A PSO-TRAINED ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR FAULT CLASSIFICATION

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Abstract: When a fault occurs during an industrial inspection, workmen have to manually find the location and type of the fault in order to remove it. It is often difficult to accurately find the location and type of fault. Hence, development of an offline intelligent fault diagnosis system for process control industry is of great importance since successful detection of fault is a precursor to fault isolation using corrective actions. This paper presents a novel hybrid Particle Swarm Optimization (PSO) and Subtractive Clustering (SC) based Neuro-Fuzzy Inference System (ANFIS) designed for fault detection. The proposed model uses the PSO algorithm to find optimal parameters for (SC) based ANFIS training. The developed PSO-SC-ANFIS scheme provides critical information about the presence or absence of a fault. The proposed scheme is evaluated on a laboratory scale benchmark two-tank process. Leakage fault is detected and results are presented at the end of the paper showing successful diagnosis of most incipient faults when subjected to a fresh set of data.

1 INTRODUCTION

Reliability, survivability, and classification are becoming major concerns in the development of most advanced systems and processes. Successful monitoring of process control equipment with the aid of intelligent fault detection and classification techniques can result in detecting equipment malfunctions and potential causes of failure in a timely fashion and while the process is still running. This can prevent unnecessary and costly breakdowns and potentially fatal casualties, avoid environmental pollution and can, on the whole, increase the lifetime of the equipment and prevent enormous economic losses. Existing Artificial Neural Network (ANN)-based fault diagnosis approaches are effective in diagnosing and locating the fault states of process control equipments.

In this paper, a recently developed optimization technique, Particle Swarm Optimization (PSO) (Kennedy, J., Eberhart, R., 2001) is used to train Subtractive Clustering (SC)-based Adaptive Neuro-Fuzzy Inference System (ANFIS). PSO has attracted much attention among researchers and has been used to solve complex optimization problems with wide applications in different fields (Eberhart, R., Shi, Y., 1998). The developed PSO-SC-ANFIS is trained on data collected from a laboratory-scale benchmark coupled tanks. The trained ANFIS is then validated on a fresh set of data to detect incipient leakage faults in the tank.

The paper is organized as follows. Section 2 reviews recent related works in the literature. The dual-tank system used as a test-bed is described, and its model derived in section 3. Section 4 describes in detail the implementation of the proposed scheme and discusses simulation results obtained. Finally, discussions and conclusions are drawn in section 5.

2 RELATED WORKS

Artificial intelligence (AI) techniques have seen an increased interest in solving fault diagnostic problems. Application of Neural Network-based AI techniques for fault diagnosis of systems like power transformers (Ping, Y. Q., Wude, X., Zhida, L., 2005; Ping, Q., Qun, L. M., Yun, M. X., Jun, W., 2009) and rotating machines (Dou, W., Liu, Z. S., Wang, D. H., 2007; Wei, D., Sheng, L. Z., Xiaowei, W., 2007) can be found in the literature. An important requirement for training an artificially intelligent system that is required to predict the behavior of the plant is tun-

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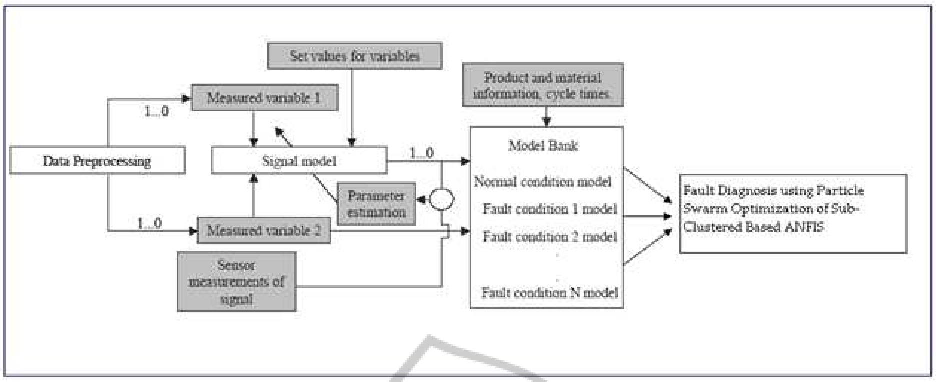

