Failure accommodation of optical fiber current sensors using integrated adaptive neuro-fuzzy inference scheme

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In this paper, an integrated neuro-fuzzy inference scheme is used to accommodate failures of optical fiber current sensors. The proposed scheme includes three stages; namely: Sensor Failures Detection (SFD) stage, Sensor Failures Identification (SFI) stage, and Sensor Failures Accommodation (SFA) stage. In SFD stage, characterized signals called "residuals" are generated to declare occurrence of failures. The SFI stage receives residual signals and produces characterized signals that identify faulty sensors. The SFA stage uses a group of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to substitute failed sensors and continue the operation in a smooth manner. The proposed scheme is applied to accommodate abrupt failures of optical fiber current sensors in a boiler-turbine process. Simulation of the proposed scheme proves high accuracy and less mathematical burdens.

تم في هذا البحث تطوير منظومة متكاملة للتواؤم مع أعطال مستشعرات التيار ذات الألياف الضوئية. تعتمد المنظومة في عملها على مجموعة من الشبكات العصبية المفعلة بالمنطق المبهم. تتكون المنظومة المقترحة من ثلاث مراحل تقوم المرحلة الأولى بتوليد الإشارات المميزة لحدوث عطل بمستشعر أو أكثر ويطلق على هذه المرحلة " مرحلة تمييز حدوث العطل ". تقوم المرحلة الثانية باستقبال الإشارات الصادرة من المرحلة الأولى وتوليد الإشارات المحدِدة للمستشعر أو مجموعة المستشعرات المعطلة ويطلق على هذه المرحلة " مرحلة تحديد المستشعرات المعطلة ". تقوم المرحلة الثالثة بتشغيل مجموعة من الشبكات العصبية المفعلة بالمنطق المبهم لتحل محل المستشعرات المعطلة ويطلق على هذه المرحلة " مرحلة التواؤم مع الأعطال ". تم تطبيق المنظومة المقترحة للتواؤم مع أعطال مستشعرات التيار الناتج من مولد توربيني وقد أثبتت نتائج محاكاة المنظومة المقترحة دقة أدائها لوظائفها المختلفة.

Keywords: Optical fiber current sensors, Adaptive neuro-fuzzy inference system (ANFIS), Sensor failures detection (SFD), Sensor failures identification (SFI), Sensor failures accommodation (SFA)

1. Introduction

In the recent years, the intensive research works have been done in the field of application of analytical redundancy for diagnostics and system reconfiguration. The theory of fault tolerant system has been strongly developed nowadays. The survey papers in this field were published by Patton [1] and Blanke et al. [2]. A lot of contributions were devoted to the applications of fault tolerant systems by Yang and Lu [3]. Kee Son et al. [4] and Candau [5]. The general idea of application of fuzzy neural networks for instrumentation fault diagnoses was presented by Syfert and Koscielny [6].

In the present paper, an adaptive neural network inference scheme is used to accommodate abrupt failures of optical fiber current sensors in a boiler-turbine process. The paper is organized as follows: section 2 introduces the concepts of Adaptive Neuro-Fuzzy Inference System (ANFIS). Section 3 describes the boiler-turbine process. Section 4 illustrates the theory of optical fiber current sensors. The proposed scheme is explained in section 5. Simulation of the proposed scheme, results of simulations, and conclusions are discussed in section 6.

2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS as described in [7] is a feed forward network structure consisting of nodes, some of these nodes are adaptive, which means that each output of these nodes depends on the parameter(s) pertaining to this node. ANFIS receives a group of pairs of data and uses a numerical hybrid iterative procedures to update the node's parameters. Without loss of generality, ANFIS having two inputs (*X, Y*) and output *F* with two fuzzy if-then rules is shown in fig. 1.

Suppose that the rule base of the ANFIS shown in fig. 1 contains the following rules:

Rule 1: if X is A_1 and Y is B_1 then $F_1 = p_1X + q_1 Y + r_1$,

Rule 2: if X is A_2 and Y is B_2 then $F_2 = p_2X + q_2 Y + r_2$.

The output of different layers can be described as follows:

Layer 1: every node i in this layer has the following function:

$$O_i^1(X) = \mu_{A.i}(x)\,, \tag{1}$$

where;

X is the input to the node i ,

A_i is the linguistic label (small, large, … etc.) , and

$\mu_{Ai}^{(x)}$ is the membership function; such that.

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{X - C_i}{a_i}\right)^2\right]^{bi}}\,, \tag{2}$$

where; $\{a_i, b_i, c_i\}$ are premise parameters.

