Volume 4, Number 1 pp.113- 123, 2012

KUFA JOURNAL
OF ENGINEERING
ISSN 2071-5528
PRINTED IN IRAQ

Intelligent sensor fault detection based on soft computing

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(Received:24/10/2010 ; Accepted :22/2/2012)

Abstract

Sensor fault detection is carried out based on the characteristics of the soft computing techniques; neural network and adaptive neural fuzzy inference system ANFIS. In this paper, a neural network (non-model based technique) and ANFIS has been used for detection and isolation of temperature sensor fault TMP36. The measured states are then compared with true estimated states and if their difference exceeds threshold value, the particular sensor measurement is ignored and replaced by the true estimated state. Residual generation is an essential part of model-based fault detection schemes. This paper develops and implements neural-network and ANFIS based system identification techniques for nonlinear systems with the specific goal of residual generation for fault detection purposes. The two approaches are tested on a temperature sensor model. Performance comparisons of the two neural network and ANFIS are presented.

***Keywords*: Sensor fault detection, neural network, ANFIS, Residual generation, temperature sensor**

كشف اخطاء الحساسات الذكية بالاستناد الى نظم الحوسبة المرنة

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جامعة الكوفة

الخلاصة

تم الكشف عن العطل في متحسس بالاستناد الى خصائص الشبكة العصبية ونظام الاستدلال الضبابي العصبي التكيفي. في هذا البحث تم استخدام الشبكة العصبية (تقنية لا تستند الى النموذج الرياضي) ونظام الاستدلال الضبابي العصبي التكيفي (ANFIS) للكشف عن العطل في متحسس درجة الحرارة TMP36. ثّم بعد ذلك تم مقارنة قياس الخرج للمتحسس الحقيقي مع قراءات النموذج التي تم بناؤها وإذا ما تجاوزُ الفرق قيمةَ العتبةَ. إن القيمة المتبقية من عملية المقارنة (الفرق) لها دور أساسي في مخططاتِ كشفِ العيبِ (العطل) المستندة إلى نموذَج. في هذا البحث تم تُطوّرُوتُطبيّقُ شبكة عصبيةَ ونظام الاستدلال الضبابي العصبي التكيفي للتعامل مع الأنظمةِ اللاخطّيةِ بالاستناد إلى القيمة المتبقية لأغراضِ كشفِ العيبِ. إنّ الشبكتين تم اختبارهما على نموذج متحّسِ درجةِ الحرارةِ ومقارنة أداءِ كل مِنْ الشبكة العصبيةِ ونظام الاستدلال الضبابي العصبي التكيفي.

الكلمات الدلالية : اكتشاف اخطاء المتحسسات ، الشبكات العصبية ، ANFIS ، توليد Residual ، متحسس درجة حرارة.

1. Introduction

A sensor (instrument) often comprises of different parts such as sensing device, transducer, signal processor, and communication interface. Any of these parts may malfunction, causing the sensor to generate signals with unacceptable deviation from its normal signals. A sensor is declared faulty when it displays a non-permitted deviation from the characteristic properties. This deviation may appear in four forms namely (bias, drift, complete failure and precision degradation). A sensor is declared faulty when it displays a non-permitted deviation from the characteristic properties. This deviation may appear in three forms namely {drift (or incipient), complete failure (abrupt) and intermittent}. Drift referred to a case where the difference between sensor reading and actual value changes linearly with time. If the sensor reading remains constant regardless of the changes in actual value, it is known as complete failure. The case where the sensor reading is discontinuous with time, it is known as intermittent fault (Nasir Mehranbod, 2002).

The early detection of faults (just beginning and still developing) can help avoiding system from shutdown, breakdown and even catastrophes involving human fatalities and material damage. Computational intelligence techniques are being investigated as an extension to the traditional fault diagnosis methods (Faisel J Uppal & Ron J Patton, 2002). In the last ten years, the field of fault detection has attracted the attention of many researchers, both from the technical area as well as medical area.