Figure 1: Proposed scheme.

ing its key parameters to optimal values during its training. With the rapid rise of heuristic algorithms, researchers have found more reliable means to find optimal solutions to AI learning problems. Genetic Algorithm (GA) (Dou, W., Liu, Z. S., Wang, D. H., 2007; Wei, D., Sheng, L. Z., Xiaowei, W., 2007; Elhadef, M., Ayeb, B., 2000), Particle Swarm Optimization (PSO) (Hongxia, P., Jinying, H., Hongwei, M., 2009), and Grid Search based methods (Duan, F., Zivanovic, R., 2009) are among several other techniques that have seen an increased interest and use in solving AI-based fault diagnostic problems. Various techniques such as ANN, Fuzzy Logic (FL) and GA are used to develop models for FDI techniques. These models can be trained and used to represent a wide class of nonlinear systems with an arbitrary accuracy. Among these techniques, ANN-based techniques are well recognized for their ability to approximate nonlinear functions and for their learning ability (Zhang, G. Q. P., 2000). For these reasons, they have been used as models to generate residuals for fault detection purposes (Wang, Y., Chan C. W., Cheung, K. C., 2001). However, it is desirable that a fault diagnostic system should be able to incorporate the experience of the operators (De Miguel, L. J., Blazquez, L. F., 2005). To achieve such an aim, researchers have resorted to the use of fuzzy reasoning which allows symbolic generalization of numerical data using fuzzy rules, and which supports direct integration of operator's experience in the decision-making process of FDI in order to achieve more reliable fault diagnosis. In this paper, a PSO-trained SC-ANFIS is proposed to meet the requirements for a quick and reliable fault detection scheme. The proposed scheme has been evaluated on a laboratory-scale based two-tank system. It is the most used prototype applied in waste water treatment plants, petro-chemical plants, and oil/gas processing plants. The main contribution of the paper is the implementation of the proposed PSO-SC-Adaptive Neuro-Fuzzy system and its application to the fault diagnosis problem.

3 FAULT DIAGNOSIS PROBLEM STATEMENT

3.1 Experimental Setup and Process Data Collection

The Benchmarked laboratory-scale two-tank process control system has been used to collect data at a sampling rate of 50 milliseconds. Hydraulic height and liquid output flow-rate of the second tank are the inputs while leakage fault level on a discrete scale of 1 to 4 is the considered output. The proposed scheme is shown in Figure 1. A Proportional Integral (PI) controller works in a closed loop configuration. Data is collected by introducing leakage fault in the closed loop system. This is done through the pipe clogs of the system using drainage valve between the two tanks. The PI controller tends to treat the introduced fault as a disturbance and acts to suppress it. The objective of the benchmark dual-tank system is to reach a reference height of 200 ml in the second tank. The closed-loop nature of the experiment also tends to suppress the faults introduced in the system, thereby making it more difficult to detect these faults.

3.2 Model of the Coupled Tank System

The physical system under evaluation is formed of two tanks connected by a pipe. 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 200 ml, as shown in

Figure 2. A step input is applied to the dc motor-pump system to fill the first tank. Varying levels of leakage faults are introduced and the liquid height and the output flow-rate of the second tank are both measured. The model relating the input control signal to the motor, u, and the flow Q_i is given below.