Layer 2: every node in this layer multiplies the incoming signals and sends the product out.

$$O_i^2 = w_i = \mu_{A.i}(x) \times \mu_{Bi}(y)\,. \tag{3}$$

Layer 3: the *i-th* node in this layer calculates the ratio of the *i-th* rule firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad \text{i = 1, 2, …} \tag{4}$$

Layer 4: every node i in this layer has the following function:

$$O_i^4(X) = \overline{w_i}F_i = \overline{w_i}(P_iX + q_iY + r_i)\,, \tag{5}$$

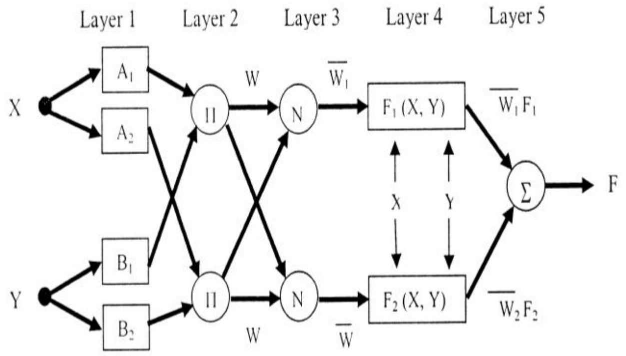

Fig. 1. ANFIS architecture.

where; $\{P_i, q_i, r_i\}$ are consequent parameters

Layer 5: the single node in this layer computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5(X) = \sum_i \overline{w_i}F_i = \frac{\sum_i w_iF_i}{\sum_i w_i}\,. \tag{6}$$

It is noted that, only layer 1 and layer 4 contain modifiable parameters. Learning or adjusting of these parameters is a two step process. First, while holding the premise parameters fixed, the information is propagated forward in the network until layer 4 where the consequent parameters are identified based on least squares estimate [7]. Then, in the backward path the consequent parameters are held fixed while the error is propagated and the premise parameters are calculated using gardient descent algorithm [7].

The ANFIS available in the fuzzy logic toolbox of MATLAB makes its use more easier. The only user specified information is the number of membership functions in the universe of discourse for each input and, of course, the input-output training information.

3. Boiler-turbine process

The mathematical model proposed by Astrom et al. [8] to solve the non-linear dynamics of the boiler-turbine was:

$$\dot{X}1 = 0.9U1 - 0.0018U2X1^{9/8} - 0.15U3\,, \tag{7}$$

$$\dot{X}2 = [(0.73U2 - 0.16)X1^{9/8} - X2]/10\,, \tag{8}$$

where;
$U1$ is the fuel flow rate,
$U2$ is the steam flow rate,
$U3$ is the feed water flow rate,
$X1$ is the magnitude of steam pressure,
$\dot{X}1$ is the rate of change of steam pressure,
$X2$ is the magnitude of generated electric power, and
$\dot{X}2$ is the rate of change of generated electric power.

Fig. 2 illustrates the boiler-turbine process proposed by Astrom et al.

The process is designed such that maximum power is generated when all $U1$, $U2$, and $U3$ represent step inputs. The value of total maximum power generated from the turbine is the summation of three phase powers which is given by:

$$P_{max} = 3V_{PHmax} I_{PHmax} COS\Phi , \quad (9)$$

where; V_{PHmax} = 500 KV, I_{PHmax} = 200 amp. , and $COS\Phi$ = 0.85.

Substitution of V_{PHmax}, I_{PHmax}, and $COS\Phi$ in eq. (8) yields P_{max} = 255 MW. It is evident that three current sensors are required to measure current (one sensor for each phase). For excellent insulation, larger dynamic frequency range and avoiding hysteresis problems optical fiber current sensors are recommended.

4. Theory of optical fiber current sensors [9]

When linearly polarized light passes through a transparent, diamagnetic material through which a magnetic field is also passing in the same direction, the polarized vector "E" of the emergent ray rotates by an angle "α" , such that:

$$\alpha = V \oint H.dL , \quad (10)$$

where;
E is the electric field vector perpendicular to the magnetic field vector of an electromagnetic wave (light),
V is the Verdit constant of the used material,
H is the magnetic field intensity vector, and
dL is the light propagation path which encloses the magnetic field.

From Ampere's circuital law:

$$\oint H.dL = I , \quad (11)$$

where;
I is the current enclosed by one optical path loop.

Then; substitution of eq. (11) into eq. (10) yields:

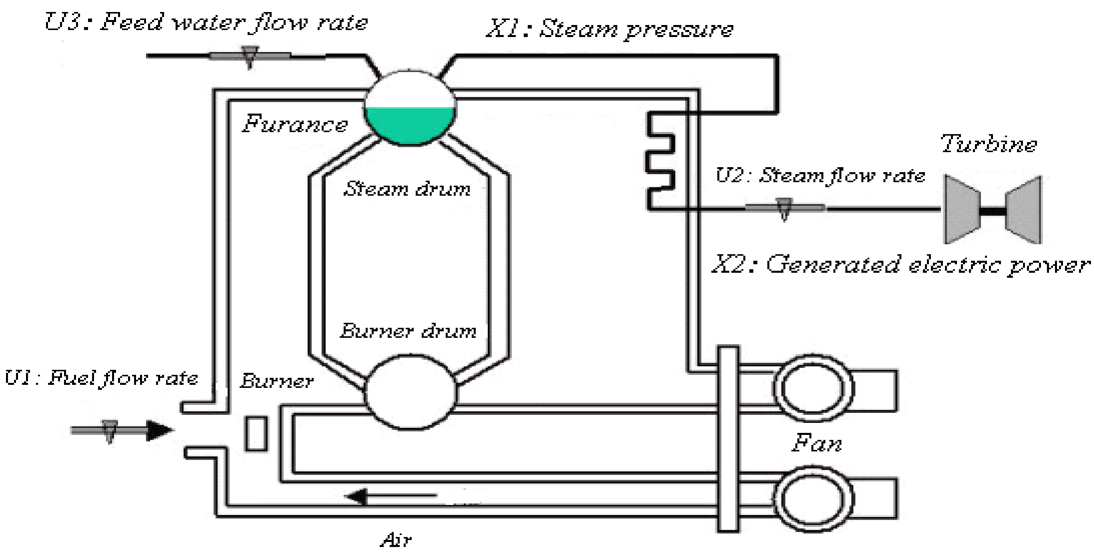

Fig. 2. Boiler-turbine process proposed by Astrom et al. [8].

$$\alpha = VI. \tag{12}$$

Then; for N optical paths (i.e. N turns), the rotation is given by:

$$\alpha = NVI. \tag{13}$$

Fig. 3 illustrates the complete arrangement of optical fiber current sensor.

