Development of neuro-fuzzy scheme for detecting, identifying, and classifying multiple failures in sensors

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The main aim of this work is to propose a two-stage neuro-fuzzy approach as a Failure Detection and Identification (FDI) scheme in dynamic processes. The first stage of the scheme is responsible for failure detection and is implemented using a Neuro-Fuzzy (N-F) model. The second stage of the scheme is responsible for failure identification and classification. The second stage is built using a Hierarchical Structure of Multilayer Feedforward Neural Networks (HSMFNN). The proposed scheme is applied on highly nonlinear boiler-turbine process for detecting, identifying, and classifying failures of different sensors in the process. Simulation results of the proposed scheme prove validity and high accuracy.

تم في هذا البحث تطوير منظومة هجينة من الشبكات العصبية والمنطق المبهم بغرض اكتشاف وتحديد وتصنيف الأعطال المتزامنة في المستشعرات. تتكون المنظومة المقترحة من مرحلتين. تقوم المرحلة الأولي باستقبال الإشارات الصادرة من المستشعرات المختلفة وإصدار الإشارات المميزة لحدوث عطل في مستشعر ما أو مجموعة من المستشعرات من خلال مجموعة من الشبكات العصبية المفعلة بالمنطق المبهم تحاكي عمل المستشعرات المختلفة. تقوم المرحلة الثانية باستقبال الإشارات الصادرة من المرحلة الأولي وتتعامل معها من خلال ثلاث مستويات متوالية (مستويين من الشبكات العصبية متعددة الطبقات ومستوى أخير يمثل مشغل مبنى علي المنطق المبهم) وتمدنا – أى المرحلة الثانية - بالإشارات التي تحدد المستشعر التالف (او مجموعة المستشعرات التالفة فى حالة وجود عطل بأكثر من مستشعر). يمكن تصنيف نوع العطل من خلال الإشارات الصادرة من المرحلة الثانية. تمت محاكاة المنظومة المقترحة لتشخيص أعطال مستشعرات نموذج محطة بخارية لتوليد الكهرباء وأثبتت نتائج المحاكاة صلاحية المنظومة المقترحة للتطبيق ودقة نتائجها.

Keywords: Abrupt failure, Incipient failure, Adaptive Neuro-Fuzzy Inference System (ANFIS), Failure Detection and Identification (FDI), Hierarchical Structure of Multilayer Feedforward Neural Networks (HSMFNN).

1. Introduction

In dynamical processes, faults may be divided into two main classes: abrupt faults and incipient faults. Abrupt faults give rise to jumps in the process parameters, resulting in an appreciable deviation from normal system behaviors. On the other hand, incipient faults affect the process behavior slowly and may take a long time before being detected.

The use of Artificial Neural Networks (ANNs) for Failure Detection and Identification (FDI) purposes has received increasing attention in both research and application [1-7].

Neuro-Fuzzy (NF) methods have also played an important role in FDI due to their capability to use simultaneously quantitative and qualitative knowledge and the ability to represent some kind of uncertainty present in real process [8, 9].

In the most FDI schemes two stages should be developed, namely; failure detection stage and failure identification stage. This paper proposes a scheme with failure identification stage formed by Hierarchical Structure of Multilayer Feedforward Neural Networks (HSMFNN) that has the advantages of the ability to learn. The proposed scheme is applied to detect, identify, and classify abrupt and incipient multiple sensor failures in highly non-linear boiler-turbine process.

The paper is organized as follows: section 2 introduces the description of the failure detection stage. Section 3 provides the description of failure identification stage. Section 4 addresses the dynamic behavior of the boiler-turbine process as a case study. Section 5 presents the simulation of failures of sensory system of the case study and the response of the proposed scheme. Finally in section 6 some concluding remarks are given.

2. Proposed failures detection stage

The proposed failures detection stage is implemented using the idea of model based failure detection which considers the comparison of the model output with the real values measured from the process, thereby generating the residuals which are failure indicators [10, 11].

The proposed failure detection approach utilizes an Adaptive Neuro-Fuzzy Inference System (ANFIS) to model the different sensors for the given process. ANFIS as addressed in [12] is a feedforward network structure consisting of nodes, some of these nodes are adaptive, which means each output of these nodes depends on the parameter (s) pertaining to them. ANFIS receives a group of pairs of data and use numerical hybrid iterative procedures to update the nodes parameters. ANFIS having two inputs X, Y and one output F with two fuzzy if-then rules is shown in fig. 1.