$$Q_i = -a_m Q_i + b_m \phi(u), \qquad (1)$$

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

$$Q_l = C_{dl}\sqrt{2gH_1}. \qquad (2)$$

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

$$A_1 \frac{dH_1}{dt} = Q_i - C_{12}\phi(H_1 - H_2) - C_l\phi(H_1), \qquad (3)$$

$$A_2 \frac{dH_2}{dt} = C_{12}\phi(H_1 - H_2) - C_0\phi(H_2), \qquad (4)$$

where $\phi(.) = sign(.)\sqrt{2g(.)}, Q_l = C_l\phi(H_1)$ is the leakage flow rate, $Q_0 = C_0\phi(H_2)$ 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, $g = 980cm/sec^2$ is the gravitational constant, C_{12} and C_0 are the discharge coefficient of the inter-tank and output valves respectively. The model of the two-tank fluid control system is of second order and is nonlinear with smooth square-root type nonlinearity. For design purposes, a linearized model of the fluid system is required and is given as

$$\frac{dh_1}{dt} = b_1 q_i - (a_1 + \alpha)h_1 + a_1 h_2, \qquad (5)$$

$$\frac{dh_2}{dt} = a_2 h_1 - (a_2 - \beta)h_2, \qquad (6)$$

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

$$b_1 = \frac{1}{A_1},\; a_1 = \frac{C_{db}}{2\sqrt{2g(H_1^0 - H_2^0)}}, \beta = \frac{C_0}{2\sqrt{2gH_2^0}}, \qquad (7)$$

$$a_2 = a_1 + \frac{C_{d0}}{2\sqrt{2gH_2^0}}, \alpha = \frac{C_{dl}}{2\sqrt{2gH_1^0}}. \qquad (8)$$

The parameter indicates the amount of leakage. A PI controller, with gains k_P and k_I is used to maintain the level of Tank 2 at the desired reference input r.

$$\dot{x_3} = e = r - h_2, \qquad (9)$$

$$u = k_P e + k_I x_3 \qquad (10)$$

The state space model is given by:

$$x = \begin{bmatrix} h_1 & h_3 & x_3 & q_i \end{bmatrix}^T,$$

$$A = \begin{bmatrix} -a_1 - \alpha & a_1 & 0 & b_1 \\ a_2 & -a_2 - \beta & 0 & 0 \\ 0 & -1 & 0 & 0 \\ -b_m k_P & 0 & b_m k_I & -a_m \end{bmatrix},$$

$$B = \begin{bmatrix} 0 & 0 & 1 & b_m k_P \end{bmatrix}^T,$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix},$$

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. $q_l = \alpha h_1$, $q_0 = \beta h_2$.

4 ANFIS BASED FAULT DIAGNOSIS USING SUBTRACTIVE CLUSTERING

Subtractive Clustering (SC) technique is used to formulate an ANFIS. The procedure for Subtractive Clustering seeks optimal data point by dividing the data into clusters and defining a cluster center based on the density of surrounding data points. A flowchart for SC-ANFIS is shown in the Figure 3. A radius for each cluster is chosen. All the data points within the radial distance 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 radial distance of a cluster center. Given proper cluster radii, the SC algorithm finds optimal data point to define a cluster center based on the density of surrounding data points.

4.1 Objective Function and SC-ANFIS Tuning

In order to stress the importance of a proper cluster radius while performing subtractive clustering, a random radius size is chosen for all three inputs and outputs. Two radii sizes of 0.7 and 0.2 are chosen at random to develop two SC based ANFIS. However, prediction errors for both the developed SC-ANFIS systems with radii 0.7 and 0.2, shown in Figure 8 motivate us to tune the cluster radii in order to reduce these high errors. For this purpose, an objective function based on squared error is minimized using PSO, and optimal cluster radii are searched.

An objective function J defined below is proposed.