As illustrated in fig. 3, small changes of optical rotation can be detected using what is known "Wollaston prism". Wollaston prism (WP) separates the magneto-optically rotated E vector of the emergent light into two orthogonal components, the ray will have its E vector directed in the X-direction (the X-component E_{XR}), and its E vector directed in the Y-direction (the Y-component E_{YR}). X-direction is the direction of E when the phase current is equal to zero.

The photodetector (PD1, PD2) outputs are then proportional to E^2_{XR} ad E^2_{YR} (due to photo detector input-output characteristics). If the Wollaston prism is rotated by 45° clockwise with respect to X-axis of the polarized input ray, the intensity components of will be:

$$I_E = KE^2 \cos^2 (45 - \alpha). \tag{14}$$

$$I_o = KE^2 \sin^2 (45 - \alpha). \tag{15}$$

I_E and I_o are processed such that the output voltage, V_O, is given by:

$$V_o = K_D \frac{I_E - I_O}{I_E + I_O}, \tag{16}$$

where; K_D is the wave number which takes values between 488 cm^{-1} to 3120 cm^{-1}. [optical fiber datasheets, jtingram sales and markiting].

Substitution of eqs. (14) and (15) into eq. (16) yields:

$$V_o = K_D \sin (2\,\alpha). \tag{17}$$

If α is small (i.e. ≤ 7^o) and being in radians, the output voltage can be given as:

$$V_o = K_D (2\,\alpha). \tag{18}$$

Substitution of eq. (13) into eq. (18) yields:

$$V_o = 2\,K_D NVI. \tag{19}$$

5. Proposed failure accommodation scheme

An integrated neuro-fuzzy inference scheme to accommodate failures of optical fiber current sensors is described in this section. The first stage of the proposed scheme is SFD stage, through which residuals are generated. The residuals at the specific instant are the difference between the outputs of actual current sensors and their ANFIS models at that instant. The model of each current sensor is built using eq. (19) with N = 20, $V = 2.92517\times10^{-5}$ *rad.* /amp., and K_D = 19 m^{-1}, which yields:

$$V_o = 2.223 \times 10^{-2} \times I, \quad \text{volts} \tag{20}$$

where; I is the phase current in amperes.

Table 1 illustrates the data upon which the ANFIS current sensor model is trained.

Fig. 4 illustrates the proposed ANFIS used as current sensor model for one phase three identical ANFISs are used, one for each phase, resulting in three residual signals (i.e. one residual signal dedicated to each sensor).

The second stage of the proposed scheme is SFI stage, through which the signal identifying the failed sensor is produced. SFI stage is developed using one ANFIS with three inputs (residual signals) and one output. The ANFIS for SFI purpose is trained such that it produces a value of ' 1 ' if the 1st sensor is open or short circuited and produces ' 2 ' if the 2nd sensor is open or short circuited and produces ' 3 ' if the 3rd sensor is open or short circuited.

From simulation of failures of different sensors, it is obtained that the specific sensor is declared faulty if its residual is ≥ 0.7 or ≤ -0.7. Table 2 illustrates the data upon which the ANFIS for SFI purpose is trained.

Fig. 5 illustrates the proposed ANFIS for SFI purpose.

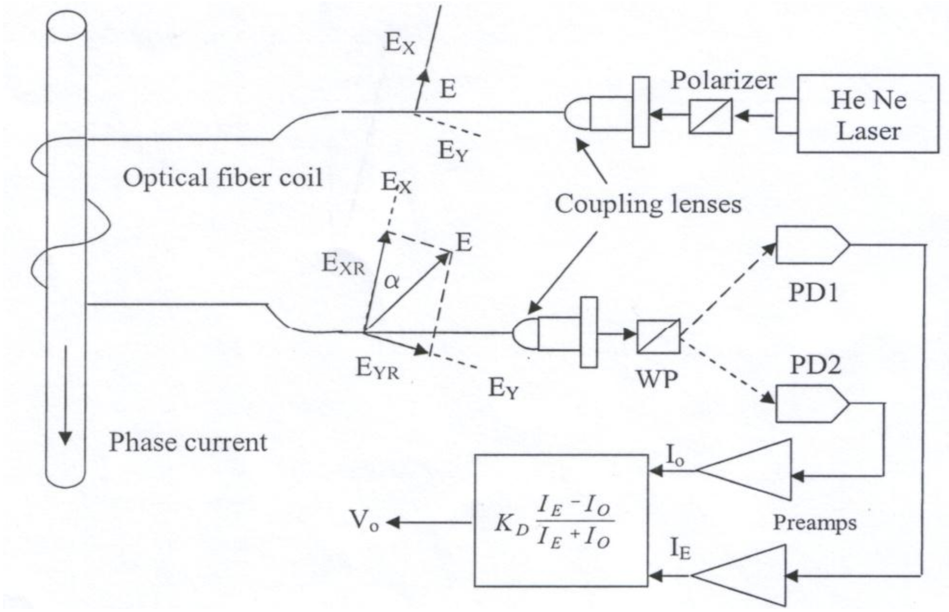

Fig. 3. Complete arrangement of optical fiber current sensor.

