A Tabu-Search Based Neuro-Fuzzy Inference System for Fault Diagnosis

Haris M. Khalid * **S.Z. Rizvi** ** **Rajamani Doraiswami** *** **Lahouari Cheded** **** **Amar Khoukhi** †

* *King Fahd University of Petroleum & Minerals, Saudi Arabia, (e-mail: mhariskh@kfupm.edu.sa).*
** *King Fahd University of Petroleum & Minerals, Saudi Arabia, (e-mail: srizvi@kfupm.edu.sa).*
*** *University of New Burnswick & National Science and Engineering Research Council (NSERC), Canada, (e-mail: dorai@unb.ca)*
**** *King Fahd University of Petroleum & Minerals, Saudi Arabia, (e-mail: cheded@kfupm.edu.sa).*
† *King Fahd University of Petroleum & Minerals, Saudi Arabia, (e-mail: amar@kfupm.edu.sa).*

Abstract: This paper presents a novel hybrid Tabu Search (TS) Subtractive Clustering (SC) based Neuro-Fuzzy Inference System (ANFIS) design for fault detection. The proposed model uses the TS algorithm to find optimal parameters for Subtractive Clustering (SC) based ANFIS. The developed TS-SC-ANFIS scheme provides critical information about the presence or absence of a fault. The TS being an efficient local search technique, shows remarkable success in finding optimal cluster parameters which proves instrumental in ANFIS training, making it efficient in fault detection. The proposed scheme is evaluated on a laboratory scale coupled-tank system. Fault detection results presented at the end of the paper using fresh set of data show successful diagnosis of most incipient leakage faults in the coupled-tank system.

Keywords: Tabu Search, Subtractive Clustering, Neuro-Fuzzy, Soft Computing, Artificial Neural Network, ANFIS, Fault Detection, Benchmark Laboratory Scale Two-Tank System.

1. INTRODUCTION

In the process control industry, fault is an undesirable factor in any process. It affects the efficiency of system operation and reduces economic benefit to the industry. 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, and to cause reductions in plant shutdowns. Successful fault diagnosis in process control equipments using intelligent fault classification techniques can result in predicting equipment life and detecting malfunctions and potential causes of failure well ahead of time. This can lead to prevention of expensive breakdowns and potentially fatal casualties, and can therefore increase the lifetime of the equipment and yield economic benefits. The importance of fault classification and detection is therefore non-trivial.

Artificial intelligence (AI) techniques have seen an increased interest in solving fault diagnosis problems. Application of Neural Networks based AI techniques for fault diagnosis have been used for power transformers by Ping et al. (2005, 2009), and for rotating machines by Dou et al. (2007) and Wei et al. (2007). An important requirement for training an AI system that is required to predict the behaviour of the plant is optimal values of its key parameters 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), as seen in Dou et al. (2007), Wei et al. (2007) and Elhadef and Ayeb (2000), Particle Swarm Optimisation (PSO) as seen in Hongxia et al. (2009), and Grid Search based methods as described in Duan and Zivanovic (2009) are among several others that have seen an increased interest in solving AI based fault diagnostic problems.

In the recent past, Tabu Search (TS) algorithm has surfaced as a highly promising heuristic algorithm for solving combinatorial optimisation problems. It was proposed in detail in Glover (1989, 1990a, 1990b, 1993). TS uses a memory of search history to prevent cycling and entrapment in local optima. It has been shown in the literature that, under certain conditions, the TS algorithm can yield global optimal solution with probability one (Glover, 1990b). In the recent past, TS has been used to solve a number of optimisation problems in the power and process control industry, however, to the best of the authors' knowledge, the use of TS for fault diagnosis in processes has remained scarce to date.

This paper presents a new Adaptive-Neuro-Fuzzy Inference System (ANFIS) design using TS based Subtractive Clustering (SC). TS is used to find optimal values of SC parameters. A benchmark laboratory scale two-tank model is used for data collection over a lengthy period of time. Fault is induced in the process during data collection and inputs and outputs are recorded. Once the data is collected, the proposed TS-SC-ANFIS is trained using this sampled data. The developed TS-SC-ANFIS is validated using a fresh set of data and results are presented in this paper to evaluate the performance of the proposed scheme.