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

Rule 1:
If X is A_1 and Y is B_1 then $F_1 = p_1 X + q_1 Y + r_1$

Rule 2:
If X is A_2 and Y is B_2 then $F_2 = p_2 X + q_2 Y + r_2$

The output of different layers can be described as follows:
Layer 1: every node i in this layer has the following functio

$$O_i^1(X) = \mu_{Ai}(X), \tag{1}$$

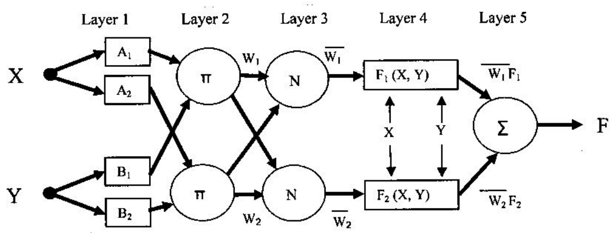

Fig. 1. ANFIS architecture.

where;
X is the input to the node i
Ai is the linguistic label (small, large … etc.), and
$\mu_{Ai}(X)$ is the membership function; such that;

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

where; $\{a_i, b_i, c_i\}$ are the premise parameters.
Layer 2: every node in this layer multiplies the incoming signals and sends the product out.

$$O_i^2 = w_i = \mu_{Ai}(X) \times \mu_{Bi}(Y). \tag{3}$$

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:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}; \qquad i = 1, 2, \ldots \tag{4}$$

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

$$O_i^4(X) = \overline{w}_i F_i = \overline{w}_i (p_i X + q_i Y + r_i); \tag{5}$$

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,

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

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. Then, in the backward path the consequent parameters are held fixed while the error is propagated and the premise parameters are calculated using gradient descent algorithm.

For process containing n sensors, a number of n ANFISs are required to model all existing sensors.

3. Proposed failure identification and classification stage

The HSMFNN is proposed to identify and classify multiple simultaneous faults. The hierarchical structure has three levels; namely lower level, medium level, and upper level [13]. Fuzzy operators are used within the HSMFNN, n neuro-fuzzy ANDs connect between lower level neural network and medium level neural networks and n neuro-fuzzy ORs constitute the upper level. Figure 2 depicts a HSMFNN with m input residuals – n output failure classifiers.

The lower level with m input – n output feedforward multilayer neural network FFMNN receives residual signals $(R_1, R_2, ..., R_m)$ and produces signals $(Y_1, Y_2, ..., Y_n)$, Y_i has a value ranging from 0 to 1, where; $i = 1, 2, \dots\ n$.

The medium level consists of n-FFMNNs, each is identical to the lower level neural network. The number n is equal to the number of sensors considered. The inputs to each neural network of the medium level are the residuals fuzzy ANDed with each output of the lower level neural network and can be written as:

$$\begin{array}{l} \min(R_1, Y_1), \min(R_2, Y_1), \dots, \min(R_m, Y_1), \\ \min(R_1, Y_2), \min(R_2, Y_2), \dots, \min(R_m, Y_2), \\ \quad\bullet \qquad\qquad \bullet \qquad\qquad \bullet \\ \quad\bullet \qquad\qquad \bullet \qquad\qquad \bullet \\ \min(R_1, Y_n), \min(R_2, Y_n), \dots, \min(R_m, Y_n). \end{array} \quad (7)$$

Based on fuzzy AND operator, the value of any input to any neural network of the medium level is ranging from 0 to 1.

The outputs of each medium layer neural network are $(Z_1, Z_2, ..., Z_n)$ and also each output is ranging from 0 to 1.

Fuzzy OR operators constituting the upper level are used to produce the final signals that specify the faulty sensor (sensors) with classification of the failure type. Based on the fuzzy OR operator, the outputs of upper level can be written as:

$$\begin{array}{l} F_1 = \max(Z_1 \text{ of } NN_1, Z_1 \text{ of } NN_2, \dots, Z_1 \text{ of } NN_n), \\ F_2 = \max(Z_2 \text{ of } NN_1, Z_2 \text{ of } NN_2, \dots, Z_2 \text{ of } NN_n), \\ \quad\bullet \qquad\qquad \bullet \qquad\qquad \bullet \\ \quad\bullet \qquad\qquad \bullet \qquad\qquad \bullet \\ F_n = \max(Z_n \text{ of } NN_1, Z_n \text{ of } NN_2, \dots, Z_n \text{ of } NN_n). \end{array} \quad (8)$$