Table 1
Data used to train ANFIS to model optical current sensor at no failure

I	0	20	40	60	80	100	120	140	160	180	200	240
V_o	0	0.445	0.889	1.334	1.779	2.223	2.668	3.112	3.557	4.002	4.446	5.336

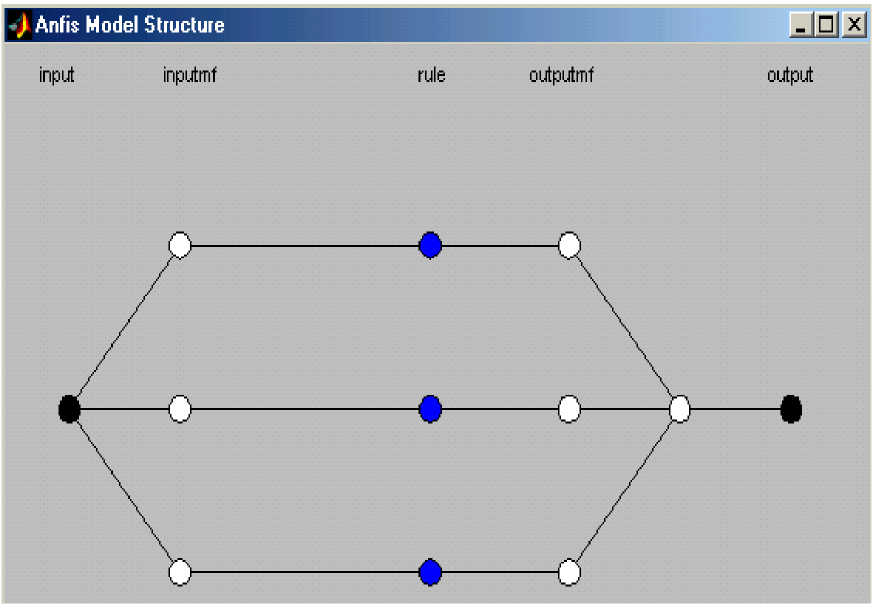

Fig. 4. Proposed ANFIS used as current sensor model for one phase.

Table 2
Data used to train ANFIS for SFI purpose

Residual 1	0	0.05	0.1	0.15	0.2	0.3	0.4	0.5	0.7	1
Residual 2	0	0	0	0	0	0	0	0	0	0
Residual 3	0	0	0	0	0	0	0	0	0	0
ANFIS output	0	0	0	0	0	0	0	0	1	1
Residual 1	2	3	4	-0.05	-0.1	-0.15	-0.2	-0.3	-0.4	-0.5
Residual 2	0	0	0	0	0	0	0	0	0	0
Residual 3	0	0	0	0	0	0	0	0	0	0
ANFIS output	1	1	1	0	0	0	0	0	0	0
Residual 1	-0.7	-1	-2	-3	-4	0	0	0	0	0
Residual 2	0	0	0	0	0	0.05	0.1	0.15	0.2	0.3
Residual 3	0	0	0	0	0	0	0	0	0	0
ANFIS output	1	1	1	1	1	0	0	0	0	0
Residual 1	0	0	0	0	0	0	0	0	0	0
Residual 2	0.4	0.5	0.7	1	2	3	4	-0.05	-0.1	-0.15
Residual 3	0	0	0	0	0	0	0	0	0	0
ANFIS output	0	0	2	2	2	2	2	0	0	0
Residual 1	0	0	0	0	0	0	0	0	0	0
Residual 2	-0.2	-0.3	-0.4	-0.5	-0.7	-1	-2	-3	-4	0
Residual 3	0	0	0	0	0	0	0	0	0	0.05
ANFIS output	0	0	0	0	2	2	2	2	2	0
Residual 1	0	0	0	0	0	0	0	0	0	0
Residual 2	0	0	0	0	0	0	0	0	0	0
Residual 3	0.1	0.15	0.2	0.3	0.4	0.5	0.7	1	2	3
ANFIS output	0	0	0	0	0	0	3	3	3	3
Residual 1	0	0	0	0	0	0	0	0	0	0
Residual 2	0	0	0	0	0	0	0	0	0	0
Residual 3	4	-0.05	-0.1	-0.15	-0.2	-0.3	-0.4	-0.5	-0.7	-1
ANFIS output	3	0	0	0	0	0	0	0	3	3
Residual 1	0			0			0			
Residual 2	0			0			0			
Residual 3	-2			-3			-4			
ANFIS output	3			3			3			

The third stage of the proposed scheme is SFA stage which receives the signal identifying the failed sensor and use simple logic to replace the faulty sensor by an ANFIS accommodator. The schematic diagram of the proposed integrated neuro-fuzzy inference scheme for failures accommodation of optical fiber current sensors is shown in fig.6.