The paper is arranged as follows. Section 2 describes the fault detection problem at hand and briefs the reader about the experimental setup, the model of the process, and the way the data was collected. Section 3 describes the formulation of the problem into an optimisation problem and takes a look at the selection of a proper cost function. Section 4 describes the Tabu-Search algorithm in detail. Section 5 takes a look at simulation results and section 6 seeks to draw concluding remarks.

2. FAULT DIAGNOSIS PROBLEM STATEMENT

2.1 Process description and data collection

A Benchmark laboratory-scale two-tank process control system has been used to collect data at a sampling rate of 50 milliseconds. The system is considered as a multi-input single-output (MISO) process with hydraulic height and liquid output flow-rate of the second tank being the two inputs while leakage fault level on a discrete scale of 1 to 4 being the output. The proposed scheme is shown in Figure 1. The objective of the benchmark dual-tank system is to reach a reference height of 200ml in the second tank. To achieve this objective, 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 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.

2.2 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 between the two tanks. 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 Figure 4.

A step input is applied to the dc motor-pump system to fill the first tank. The opening of the drainage valve introduces a leakage in the tank. Leakage faults are thus introduced and the liquid height in the second tank, H_2, and the flow rate, Q_0, are both measured. The National Instruments LabView® package is employed to collect the data. The model relating the input control signal u to the motor, and the flow Q_i is given below.

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

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

$$Q_l = C_{dl}\sqrt{2gH_1}. \tag{2}$$

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

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

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

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

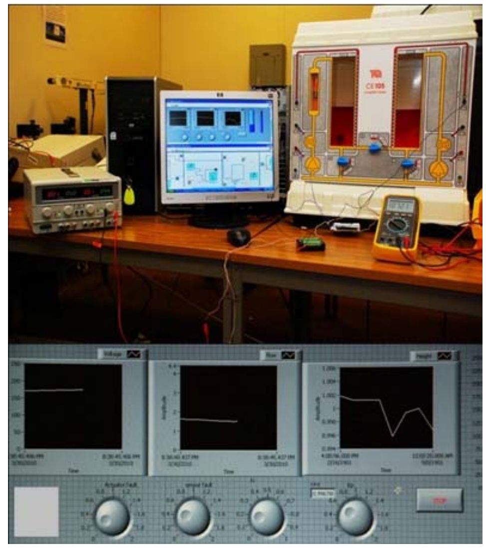

Fig. 2. (a) The two tank system interfaced with the LabView® through a DAQ and the amplifier for the magnified voltage, (b) The Labview setup of the apparatus including the circuit window and the block diagram of the experiment.

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_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 linearised model of the fluid system is required and is given as

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

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

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

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

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

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 Tank 2 at the desired reference input r.

$$\dot{x_3} = e = r - h_2, \tag{9}$$

$$u = k_P e + k_I x_3 \tag{10}$$

The state space model is given by:

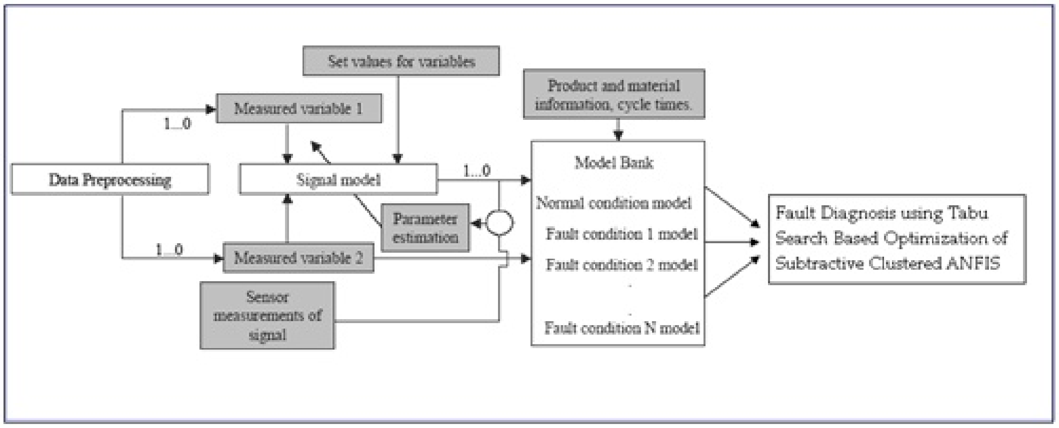

Fig. 1. Proposed Scheme

$$
\begin{aligned}
x &= [\, h_1 \;\; h_3 \;\; x_3 \;\; q_i \,]^T, \\
A &= \begin{bmatrix} -a_1-\alpha & a_1 & 0 & b_1 \\ a_2 & -a_2-\beta & 0 & 0 \\ 0 & -1 & 0 & 0 \\ -b_m k_P & 0 & b_m k_I & -a_m \end{bmatrix}, \\
B &= [\, 0 \;\; 0 \;\; 1 \;\; b_m k_P \,]^T, \\
C &= [\, 1 \;\; 0 \;\; 0 \;\; 0 \,],
\end{aligned}
$$

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 linearisation whereas the parameters α and β are respectively associated with the leakage and the output flow rate, i.e. $q_l = \alpha h_1$, $q_0 = \beta h_2$.

3. ANFIS BASED FAULT DIAGNOSIS USING SUBTRACTIVE CLUSTERING

Subtractive Clustering (SC) technique is used to formulate an ANFIS. The SC algorithm seeks optimal data-point by defining a cluster centre based on the density of surrounding data points as 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 centre. This process is repeated until all the data is within radial distance of a cluster centre. Given proper cluster radii, The SC algorithm finds optimal data point to define a cluster centre based on the density of surrounding data points.

An objective function J defined below is proposed.

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

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

minimise J, subject to the constraints

$$r_i^{min} \le r_i \le r_i^{max}, \quad i = 1,2,3. \qquad (12)$$

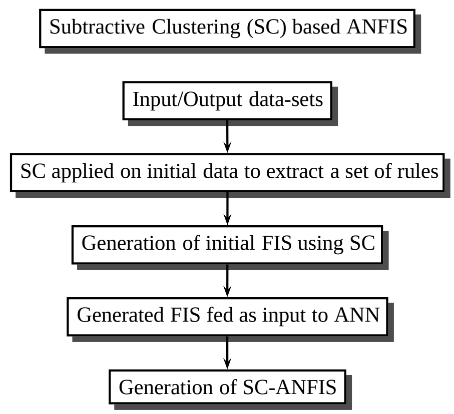

Fig. 3. Flowchart for SC-ANFIS

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 $r_1^{max} = 90, r_2^{max} = 2, and r_3^{max} = 1.5$. The TS algorithm is applied to this problem in order to find optimal or near optimal value of r_1, r_2, and r_3.

The importance of a proper cluster radius can be gauged from Figure 8. The histogram in Figure 8 shows mean squared output error on a scale of 1 to 4 for SC-ANFIS based fault prediction compared with TS-SC-ANFIS based fault prediction performed on a fresh set of data. The first two bars show the output error of SC-ANFIS based prediction with randomly selected cluster radii within the range defined above. The third bar shows TS optimised SC-ANFIS. It is seen that TS-SC-ANFIS shows considerable improvement over SC-ANFIS.

4. THE TABU SEARCH ALGORITHM

Tabu Search is an iterative heuristic algorithm used for solving combinatorial optimisation problems. Starts from any initial solution, the TS algorithm attempts to determine a better solution. The TS algorithm was proposed in its present form by Glover.