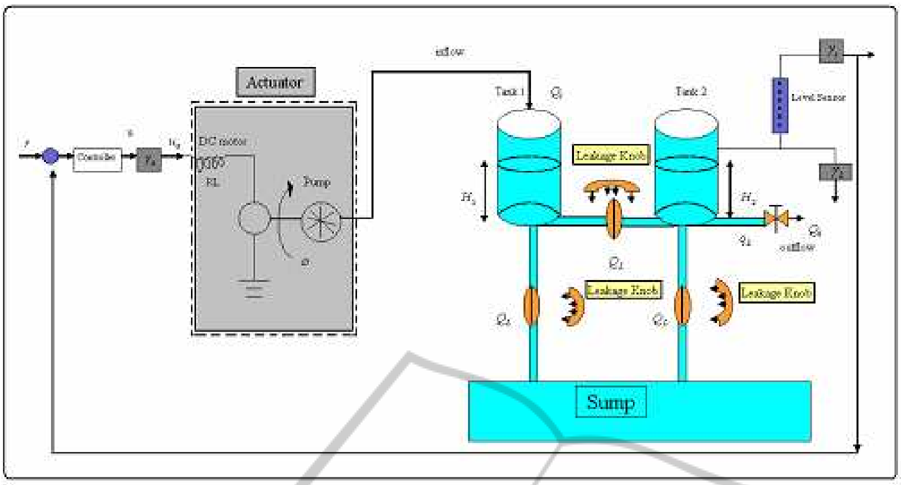

Figure 2: Two tank model.

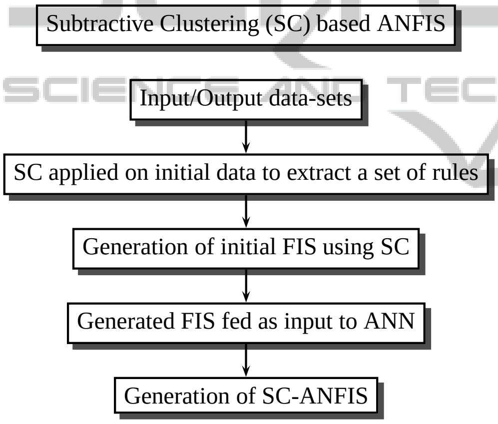

Figure 3: Flowchart for SC-ANFIS.

$$J = \sum_{n=1}^{N} \frac{(\hat{y}(n) - y(n))^2}{N} \tag{11}$$

where N denotes the number of data points, $\hat{y}(n)$ and $y(n)$ denote the n^{th} sample of predicted and actual outputs respectively.

The problem constraints are the bounds on the size of radii for the two inputs and one output. The problem can be formulated as

minimize J, subject to the constraints

$$r_i^{min} \leq r_i \leq r_i^{max}, \quad i = 1,2,3. \tag{12}$$

The minimum value of $r_{1,2,3}^{min}$ is set to 0.1 while the maximum values are set to half the range of respective inputs and outputs giving $r_1^{max} = 90, r_2^{max} = 2, and r_3^{max} = 1.5$. PSO is applied to this problem in order to find optimal or near optimal value of r_1, r_2, and r_3.

4.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary technique used to solve optimization problems (Kennedy, J., Eberhart, R., 2001). It uses 'swarm intelligence' and has been motivated by the behavior of organisms that stick together in social colonies such as school of fish and flocks of birds.

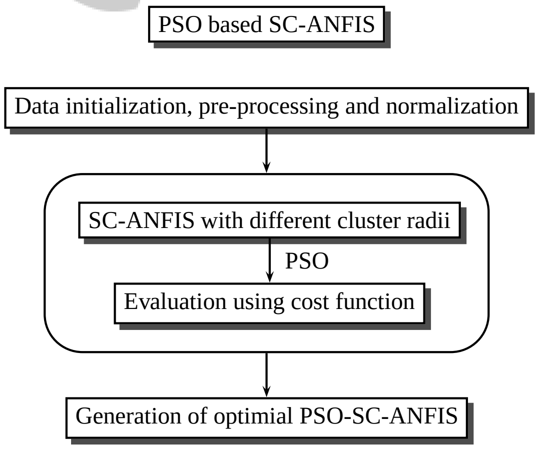

Figure 4: Flowchart for hybrid PSO-SC-ANFIS scheme.