Generally, in an industrial control system a fault may occur in the process components, in the Control loop (controller and actuators) and in the measurement sensors of the input and output variables (Vasile Palade, et al, 2002). Similar process descriptions have been provided by (Issermann, 1984 and Rossi and Braun, 1997). The first step is to monitor the physical system or device and detect any abnormal conditions (problems). This step is generally referred to as fault detection. When an abnormal condition is detected, fault diagnosis is used to evaluate the fault and determine its causes (Srinivas Katipamula, & Michael R. Brambley, 2005). Neural networks and fuzzy logic techniques are now being investigated as powerful modeling and decision making tools, along with the more traditional use of non-linear and robust observers, parity space methods and hypothesis testing theory. We will use soft computing techniques for modeling any system or sensor and make it the same behavior of this system to generate the residual (error) between system and model and then use this model to detect the fault if occurred. This work was done by using Matlab 7.6.0.324 (The MathWorks inc., 2008).

2. Neural Networks and Adaptive Neural Fuzzy Inference System (ANFIS)

2.1 Neural Networks

A neural network is a processing system that consists of a number of highly interconnected units called neurons. One of the main features of neural networks is their ability to learn from examples. Hence, they can be trained to represent relationships between past values of residual data (generated by another neural network) and those identified with some known fault conditions. The configuration used by (Chen & Patton, 1999) involved a multi-layer feed forward network configuration (R J Patton, et al, 2001). Figure (1) shows the general architecture of Feedforward Neural Network.

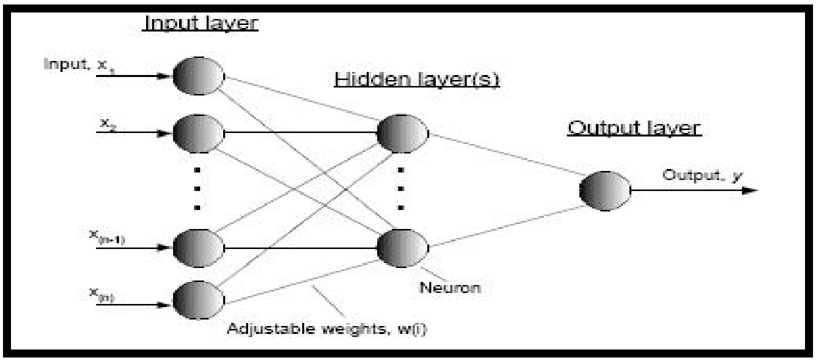

Figure (1) Feedforward Neural Network Model

The design of neural network is crucial in the process modeling. The architecture type, transfer function, number and the size of hidden layer and learning rate play an important key to determine the best neural network architecture. A multilayer feedforward neural network has been proposed in this study. This structure has been used based on the simplicity process chooses and it is enough to classify different fault generated from the normal operations. It is also the most popular network architecture (Syed Azhar Syed Abdurrahman, 2007).

The development of the process predictor involves selecting suitable artificial neural network (ANN) architecture to differentiate between the abnormal behaviors of the process with the normal condition. The difference between the actual plant signal and the estimated normal plant signal is termed as residual (Dinie Bin Muhammad, 2007). The studies on the use of NN's for fault detection have been structured around several concepts. One of these concepts is to estimate system output, given a number of previous inputs and output values. Another approach is to train the NN for on-line or off-line estimation of certain system parameters. The NN is trained to estimate system parameters under different fault conditions using appropriate inputs and outputs (and/or certain observed variables) of the system, in a supervised learning environment (Sinan Altug, et al, 1999).

2.2 Adaptive Neuro - Fuzzy Inference System (ANFIS)

The idea behind the fusion of these two technologies is to use the learning ability of NN's to implement and automate the fuzzy systems; which utilize the high-level human-like reasoning capability. The artificial NN fault detection method, by itself, cannot provide heuristic knowledge of the fault detection process because of its black box approach. On the other hand, fuzzy logic is a tool that can easily implement and utilize heuristic reasoning, but it is, in general, difficult to provide exact solutions. Fuzzy sets have been used for fault detection. However, most of these schemes are "static," i.e., a general fuzzy inference system is formed and is not allowed to change throughout the experiments (Sinan Altug, et al, 1999).

The faults are classified using this static inference engine, rather than adapting to different operating conditions. With the combined synergy of fuzzy logic and NN's, a better understanding of the detection process of the system can be achieved and, also, the fault detector can be adapted to provide more accurate solutions under different operation conditions (Sinan Altug, et al,1999). Neurofuzzy networks come to be a powerful alternative strategy to develop fuzzy systems, since they are capable of learning and providing IF-THEN fuzzy rules in linguistic or explicit form. Like:

1. If x is A1 and y is B1, then $f1 = p1x + q1y + r1$ (1)
2. If x is A2 and y is B2, then $f2 = p2x + q2y + r2$ (2)

Amongst such models, ANFIS has been recognized as a reference framework, mainly for its flexible and adaptive character.

