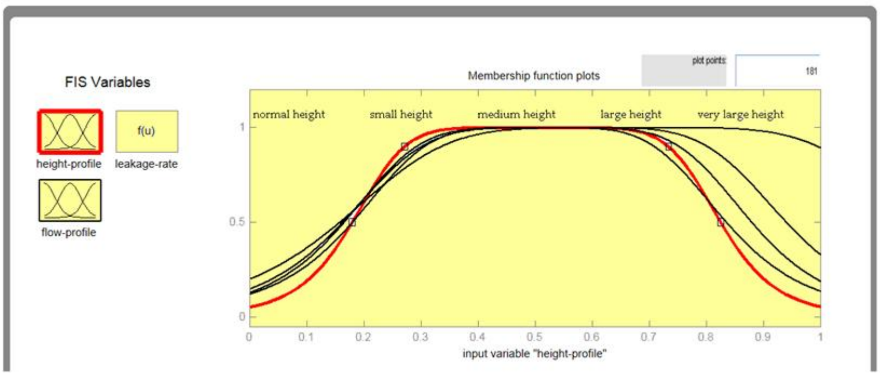

Fig. 8. Different Scenarios defined for Height Profile Input with membership function plots using gbelf function on a universe of discourse

rameters of the subtractive clustering such has radius has been performed and the performance has been validated by checking the root mean square error and the performance targets of the performance targets.

B. ANFIS Based Fault Diagnosis using Subtractive Clustering

The Subtractive Clustering technique has been applied here in order to form hybrid versions of Neuro-Fuzzy. The procedure for the Subtractive Clustering seeks the optimal data point by defining a cluster center based on the density of surrounding data points. All the data points within the RADII of this point are then removed, in order to determine the next data cluster and its center. This process is repeated until all the data is within the distance RADII of a cluster center. SUBCLUST finds the optimal data point to define a cluster center based on the density of surrounding data points. All the data points within the distance RADII of this point are then removed, in order to determine the next data cluster and its center. This process is repeated until all of the data is within the distance RADII of a cluster center.

The scheme has been followed and employed to get a final

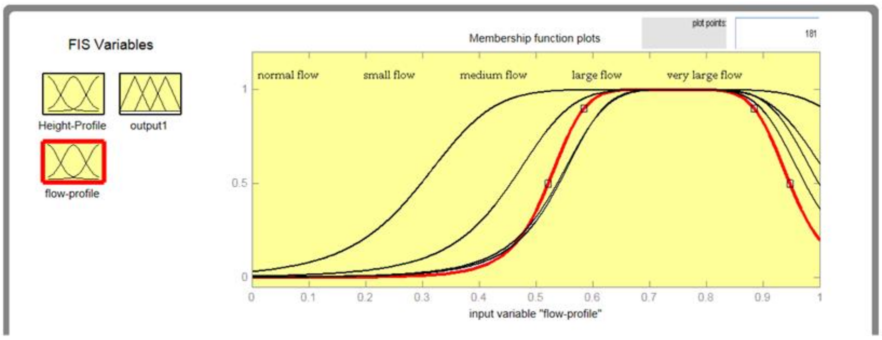

Fig. 9. Different Scenarios defined for Flow Profile Input with membership function plots using gbelf function on a universe of discourse