Typically, the sensor accommodator is a sensor model, built using ANFIS, and trained using the sensor model training data.

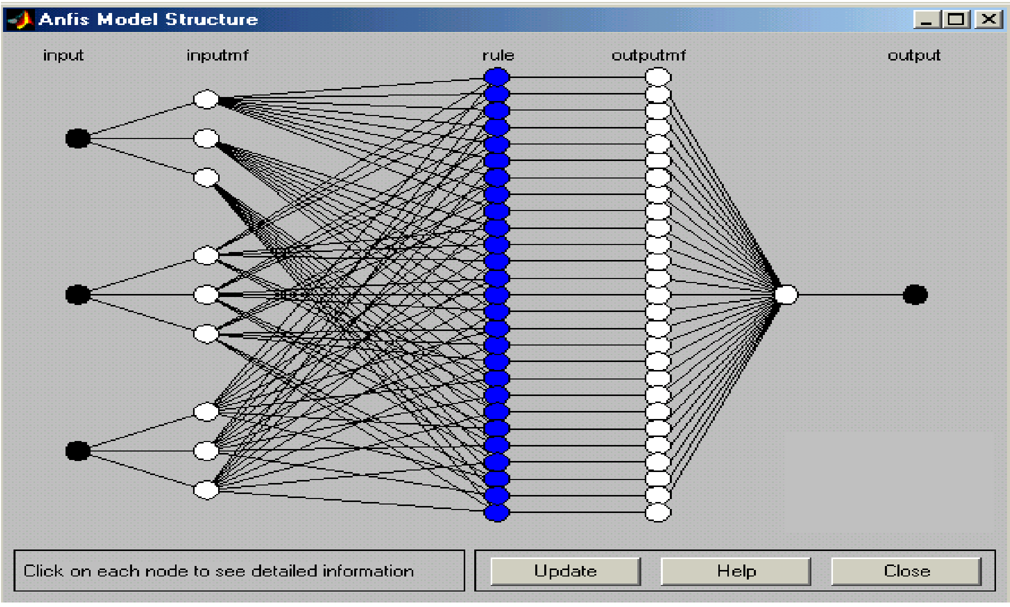

Fig. 5. Proposed ANFIS for SFI purpose.

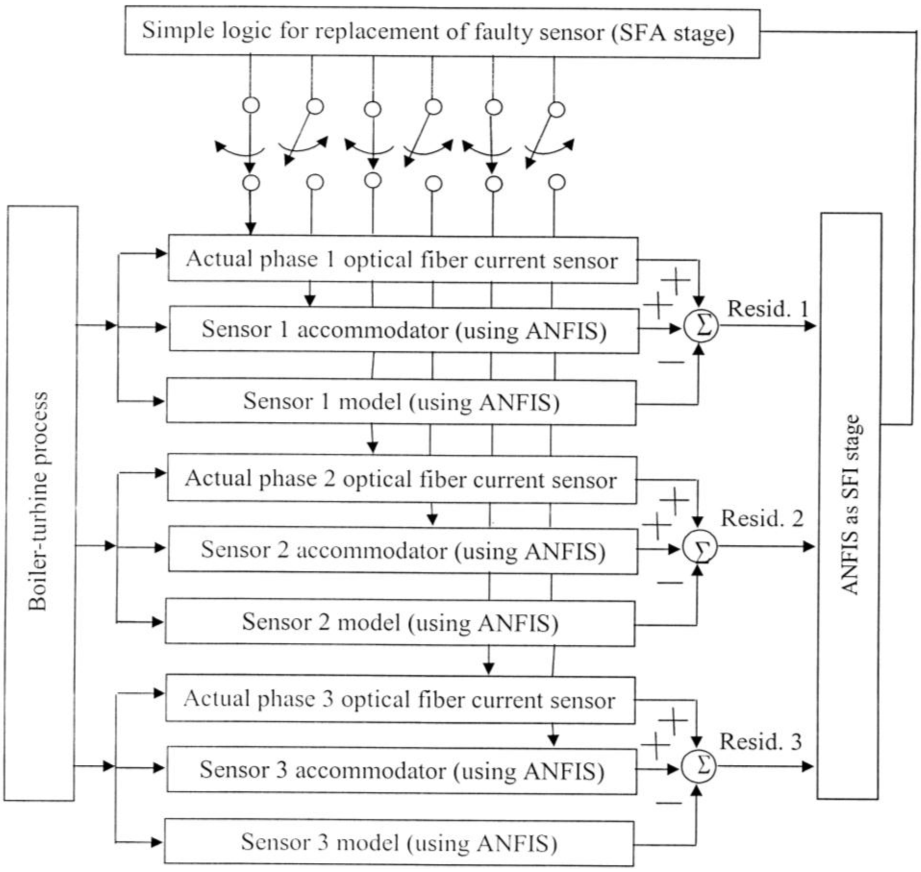

Fig. 6. An integrated neuro-fuzzy inference scheme for sensor failures accommodation.

6. Results and conclusions

The boiler-turbine process with the proposed integrated neuro-fuzzy scheme for failure accommodation of current sensors is simulated using Simulink toolbox in MATLAB. The resulted steam pressure and generated electric power for unit step inputs are shown in figs.7 and 8.