The majority of neurofuzzy models, however, address only parametric identification and learning, leaving to the designer the liability of choosing a priori the sets of fuzzy rules and the shape characteristics of the input/output membership functions (MFs). Neurofuzzy networks (NFNs) implement fuzzy rules and inference within NN architectures.

They have all the properties of standard NNs but differ slightly in the following features: (i) learning becomes capturing knowledge in the form of IF-THEN fuzzy rules; (ii) adaptation alters existing rules when the NFN is trained and the modified rule base is extracted (this can be implemented by using fixed or adaptable membership functions with adaptable rules); and (iii) generalization should be better due to the more complex modeling of the problem.

The ANFIS structure is a five layer network. It can be described as a multi-layered neural network as shown in figure (2).

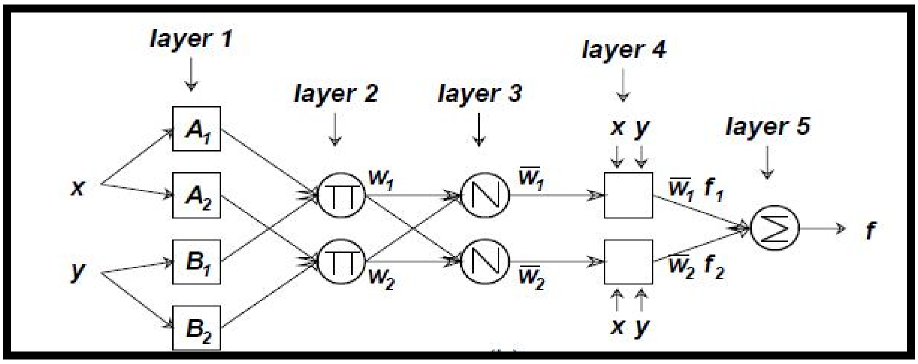

Figure (2) ANFIS structure

The feedforward equations of the ANFIS with two inputs x and y and two labels for each input and one output f shown in Figure (2) (Mahdi Aliyari Shoorehdeli , et al, 2008)

$$wi = \mu Ai(x) \times \mu Bi(x) \qquad i = 1,2 \tag{3}$$

$$\overline{wi} = \frac{wi}{w1+w2} \qquad i = 1,2 \tag{4}$$

$$f1 = p1x + q1y + r1$$

$$f2 = p2x + q2y + r2$$

$$f = \frac{w1f1+w2f2}{w1+w2} = \overline{w1}f1 + \overline{w2}f2 \tag{5}$$

Where Ai and Bi are fuzzy sets, (pi, qi, ri) is the parameter set of node i that are determined during the training process, $\bar{w}1$ and $\bar{w}2$ are the normalized values of w1 and w2 with respect to the sum represented by (w1 + w2).

Layer **1:** Input data are fuzzified and neuron values are represented by parameterized membership functions;

Layer 2: The activation of fuzzy rules is calculated via differentiable T-norms (usually, the soft-min or product);

Layer 3: A normalization operation is realized over the rules' matching values;

Layer **4:** The consequent part is obtained via linear regression or multiplication between the normalized activation level and the output of the respective rule;

Layer ***5:*** The NFN output is produced by an algebraic sum over all rules' outputs.

It is worth to note that ANFIS does not require that the designer choose a priori the number of hidden nodes, since this is automatically obtained from the number of input vectors. As well, due to the nature of the fuzzy rules under consideration, an ANFIS can only have one output, which limits its applicability to problems with one solution per time. Moreover, several types of MFs may be employed for the neurons of the input (output) layer. However, these functions usually cannot be setup at run-time (only the values of the rules can be). Thus, the prior selection of which type of MF to apply in accordance with the problem at hand turns to be a critical issue when one makes use of ANFIS (Clodoaldo Ap. M. Lima, et al, 2002).

3. Results:

We will use TMP36 (TMP36 datasheet,) sensor characteristics for modeling and fault detection in neural network and ANFIS and then compare between two methods. The characteristics of the TMP36 sensor are shown in table (1):

Table (1) TMP36 temperature sensor characteristics

Input temperature	Output voltage
-50	0.08
-25	0.31
0	0.54
25	0.77
50	1
75	1.23
100	1.46
125	1.69

3.1 Fault detection using neural network

The model is connected in parallel with the system or sensor as shown in Figure (3) to generate the residual which used in fault detection issues.