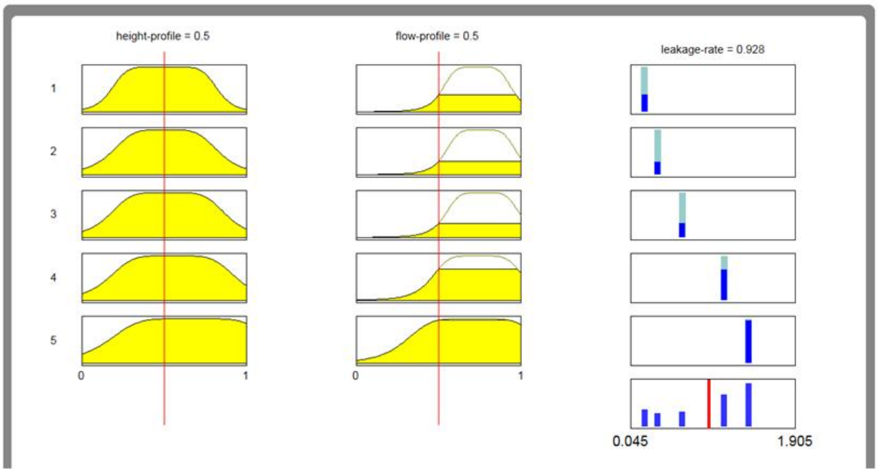

Fig. 10. Sugeno Type: Rules Viewer for Fuzzy System

trained ANFIS. It has been shown that the Predicted ANFIS is performing better in following the Original output when the radius is 0.7 rather than when the radius is 0.2 as shown in the Fig. 13 and Fig. 14 respectively.

C. Fault Detection Using Kalman Filter

The Kalman filter is designed for the normal fault-free operation. The model of the system for a fault-free, which is obtained from the system identification process described in the previous section, is given by:

$$x(k+1) = A_0 x(k) + B_0 u(k-d) + w(k) \tag{13}$$

$$y(k) = C_0 x(k) + v(k) \tag{14}$$

Where $y(k)$ is the output, e.g., the height of the water in a tank, (A_0, B_0, C_0) are obtained from the discretized model of $(A, B, C)$for the ideal fault-free case,$w(k)$ and $v(k)$ are zero-mean white plant and measurement noise signals, respectively, with covariances:

$$Q = E\left[w(k)w^T(k)\right], and \quad R = E\left[v(k)v^T(k)\right] \tag{15}$$

The plant noise,$w(k)$, is a mathematical artifice introduced to account for the uncertainty in the *a-priori* knowledge of the plant model. The larger the covariance Q is, the less accurate the model $(A_0, B_0, C_0)$is and vice versa.
The Kalman filter is given by:

$$\hat{x}(k+1) = A_0\hat{x}(k) + B_0 u(k-d) + K_0(y(k) - C_0\hat{x}(k) \tag{16}$$

$$e(k) = y(k) - C_0\hat{x}(k) \tag{17}$$

where d is the delay and e (k) the residual.
The system model has a pure time delay which is incorporated in the Kalman filter formulation. The Kalman filter estimates the states by fusing the information provided by the measurement $y(k)$ and the *a-priori* information contained in the