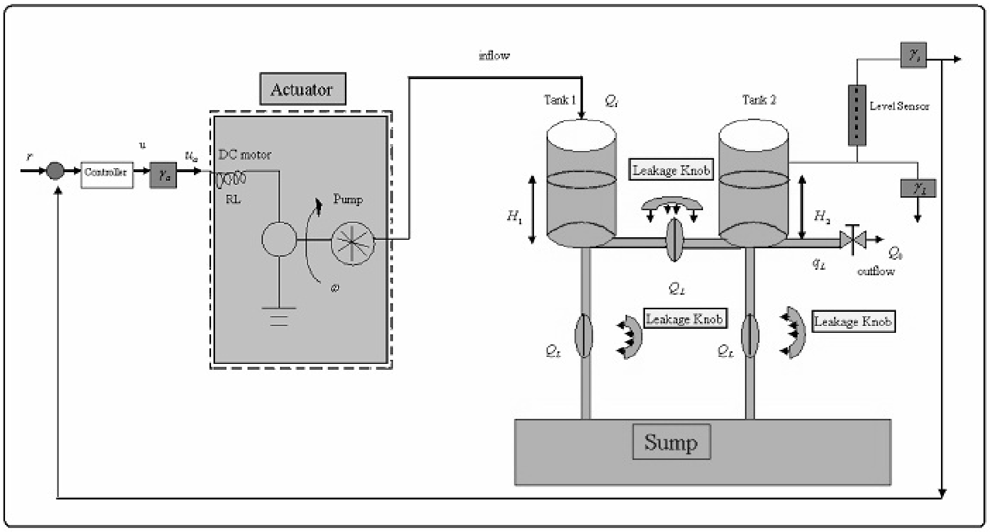

Fig. 4. Closed loop Two-tank setup.

Owing to its improved performance in solving optimisation problems, it has now become an established approach that is finding increased interest among researchers in different fields. Along with other heuristic search approaches such as Genetic Algorithm, TS has been exhibited promising results in the area of optimisation. TS is noted for its ability to avoid entrapment in local optimal solution. It does so by preventing cycling using flexible memory of search history. The basic elements of TS are briefly stated and defined as follows.

A. Current solution, $x_{current}$
It is a set of the optimised parameter values at any iteration.

B. Moves
They characterise the process of generating trial solutions that are related to x current.

C. Trial solutions x_{trial}
These are a limited set of trial solution out of a set of all possible trial solutions in the neighbourhood of x current.

D. Tabu list
A Tabu list is a list of forbidden solutions that cannot be used as x current. The TS algorithm maintains a sizeable list of Tabu solutions, and each time a solution is set as x current, it is added to the Tabu list to prevent repetition of solutions and hence entrapment in a local optimum. When the Tabu list is full, the oldest entry in the list is removed and new solutions are added to the list. The Tabu list size plays a vital role in the performance of TS algorithm. Generally, it is useful to watch out for the occurrence of cycling when the size of Tabu list is too small, and to watch for performance degradation when the size of Tabu list is too large causing too many forbiddance on moves. A Tabu list size centred on 7 is a good choice in several applications (Glover, 1990).

E. Aspiration criterion (Level)
Aspiration criteria are rules that override Tabu restrictions. If a certain move is forbidden by Tabu restriction, the aspiration criterion, if fulfilled, can make this move allowable. Different forms of aspiration criteria are used in the literature (Glover 1989, 1990a, 1990b, 1993). The AC used in the proposed technique is to override the Tabu status of a move if it yields a solution which has better objective function, J, than the one obtained earlier with the same move.

F. Stopping criteria
These are rules that provide guidance on stopping the search. The search for optimal parameters can be terminated under multiple criteria like (a) completion of predefined maximum number of iterations, or (b) stagnation in improvement of objective function. In the present work, the search terminates if a maximum of 50 iterations is reached, or if no improvement is seen over 30 iterations. The TS algorithm can be described as:

Step 1
Set the iteration counter $k = 0$ and randomly generate an initial solution $x_initial$. Set $x_{initial} = x_{current} = x_{best}$.

Step 2
Generate set of trial solutions x trials in the neighbourhood of the current solution. Sort the generated trial solutions in ascending order of their objective function values. Since the problem is a minimisation one, the top most solution is the best solution x trials 1.