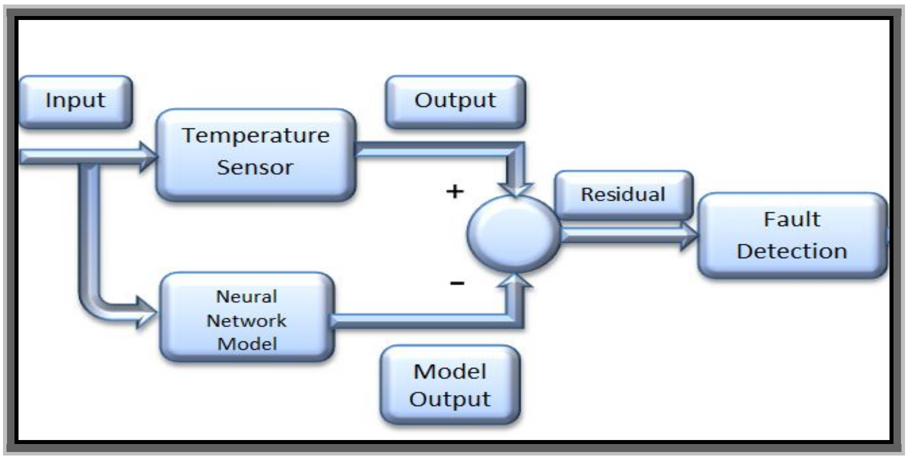

Figure (3) General schematic of residual generation using NN

After training the network with parameters given in table (2), we get results shown in figure (4) and figure (5).

Table (2) Neural network parameters for temperature sensor model

Number of neurons in hidden layer	4
Number of Epochs	2000
Learning Rate (LR)	0. 1
Momentum Coefficient (MC)	0.95
Training Function	traingdx
goal	1e-10