In PSO, each particle in the swarm represents a candidate solution to the problem at hand. The particles change their positions by flying around in a multi-dimensional search space until a relatively unchanging position has been encountered. Each particle $\mathbf{x}_j(t)$ is represented by an m dimensional vector $\mathbf{x}_j(t) = [x_{j1}(t) \cdots x_{jm}(t)]$, where m represents the number of parameters that need to be optimized. The velocity for the j^{th} particle is represented by an m di-

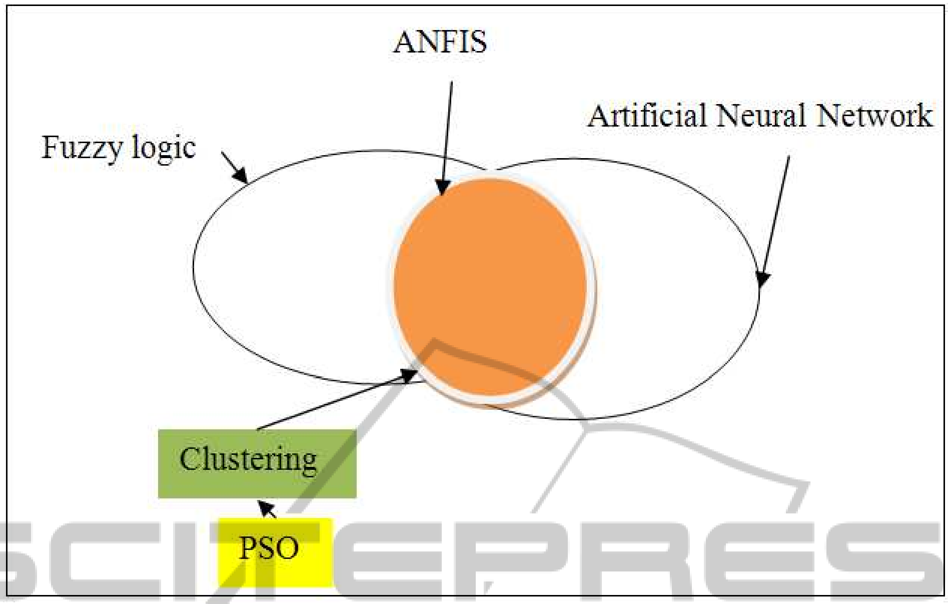

Figure 5: PSO trained SC for effective ANFIS implementation.

mensional vector $\mathbf{v}_j(t) = [v_{j1}(t) \cdots v_{jm}(t)]$. An inertia weight, w is used to control the impact of the previous velocities on the current velocity. A large initial inertia weight is recommended for global exploration and vice versa. As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is the individual or local best $\mathbf{x}_j^*(t)$.

The global best $\mathbf{x}^{**}(t)$ is the best position among all individual best positions achieved so far. A random population of m dimensional particles $\mathbf{X}(t)\ \varepsilon\ \Re^{n\times m}$ is generated, where n denotes the size of the population. The k^{th} parameter of every particle is generated within the range of the k^{th} optimized parameter $[x_k^{max}, x_k^{min}]$. Initial velocities of particles $\mathbf{V}(t)\ \varepsilon\ \Re^{n\times m}$ are generated in a similar fashion. Each particle is evaluated using an objective function J. As the iterations progress, each particle is compared with its local best and local best is updated. Inertia weight is updated according to $w = \alpha w$, where α is smaller than but close to 1. Finally velocity and position of every particle is updated. Velocity update of j^{th} particle is given by

$$\mathbf{v}_j(t+1) = w\mathbf{v}_j(t) + c_1 r_{j1}(t)\{\mathbf{x}_j^*(t) - \mathbf{x}_j(t)\} + c_2 r_{j2}(t)\{\mathbf{x}^{**}(t) - \mathbf{x}_j(t)\}], \quad (13)$$

$$\mathbf{x}_j(t+1) = \mathbf{v}_j(t) + \mathbf{x}_j(t). \quad (14)$$

where c_1 and c_2 are cognitive and social parameters and represent orientation of velocity update towards local and global best respectively.