Step 3
If $J(x^1_{trials}) > J(x_{best})$, jump to step 4, otherwise, $x_best = x^i_{trial}$ for $i = 1$, and then jump to step 4.

Step 4
Scan the Tabu list for a possibility of presence of x^i_{trial}. If it is not on the Tabu list, set $x_{current} = x^i_{trial}$, and jump to step 7. If it is on the Tabu list, go to step 5.

Step 5
If aspiration criterion is fulfilled, override the Tabu restriction,

update aspiration level, set $x_{current} = x^i_{trial}$, and go to step 6, otherwise, set $i = i+1$, and go to step 4.

Step 6
Check stopping criterion. If criterion is not satisfied, set $k = k+1$, and go back to step 2.

5. TRAINING AND PERFORMANCE OF TS-SC-ANFIS

Tabu Search based SC-ANFIS is developed. The TS algorithm is applied on the above defined problem to search for optimal radii of data clusters. The number of trial solutions is kept 15, the size of Tabu-list is kept 20, and constraints on the radii, as defined above, are observed strictly. The obtained optimal values for the three radii are $r_1 = 0.3171$, $r_2 = 0.1549$, and $r_3 = 0.8324$. The convergence of objective function is shown in Figure 6. The TS algorithm 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.

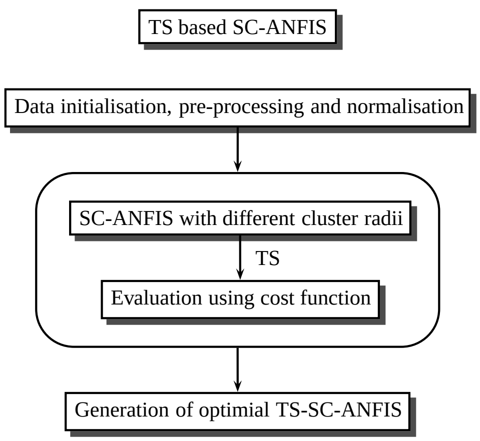

Fig. 5. Flowchart for Hybrid TS-SC-ANFIS Scheme

6. CONCLUSION

The prediction results in Figure 7 show reasonably well performance of developed TS-SC-ANFIS. Except for the data points with very small faults at the beginning of validation data, the developed TS-SC-ANFIS has predicted most fault levels correctly. It is strongly believed that many other parameters also require optimal tuning for improvement of prediction results, and it is among sincere intentions of the authors to work towards a much improved TS-SC-ANFIS in future.

ACKNOWLEDGEMENTS

The authors acknowledge the support of the National Science and Engineering Research Council (NSERC) in Canada and the Universities of New Brunswick and KFUPM in Canada and Saudi Arabia respectively.

REFERENCES

Dou, W., Liu, Z.S., and Wang, D.H. (2007) Combination Diagnosis Based on Genetic Algorithm for Rotating Machinery. *Third International Conference on Natural Computation 2007, ICNC 2007*, Vol. 4, Page(s) 307-313.

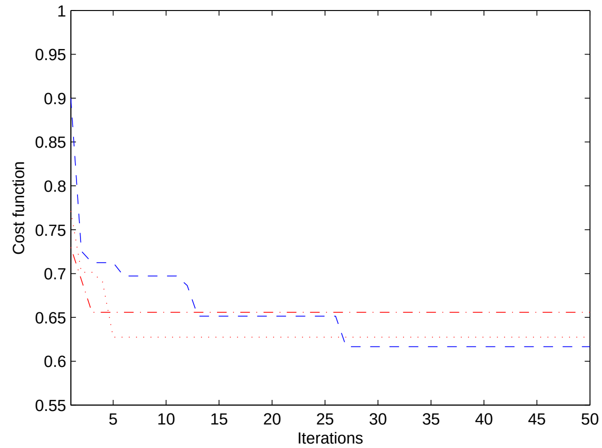

Fig. 6. Cost function convergence with different initial solutions.