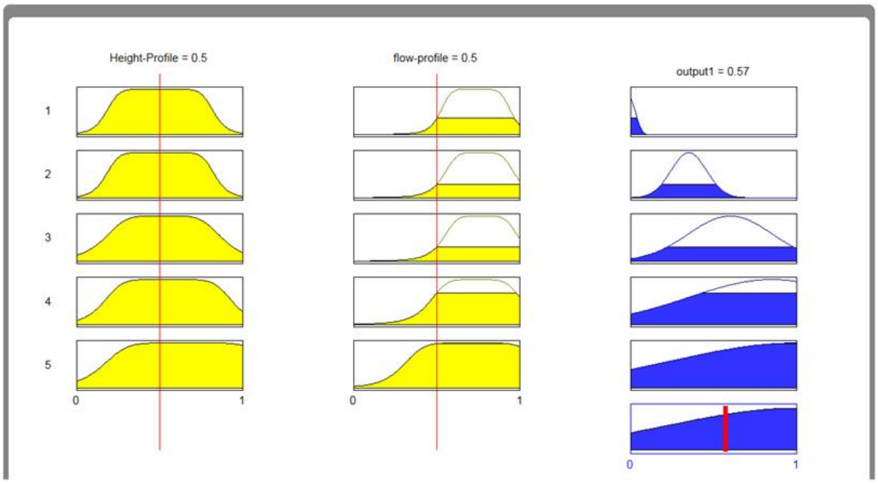

Fig. 11. Mamdani Type: Rules Viewer for Fuzzy System

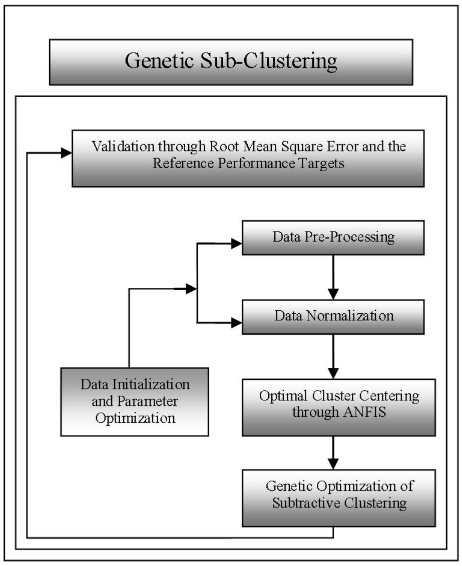

Fig. 12. Implementation Scheme (GANFIS) system)

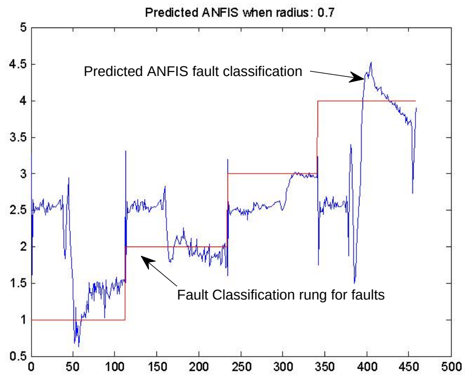

Fig. 13. Predicted ANFIS using Subtractive Clustering when radius: 0.7

model,(A_0, B_0, C_0). This fusion is based on the *a priori* information of the plant and the measurement noise covariances, *Q*, and *R*, respectively. When *Q* is small, implying that the model is accurate, the state estimate is obtained by weighting the plant model more than the measurement one. The Kalman gain, K_0, will then be small. On the other hand, when *R* is small implying that the measurement model is accurate, the state estimate is then obtained by weighting the measurement model more than the plant one. The Kalman gain, K_0, will be large in this case.

The larger K_0 is, the faster the response of the filter will be and the larger the variance of the estimation error becomes. Thus, there is a trade-off between a fast filter response and a small covariance of the residual. An adaptive on-line scheme is employed to tweak the *a- priori* choice of the covariance matrices so that an acceptable trade-off between the Kalman filter performance and the covariance of the residual is reached.

Evaluation of Fault Detection using Kalman Filter: First the fault-free model of the system is identified using a recursive least-squares identification scheme. The order of the estimated model was iterated to obtain an acceptable model structure using a combination of the AIC criterion and the identified pole locations.

The identified model is essentially a second-order system with a delay even though the theoretical model is of a fourth order. Using the fault-free model together with the covariance