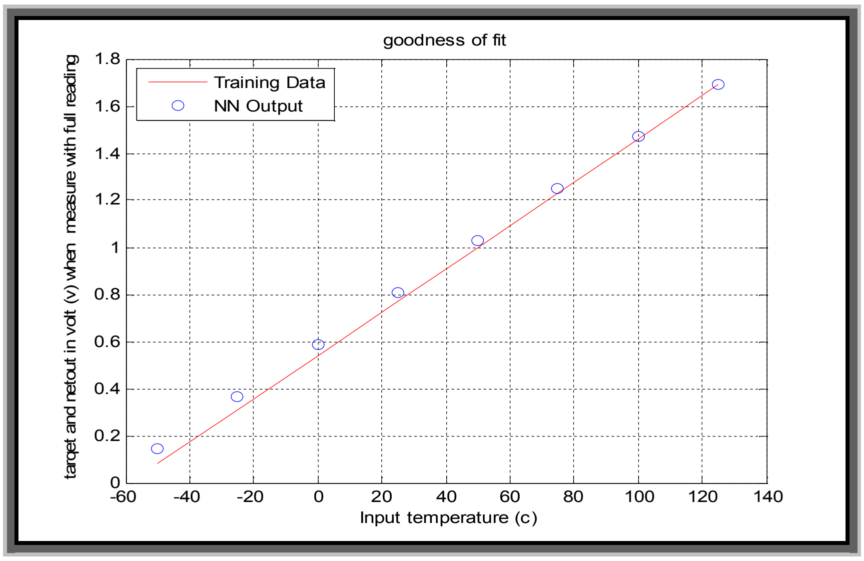

Figure (4) Goodness of fit for epoch=2000

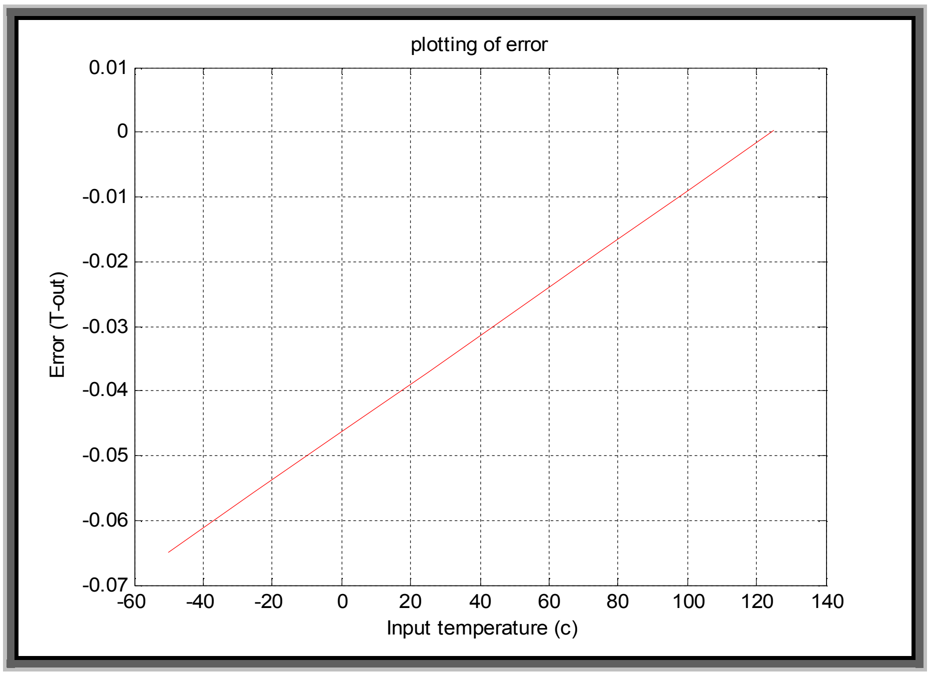

Figure (5) Plotting of error at all reading for epoch =2000

And then taking one hundred reading (one read per second) from temperature range [25-100] and creating error for threshold equal to one as shown in figure (6):

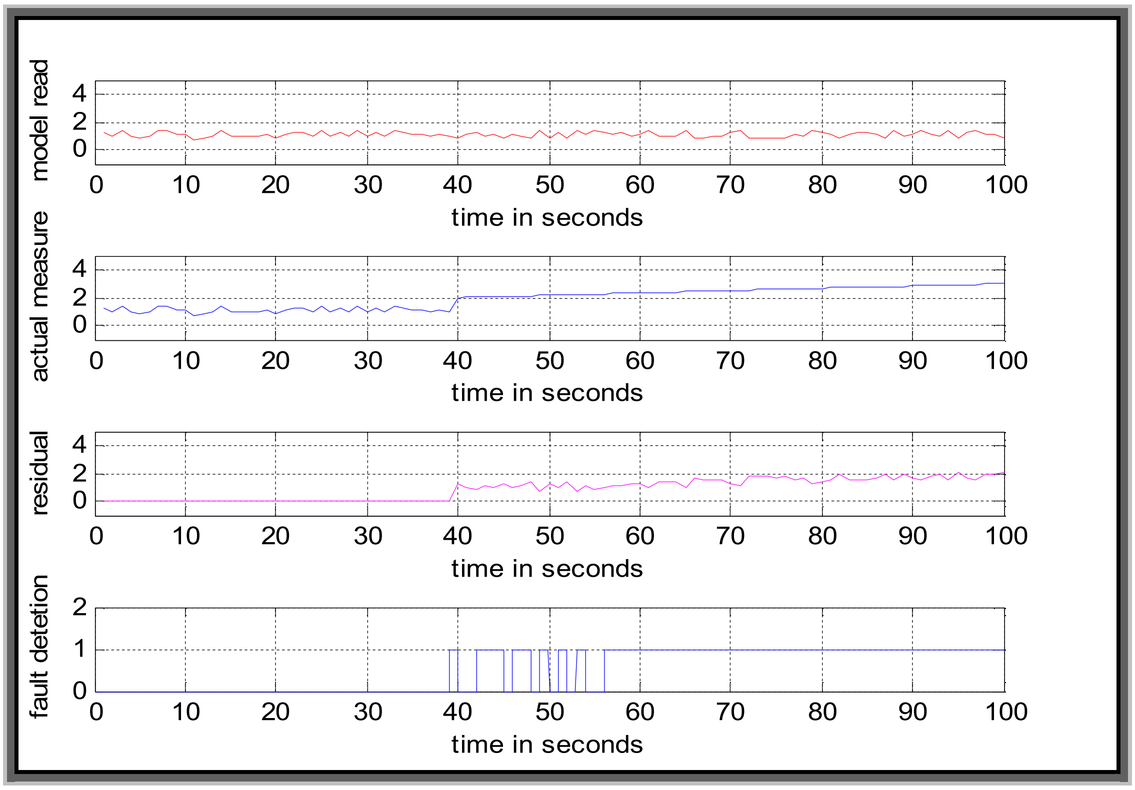

Figure (6) Fault detection of temperature sensor using NN

3.2 Fault detection using ANFIS:

The model is connected in parallel with the system or sensor as shown in Figure (7) to generate the residual which used in fault detection issues