The actual phase current, the actual sensor output, the output of ANFIS sensor model, and the residual for one sensor in case of no failures are shown in figs 9 – 12.

Sensor 1 and sensor 2 abrupt failures at instances 1000 and 1500 respectively, are simulated in figs. 13 and 15. The accordingly behavior of residual 1 and residual 2 is shown in figs. 14 and 16.

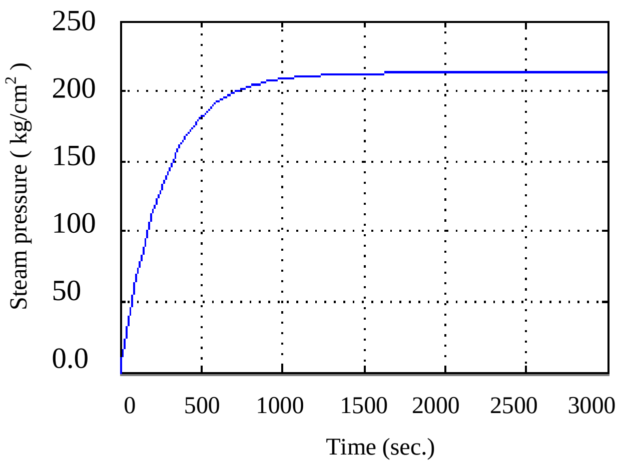

Fig. 7. Steam pressure for unit step inputs.

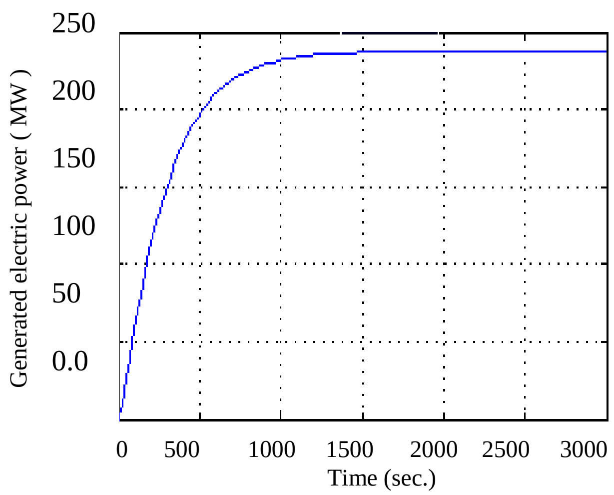

Fig. 8. Generated electric power for unit step inputs.

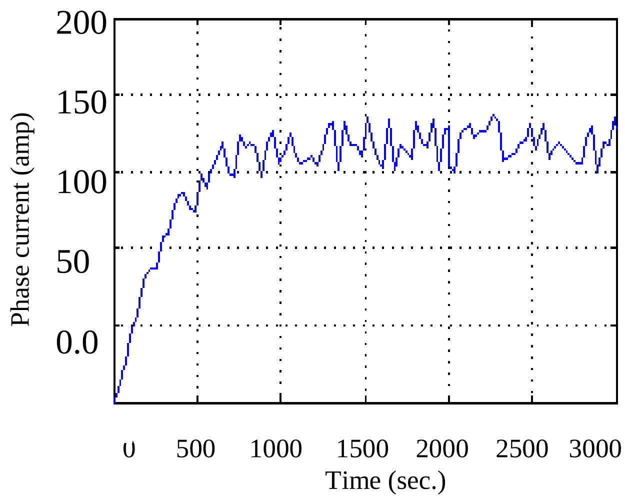

Fig. 9. Actual phase current.

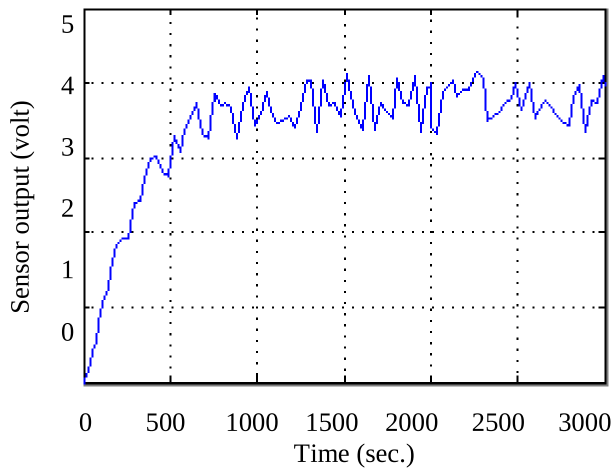

Fig. 10. Actual sensor output.

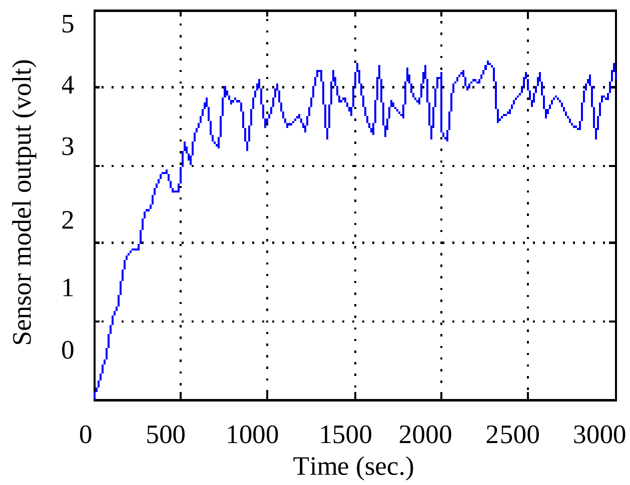

Fig. 11. Output of ANFIS sensor model.