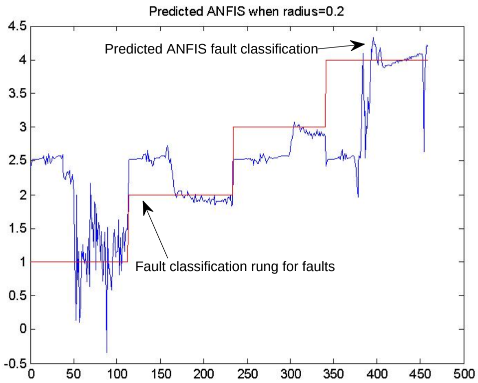

Fig. 14. Predicted ANFIS using Subtractive Clustering when radius: 0.2

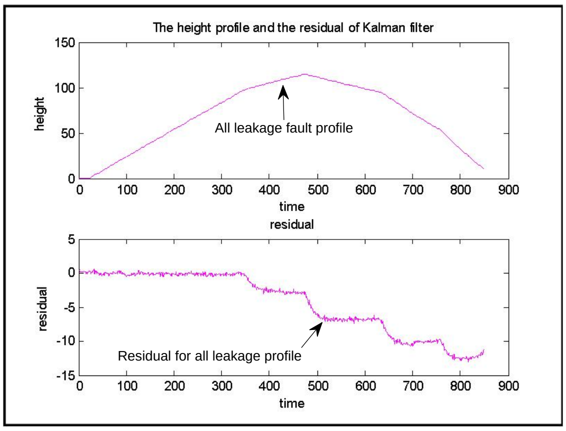

Fig. 15. Kalman filter results for a PI Controller for Flow and Height under various leakage magnitudes

of the measurement noise, R, and the plant noise covariance, Q, the Kalman filter model was finally derived. As it is difficult to obtain an estimate of the plant covariance, Q, a number of experiments were performed under different plant scenarios to tune the Kalman gain,K_0.

$$\hat{x}(k+1) = A_0\hat{x}(k) + B_0u(k-d) + K_0(y(k) - C_0\hat{x}(k) \quad (18)$$

$$e(k) = y(k) - C_0\hat{x}(k) \quad (19)$$

The Kalman filter was evaluated under different fault scenarios for an On-Off controller, a Proportional(P) controller, and a Proportional-Integral(PI) controller, as shown in Fig. (15-16).

D. *GANFIS Based Fault Diagnosis using Genetic Optimization of Subtractive Clustering*

As can be seen in the previous section that a slight change in the radius of subtractive clustering has showed in the change

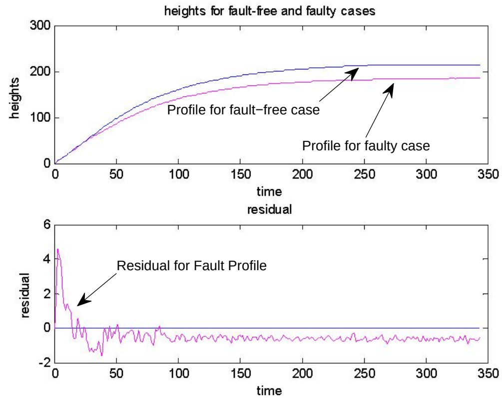

Fig. 16. Kalman filter results for an On-Off Controller for Flow and Height under various leakage magnitudes

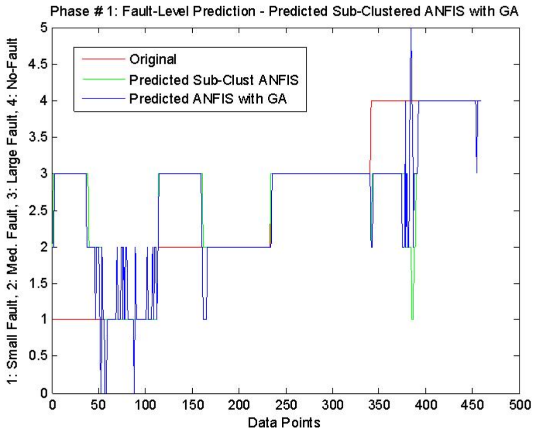

Fig. 17. (Phase 1: Four random Phases for predicted sub-clustered ANFIS with GA

of results. So, the genetic optimization of the parameters is required in order to get the optimal shape of the fault prediction. Table I given below shows the performance selection of genetic algorithm at various generations. At various sizes of epochs, the linear parameters and non-linear parameters are changing and also adapting themselves by predicting the number of rules and nodes which can best fitted for the problem and the set of data points.

Fig. (17-20) shows the four random phases in which the performance of genetic optimization can been seen. The original graph is drawn in red which is showing step sizes indicating different levels of faults. The green graph is showing the prediction with the subtractive clustering technique followed the blue graph in each of all the four phases which is showing the genetic optimization of the radius parameter of the sub-clustering technique implied.