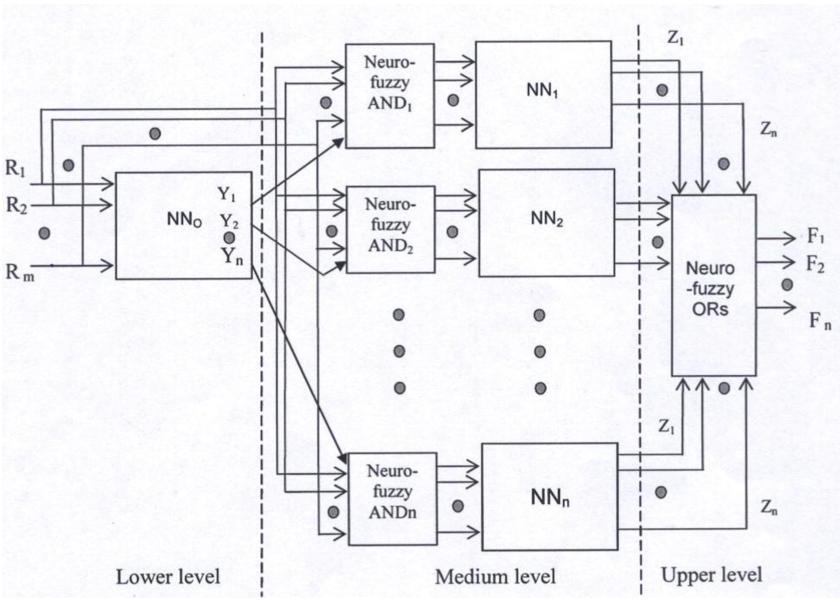

Fig. 2. The hierarchical structure of multilayer feedforward neural network..

4. Case study

In this section, the boiler-turbine process is introduced as a case study. The sensory system of the boiler-turbine process is selected to test the proposed neuro-fuzzy scheme. The mathematical model proposed by Astrom et al. to solve the non-linear dynamics of the boiler-turbine was given in [14] as:

$$\dot{x}_1 = 0.9\,u_1 - 0.0018\,u_2\,x_1^{9/8} - 0.15\,u_3\ ,$$

$$\dot{x}_2 = \frac{[(0.73\,u_2 - 0.16)x_1^{9/8} - x_2]}{10}\ , \qquad (9)$$

$$\dot{x}_3 = \frac{[141\,u_3 - (1.1\,u_2 - 0.19)x_1]}{85}\ ,$$

$$\dot{x}_4 = -0.154\,x_4 + \frac{103.5462\,u_4 - 107.48\,u_1 - 1.9515\,u_1\,x_4}{29.04\,u_4 + 1.834\,u_1}\ .$$

and;

$$a_{cs} = \frac{(1 - 0.001538\,x_3)(0.8\,x_1 - 25.6)}{x_3(1.0394 - 0.0012304\,x_1)}\ , \qquad (10)$$

$$q_e = (0.854\,u_2 - 0.147)x_1 + 45.59\,u_1 - 2.514\,u_3 - 2.096\ .$$

and;

$$y_1 = x_1\ ,$$
$$y_2 = x_2\ , \qquad (11)$$
$$y_3 = 0.05\left[0.13073\,x_3 + 100\,a_{cs} + \left(\frac{q_e}{9}\right)\right] - 67.975\ ,$$
$$y_4 = x_4\ .$$

where; u_1, u_2, u_3 *and* u_4 are process inputs, such that:
u_1 : is the fuel flow, u_2 : is the steam flow, u_3 : is the feed water flow, u_4 : is the air flow. x_1, x_2, x_3 and x_4 are process states, such that, x_1 : is the steam pressure state, x_2 : is the generated electric power state, x_3 : is the fluid density state, x_4 : is the oxygen level state, a_{cs} and q_e are two additional parameters, such that, a_{cs} : is the steam quality, q_e : is the evaporation rate, y_1, y_2, y_3 and y_4 are the process outputs, such that, y_1 : is the steam pressure, y_2 : is the generated electric power, y_3 : is the drum water level, y_4 : is the oxygen level, All inputs u_1, u_2, u_3 and u_4 are normalized, such that:
$0 \le u_1, u_2, u_3, u_4 \le 1$.

The configuration of boiler-turbine is shown in fig. 3.

The sensory system of the boiler-turbine process contains four sensors; namely: steam pressure sensor, generated electric power sensor, water level sensor, and oxygen level sensor.

Based on the pressure sensor description in [15], the pressure sensor input-output relationship can be derived as:

$$V_{steam\,pressure} = 18.205 \times 10^{-3} \times S \qquad \text{volts}, \quad (12)$$

where; S: is the steam pressure in kg / cm^2.

Based on the optical fiber current sensor description in [16], the current sensor input-output relationship can be derived as:

$$V_{current} = 2.223 \times 10^{-2} \times I_{ph} \qquad \text{volts}, \qquad (13)$$

where; I_{Ph} : is the phase current in Amps.