4.3 Training and Performance of PSO-ANFIS

PSO based ANFIS is developed. Flowchart for PSO-SC-ANFIS is shown in Figure 4. A generic concept for the implementation can be seen from the Figure 5 as well. The developed algorithm is applied on the above defined problem to search for optimal radii of data clusters. The number of iterations is kept 60, population size is kept 50, cognitive and social parameters c_1 and c_2 are kept equal to 2, and constraints on the radii, as defined above, are observed strictly. The obtained optimal values for the three radii are $r_1 = 0.3685$, $r_2 = 0.1949$, and $r_3 = 0.1614$. The convergence of objective function is shown in Figure 6. PSO converges to almost the same values of radii for every run of the algorithm. Cost function convergence to optimal or near optimal solution regardless of initial solution demonstrates the robustness of the algorithm. Simulation result for optimal radii is shown in Figure 7.

5 DISCUSSION

In this paper, a PSO optimized subtractive clustering is used to develop and train an ANFIS for fault detection. The importance of using optimum cluster radii can be gauged from the output error between actual faults and predicted faults shown in Figure 8. The figure shows a histogram for subtractive

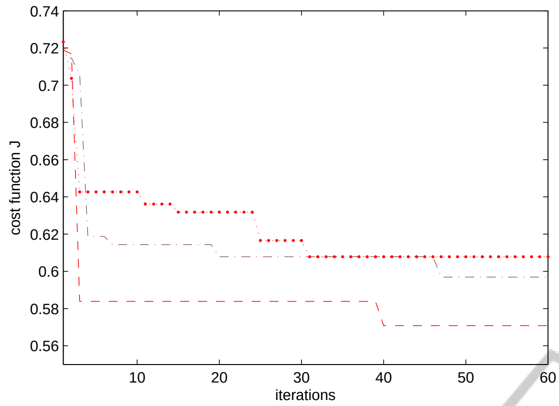

Figure 6: Cost function convergence with different initial solutions.

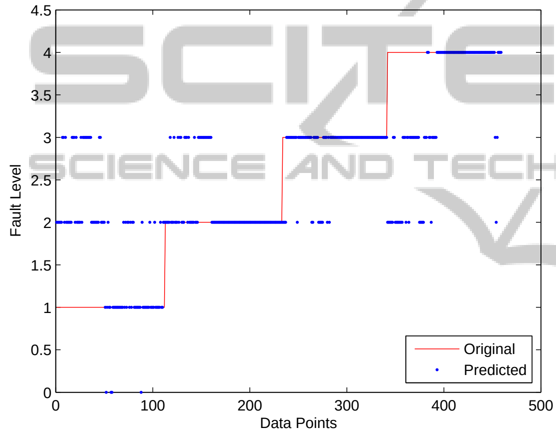

Figure 7: Leakage fault prediction results using PSO-SC-ANFIS.

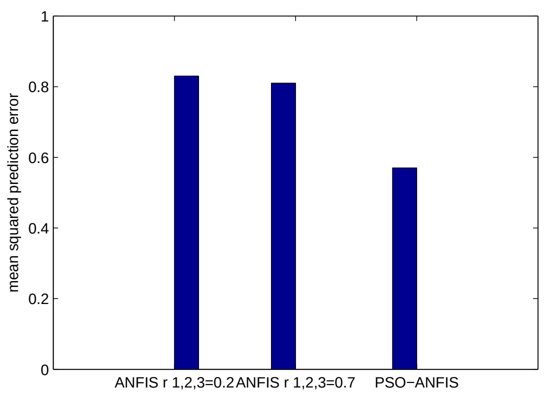

Figure 8: Prediction mean squared errors for SC-ANFIS with randomly selected radii $r_{1,2,3} = 0.2, r_{1,2,3} = 0.7$, and PSO-SC-ANFIS.

clustering based ANFIS with randomly selected radii $r_{1,2,3} = 0.7$, another ANFIS with randomly selected radii $r_{1,2,3} = 0.2$, and a PSO optimized subtractive clustering based ANFIS. The error rates for the three cases evidently place PSO-ANFIS at the top of the other two. The error rate for PSO-ANFIS highlights the performance of PSO in converging to a near optimal value for the radii of clusters. The fault detection results thus obtained are encouraging and provides motivation for more work towards further improvement.

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