TABLE I
PERFORMANCE SELECTION OF GENETIC ALGORITHM AT VARIOUS GENERATIONS

PERFORMANCE SELECTION OF GA AT VARIOUS GENERATIONS	OPTIMAL PARAMETER SELECTION BY GA AT VARIOUS GENERATIONS
Performance Selection of Genetic Algorithm at Epoch 9	GANFIS info: Number of nodes: 29 Number of linear parameters: 12 Number of nonlinear parameters: 16 Number of fuzzy rules: 4
Performance Selection of Genetic Algorithm at Epoch 30	GANFIS info: Number of nodes: 41 Number of linear parameters: 18 Number of nonlinear parameters: 24 Number of fuzzy rules: 6
Performance Selection of Genetic Algorithm at Epoch 65	GANFIS info: Number of nodes: 65 Number of linear parameters: 30 Number of nonlinear parameters: 40 Number of fuzzy rules: 10
Performance Selection of Genetic Algorithm at Epoch 90	GANFIS info: Number of nodes: 23 Number of linear parameters: 9 Number of nonlinear parameters: 12 Number of fuzzy rules: 3
Performance Selection of Genetic Algorithm at Epoch 110	GANFIS info: Number of nodes: 41 Number of linear parameters: 18 Number of nonlinear parameters: 24 Number of fuzzy rules: 6
Performance Selection of Genetic Algorithm at Epoch 125	GANFIS info: Number of nodes: 53 Number of linear parameters: 24 Number of nonlinear parameters: 32 Number of fuzzy rules: 8
Performance Selection of Genetic Algorithm at Epoch 170	GANFIS info: Number of nodes: 23 Number of linear parameters: 9 Number of nonlinear parameters: 12 Number of fuzzy rules: 3
Performance Selection of Genetic Algorithm at Epoch 210	GANFIS info: Number of nodes: 65 Number of linear parameters: 30 Number of nonlinear parameters: 40 Number of fuzzy rules: 10
Performance Selection of Genetic Algorithm at Epoch 243	GANFIS info: Number of nodes: 47 Number of linear parameters: 21 Number of nonlinear parameters: 28 Number of fuzzy rules: 7
Performance Selection of Genetic Algorithm at Epoch 300	GANFIS info: Number of nodes: 65 Number of linear parameters: 30 Number of nonlinear parameters: 40 Number of fuzzy rules: 10

These function when implemented in the genetic algorithm gives the best fitness function value as follows:
FITNESS FUNCTION VALUE: 0.187462

E. ANN-Based Fault Diagnosis

The analysis of the ANN is a difficult task and it requires an expert opinion with a hit and trial scenario by putting different types training sets and functions and finding the final outcome of the best possible hidden layers and activation layers as per according to the problem at hand. A generic model of the ANN in fault diagnosis is as follows in Fig. 21 and a generic activation evaluation on a sigmoid activation function is shown in Fig. 22.

F. Discussion

In this paper, three modeling techniques have been used, a fuzzy-logic based fault modeling, a kalman filter-based approach for fault detection and the hybrid techniques have been implemented for the fault classification. A good comparison of the techniques can been in the histographs shown in Fig. 23 and Fig. 24. The chart in Fig. 23 shows the comparison with the er-