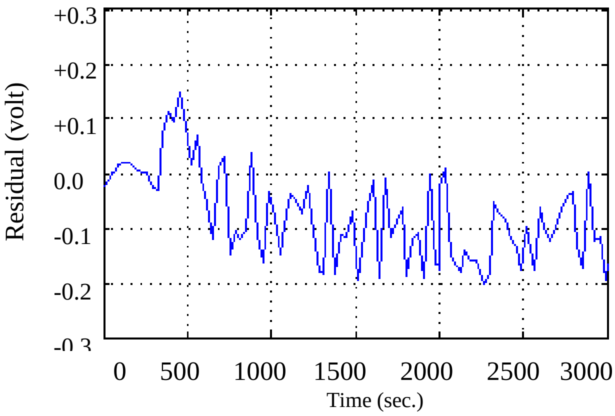

Fig. 12. Residual for one sensor at no-failure.

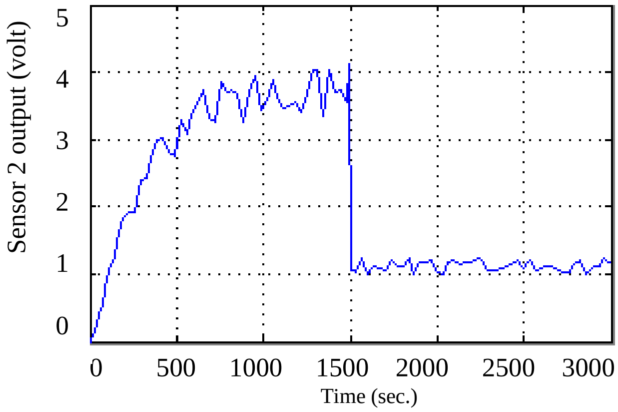

Fig. 15. Sensor 2 output when abruptly failed at instant 1500.

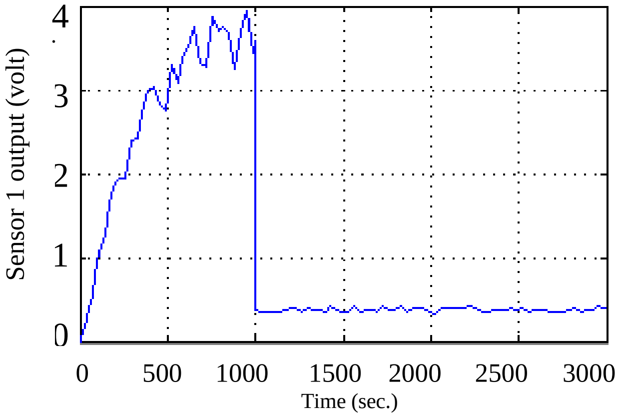

Fig. 13. Sensor 1 output when abruptly failed at instant 1000.

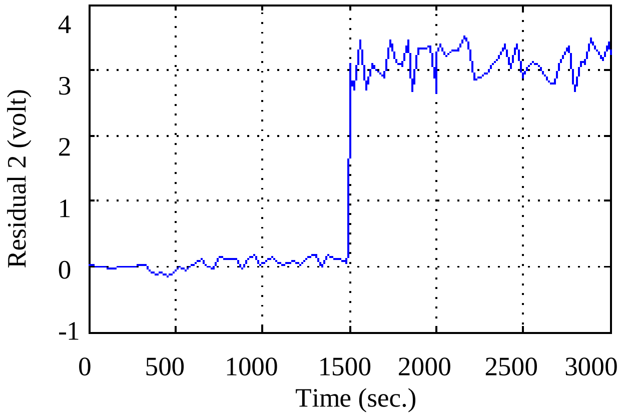

Fig. 16. Residual 2 abruptly increased at instant 1500.

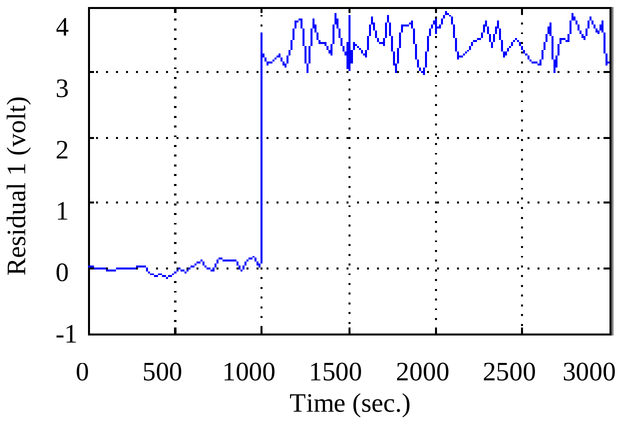

Fig. 14. Residual 1 abruptly increased at instant 1000.

To test SFI stage, the output of ANFIS for SFI purpose is checked in case of simulated failures for different sensors. The results are summarized in table 3.