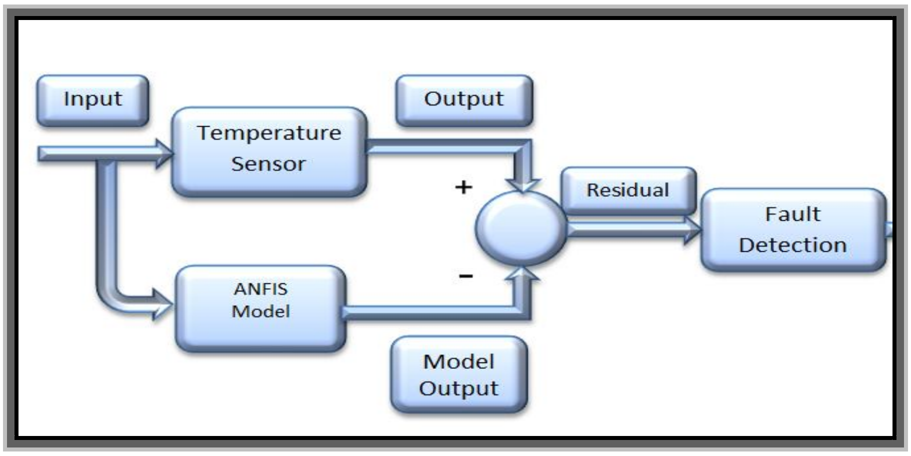

Figure (7) General schematic of residual generation using ANFIS

After training the network with parameters given in table (3), we get results shown in fig (8)

Table (3) ANFIS parameters for temperature sensor model

Number of membership function (numMFs)	2
Type of membership function (mftype)	Gauss2mf
Epochs	2

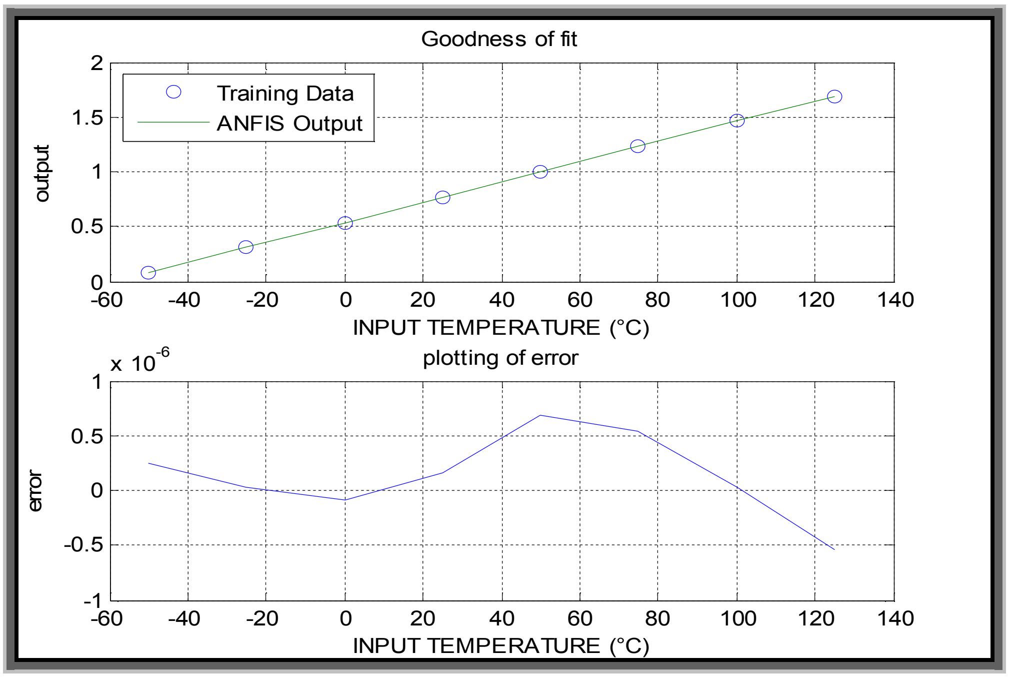

Figure (8) Goodness of fit for epochs =2 and plotting of error

Using graphics user interface with ANFISEDIT command, we obtained same results as shown in figure (9)