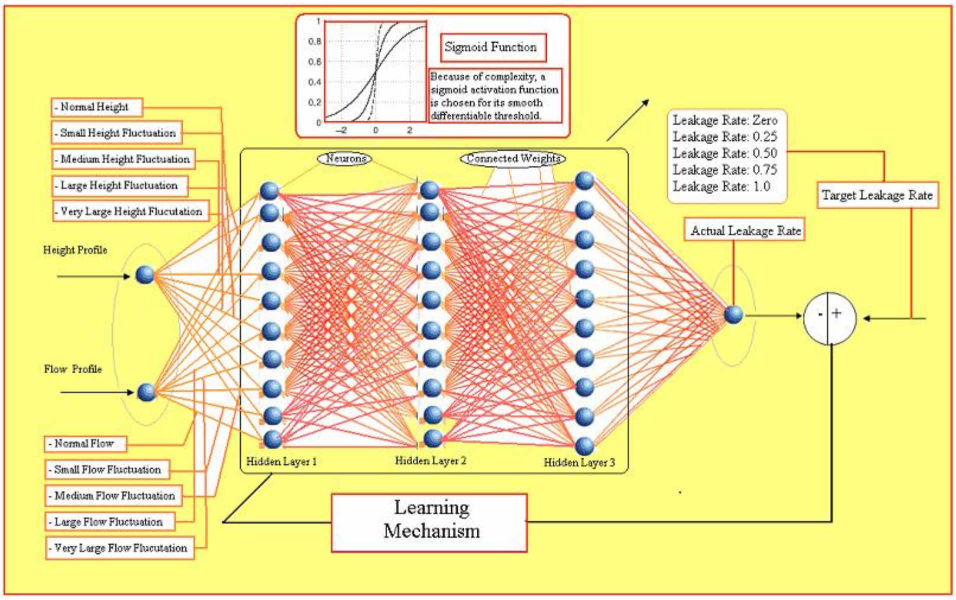

Fig. 21. Evaluation of Neural Network-Based Fault Diagnosis

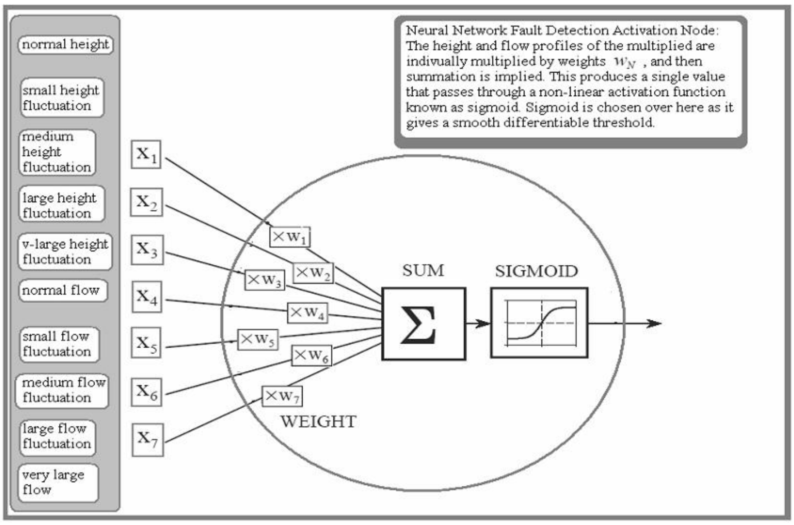

Fig. 22. Neural Network Based Activation Function Evaluation

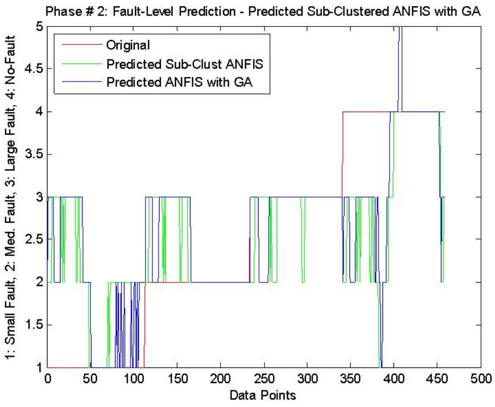

Fig. 18. (Phase 2: Four random Phases for predicted sub-clustered ANFIS with GA

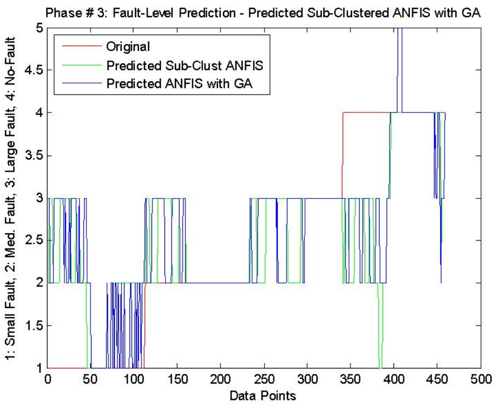

Fig. 19. (Phase 3: Four random Phases for predicted sub-clustered ANFIS with GA

ror rates between fuzzy, ANN, ANFIS and the present method of genetic neuro-fuzzy. It is to no worthy that the error rate for the GANFIS is the least one because the genetic algorithm has performed well in optimization the subtractive clustering. In Fig. 24, it can be seen, that when the radius of the subtractive clustering chosen randomly, it is showing improvements in the results.

V. Conclusion

In this paper, we presented a model-free approach to the fault diagnosis problem, based on a combination of different learning strategies like modeling with fuzzy logic, ANN, ANFIS and optimized Neuro-fuzzy. This model-free approach classifies a presence