To test the SFA logic, it is assumed that the accommodation task takes place within ten seconds. The accommodation task can be checked by the evaluation of different residual signals (i.e. when accommodation takes place the relevant residual should return back to zero). For example, the accommodation of failures of sensor 1, and sensor 2 at instants 1000, and 1500 respectively is shown in figs. 17 and 18.

Table 3
Output of ANFIS for SFI purpose in case of failure of different sensors

Failed sensor	Sens.1	Sens.2	Sens.3	Sens.1 & 2	Sens.1 & 3	Sens.2 & 3
ANFIS output	1	2	3	1.445	1.927	2.408

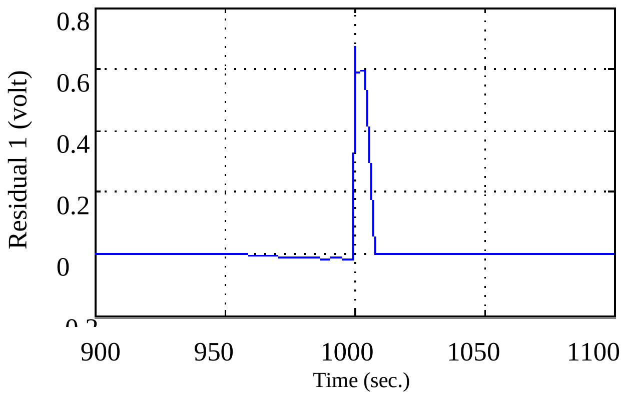

Fig. 17. Residual 1 value through accommodation of failure of sensor1.

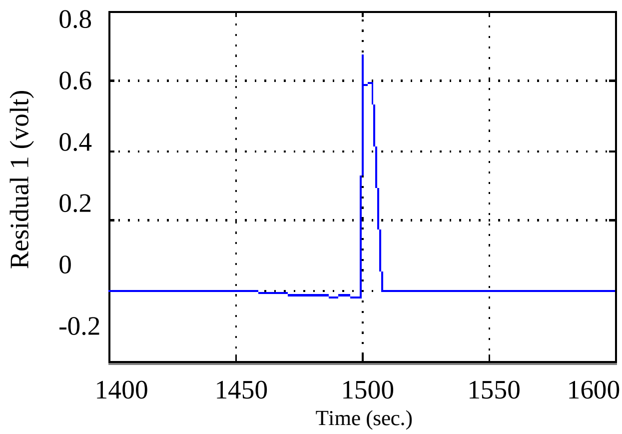

Fig. 18. Residual 2 value through accommodation of failure of sensor2.

From the simulation results of the integrated neuro-fuzzy scheme, we conclude that the proposed scheme assures high accuracy for all its stages. Moreover, although the ANFIS for SFI purpose is trained for failure of one sensor at a given instant, it achieves very reasonable results in case of failures of two sensors at the same instant. In case of failures of two sensors, the output of ANFIS for SFI stage is approximately equals "half of the summation of the numbers of faulty sensors". The logic for replacement of faulty sensor is easily modified to accommodate failures of two sensors.

References

[1] R.J. Patton, "Fault - Tolerant Control," FAC Symposium on Fault Detection, Supervision and Safety for Technical Processes-SAFEPROCESS, Kingston Upon Hull, UK, Vol. 2, pp. 1033-1055 (1997).

[2] M. Blanke, Ch. Frei, F. Kraus, R. Patton and M. Staroswiecki, "What is the Fault-Tolerant Control?," IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes - SAFEPROCESS, Budapest, Hungary, Vol. 1, pp. 40 – 51 (2000).

[3] Y. Yang and Y.Z. Lu, "Sensor Fault Tolerant Control and its Application," IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes - SAFEPROCESS, Baden, Germany, Vol. 1, pp. 55 - 60 (1997).

[4] Kee Son, Oh-Kyu Kwon and M. E. Lee, "Fault-Tolerant Model Based on Predictive Control with Application to Boiler Systems," IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes - SAFEPROCESS, Kingston Upon Hull, UK, Vol. 2, pp. 1240 – 1245 (1997).

[5] J. Candau, L.J. de Miguel and J.G. Ruiz, "Controller Reconfiguration System Using Parity Equations and Fuzzy Logic," IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes-SAFEPROCESS, Kingston Upon Hull, UK, Vol. 2, pp. 1258 – 1263 (1997).

[6] M. Syfert and J.M. Koscielny, "Fuzzy Neural Network Based Diagnostic System Application for Three-Tank System," European Control Conference, Porto, Portugal, pp. 1631-1636 (2001).

[7] J.S. Jang, "ANFIS: Adaptive-Network based Fuzzy Inference System," IEEE Trans. on Systems, Man and Cybernetics, Vol. 23, pp. 665 - 685 (1993).

[8] K.J. Åström and R.B. Bell, "Dynamic Models for Boiler Turbine-Altenator Units: Data Logs and Paramete Estimation for a 160 mw Unit," In Report TFRT-3192. Lund Institute of Technology, Sweden, (1993).

[9] J. Blake, W. Williams, C. Glasow, R. Bergh, K. Fetting, E. Hadley and G. Sanders, "Optical Current Transducers for High Voltage Applications," in Proceedings of 2nd EPRI Optical Sensor Systems Workshop, Atlanta, GA, Jan. pp. 26-28 (2000).

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