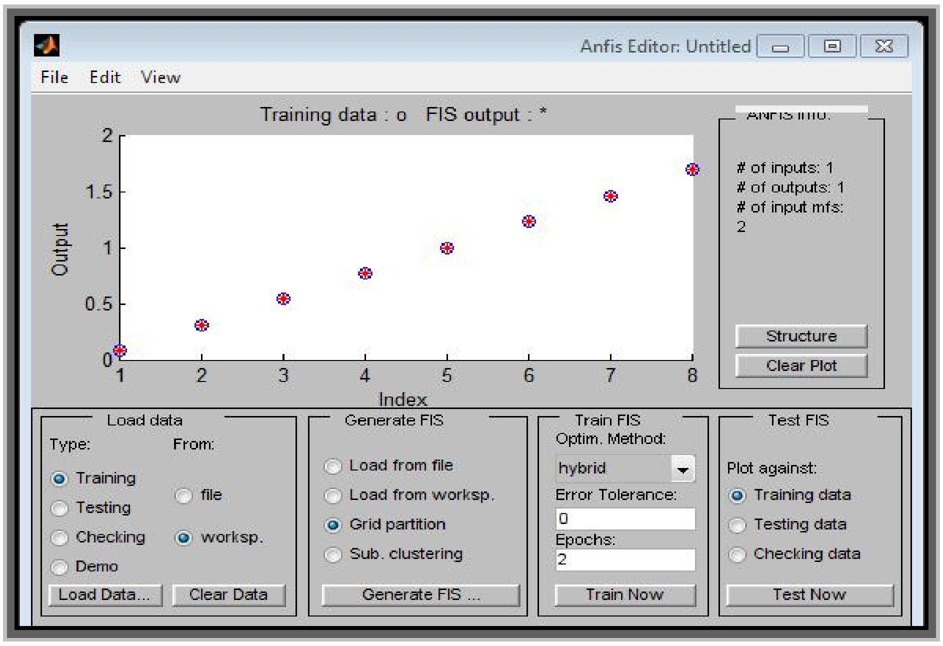

Figure (9) Simulations of net in ANFIS

And then taking one hundred reading (one read per second) from temperature range [25-100] and creating error for threshold equal to one as shown in figure (10):