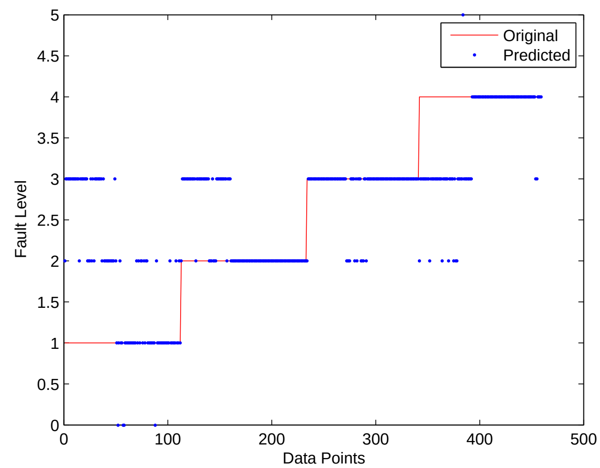

Fig. 7. Leakage fault prediction results using TS-SC-ANFIS.

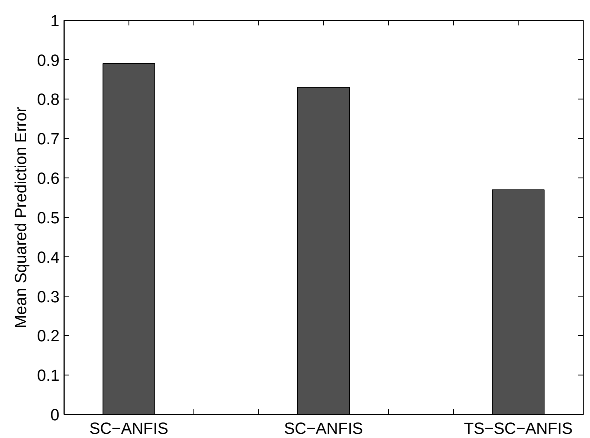

Fig. 8. Mean squared output fault prediction error for SC-ANFIS and TS-SC-ANFIS

Duan, F. and Zivanovic, R. (2009) Induction Motor Fault Diagnostics using Global Optimization Algorithm. *Australasian Universities Power Engineering Conference, AUPEC 2009*, Page(s) 1-5.

Elhadef, M. and Ayeb, B. (2000) An Evolutionary Algorithm for Identifying Faults in t-Diagnosable Systems. *The 19th IEEE Symposium on Reliable Distributed Systems, SRDS 2000*, Page(s) 74-83.

Glover, F. (1989) Tabu Search part I. *ORSA Journal on Computing*, Vol. 1, No. 3, Page(s) 190-206.

Glover, F. (1990) Artificial intelligence, heuristic frameworks and Tabu Search. *Managerial and Decision Economics, 1990*. Vol. 11. Page(s) 365-375.

Glover, F. (1990) Tabu Search part II. *ORSA Journal on Computing*, Vol. 2. No. 1. Page(s) 4-32.

Glover, F. (1993) A user's guide to Tabu Search. *Annals of Operations Reaserch*, Vol. 41, No. 1, Page(s) 3-28.

Hongxia, P., Jinying, H. and Hongwei, M. (2009) Research of Fault characteristic Extractive technology Based on Particle Swarm Optimization. *Fuzz-IEEE Conference, 2009*. Page(s) 1941-1946.

Ping, Y.Q., Wude, X. and Zhida, L. (2005) Development of an Artificial Intelligent Diagnosis System for Transformer Fault. *IEEE/PES Transmission and Distribution Conference & Exhibition: Asia and Pacific, Dalian, China, 2005* Page(s) 1-5.

Ping, Y.Q., Qun, L.M., Yun, M.X. and Jun, W. (2009) Application of artificial intelligence in power transformer fault diagnosis. *IEEE 2009 International Conference on Artificial Intelligence and Computational Intelligence*, Page(s) 442-445.

Wei, D., Sheng, L.Z. and Xiaowei, W. (2009) Application of Image Recognition Based on Artificial Immune in Rotating Machinery Fault Diagnosis. *The 1st IEEE International Conference on Bioinformatics and Biomedical Engineering, 2007. ICBBE 2007*, Page(s) 1048-1052.