of a possible fault from the profiles of the sensor outputs. Changes in the fault signatures such as settling time, steady-state value, and the coherence spectral changes give a

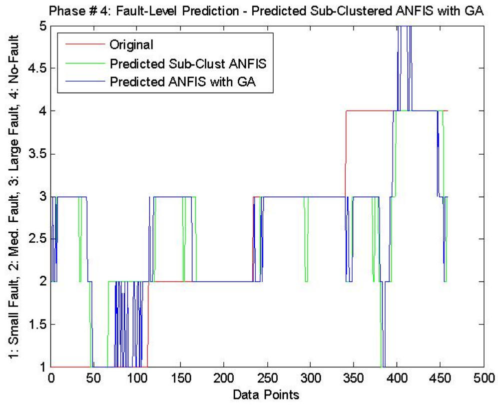

Fig. 20. (Phase 4: Four random Phases for predicted sub-clustered ANFIS with GA

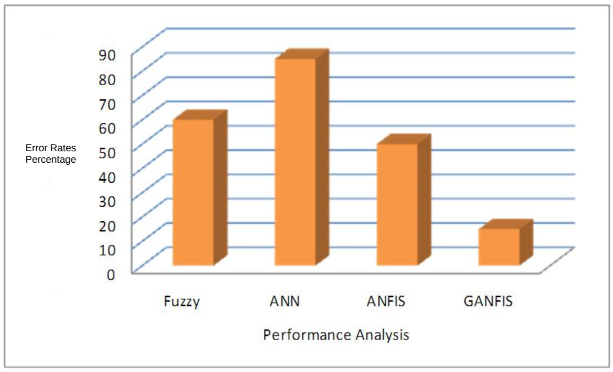

Fig. 23. Comparison of error rates

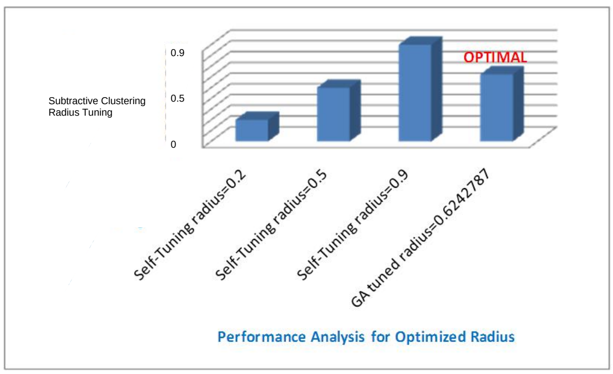

Fig. 24. Comparison of subtractive clustering radius tuning

quick indication that a fault may be in the making. An abrupt change in the sensor output profile indicates a possible onset of a fault. As such, this model free approach can be made an effective part of an overall integrated approach that tackles both fault classification and detection where detection part would be handled by an additional section using a model-based approach comprising of Kalman Filter, thus completing the structure of fault detection and classification.

ACKNOWLEDGMENTS

The authors wish to acknowledge the support of KFUPM in carrying out this work.

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