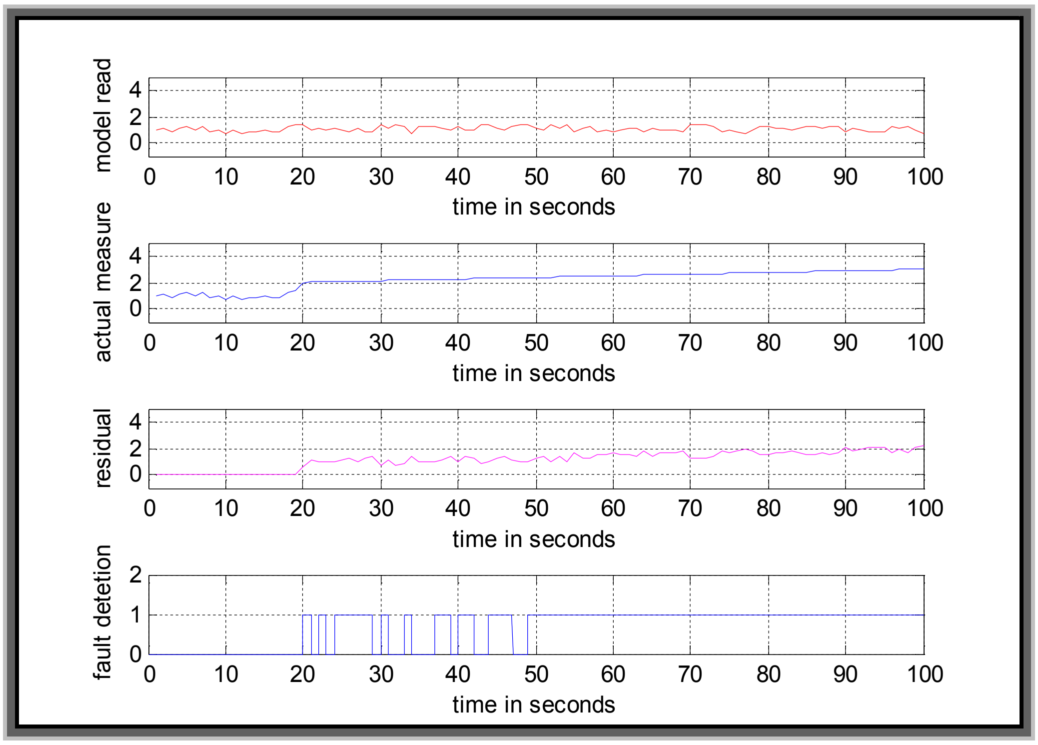

Figure (10) Fault detection of temperature sensor using ANFIS

4. Conclusions

This paper has presented a model based approach for fault detection in systems. The data required for the development of this model have been obtained through the real time operational data of the system considered. A key issue model based approach is identifying a representative set of features from which to develop the network for a particular task. Based on the results obtained, the effectiveness of the proposed method has been demonstrated through different fault detection in the temperature sensor.

With the proposed feature extraction method, an accurate ANN models can be developed in a short period of time, even for any type of actuator systems. The same models can be extended to any technical systems by considering appropriate parameters and the faults. Industrial applications of the proposed system will provide path for wide implementation because of its simplicity and efficiency. The ANFIS model was used to improve the classification accuracy when it is compared with the neural network model. Mean square error for neural network with epochs 2000 was 4.7054e-7 and with ANFIS for two epochs was 1.4352e-13.

5. References

- Clodoaldo Ap. M. Lima, Andr C L. V. Coelho, Fernando J. Von Zuben , “Fuzzy Systems Design via Ensembles of ANFIS“ , Department of Computer Engineering and Industrial Automation (DCA) School of Electrical and Computer Engineering (FEEC) State University of Campinas – Unicamp , 2002.

- DINIE BIN MUHAMMAD, “FAULT DETECTION USING NEURAL NETWORK“, UNIVERSITI MALAYSIA PAHANG, thesis, SESI PENGAJIAN: 2007/2008.

- Faisel J Uppal & Ron J Patton, “Fault Diagnosis of an Electro-pneumatic Valve Actuator Using Neural Networks with Fuzzy Capabilities“, 24-26 April 2002.

- Mahdi Aliyari Shoorehdeli & Mohammad Teshnehlab & Ali Khaki Sedigh , "Identification using ANFIS with intelligent hybrid stable learning algorithm approaches"Springer-Verlag London Limited 2008.

- Nasir Mehranbod, “A Probabilistic Approach for Sensor Fault Detection and Identification“, Thesis, November 2002.

- One Technology Way, P.O. Box 9106, Norwood, MA 02062-9106, www.analog.com,TMP36datasheet.

- R J Patton, F J Uppal & C J Lopez-Toribio, “SOFT COMPUTING APPROACHES TO FAULT DIAGNOSIS FOR DYNAMIC SYSTEMS: A SURVEY“, Control and Intelligent Systems Engineering, Faculty of Engineering and Mathematics, The University of Hull, 2001.

- Sinan Altug, Mo-Yuen Chow and H. Joel Trussell, “Fuzzy Inference Systems Implemented on Neural Architectures for Motor Fault Detection and Diagnosis“, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, VOL. 46, NO. 6, DECEMBER 1999.

- Srinivas Katipamula & Michael R. Brambley , “Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems“—A Review, Part I. VOLUME 11, NUMBER 1 HVAC&R RESEARCH JANUARY 2005.

- SYED AZHAR SYED AB. RAHMAN, “Application of Artificial Neural Network in Fault Detection Study of Batch Esterification Process“, International Journal of Engineering & Technology IJET-IJENS Vol. 10 No: 03, 2007.

- The MathWorks inc; 2008.

- Vasile Palade1, Ron J. Patton1, Faisel J. Uppal1, Joseba Quevedo2, S. Daley3, “FAULT DIAGNOSIS OF AN INDUSTRIAL GAS TURBINE USING NEURO-FUZZY METHODS“, 2002.