Based on the fluid level sensor description in [17], the water level sensor input-output relationship can be derived as:

$$V_{drum\,level} = 3.791 - \frac{1.91 \times 10^{-6} / C_p}{[10^6 + (2.533 \times 10^{-14} / C_p^2)]^{0.5}} \quad \text{volts}, \qquad (14)$$

where; C_p : is the probe capacitance in Farad.

Based on the high temperature oxygen sensor description in [18], the oxygen level sensor input-output relationship can be derived as:

$$V_{oxygen\,level} = 0.0215 \times 873 \times ln \frac{O_{2\,reference}}{O_{2\,process}} \quad \text{volts}, \qquad (15)$$

5. Simulation and results

The case study is simulated by MATLAB Simulink using eqs. (9-11). The proposed failures detection stage is simulated for four ANFISs to model the different sensors based on the relations defined in eqs. (12-15). The input-output training data for different ANFISs are illustrated in tables 1- 4.

The proposed ANFIS structure for modeling the different sensors is shown in fig. 4.

The outputs of different ANFISs as sensor models at no failure case are shown in figs. 5-8.

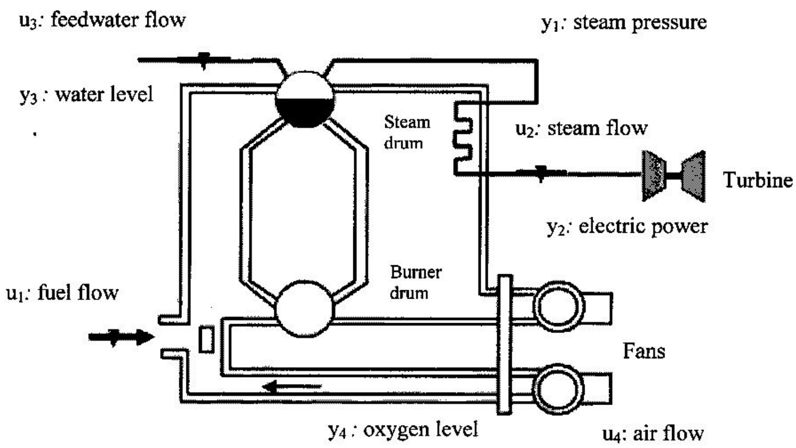

Fig. 3. Boiler-turbine configuration.

Table 1
data used to train ANFIS to model steam pressure sensor at no failure

Pressure Kg/Cm^2	0	20	40	60	80	100	120
Sensor out (volt)	0	0.364	0.728	1.092	1.456	1.821	2.185
Pressure Kg/Cm^2	140	160	180	200	220	240	260
Sensor out (volt)	2.549	2.913	3.277	3.641	4.005	4.369	4.7333

Table 2
Data used to train ANFIS to model current sensor at no failure

I_{Ph} (amp)	0	20	40	60	80	100	120
Sensor out (volt)	0	0.445	0.889	1.334	1.779	2.223	2.668
I_{Ph} (amp)	140	160	180	200	220	240	260
Sensor out (volt)	3.112	3.557	4.002	4.446	4.906	5.336	5.78

Table 3
Data used to train ANFIS to model water level sensor at no failure

Water level	0	0.5	1	1.5	2	2.5	3
Sensor out (volt)	0	1.235	1.872	2.256	2.513	2.697	2.834
Water level	3.5	4	4.5	5	5.5	6	
Sensor out (volt)	2.941	3.027	3.096	3.155	3.204	3.246	

Table 4
Data used to train ANFIS to model oxygen level sensor at no failure

Oxygen level	1	2	3	4	5	6	8	10	15	20
Sensor out (volt)	0	3.253	5.155	6.505	7.552	8.408	9.758	10.8	12.71	14.06

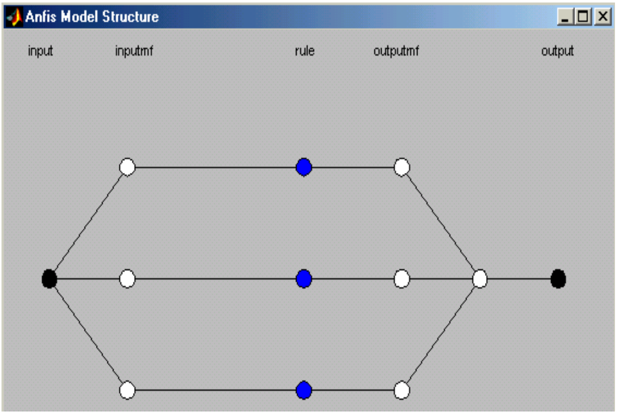

Fig. 4. ANFIS structure for modeling different sensors.

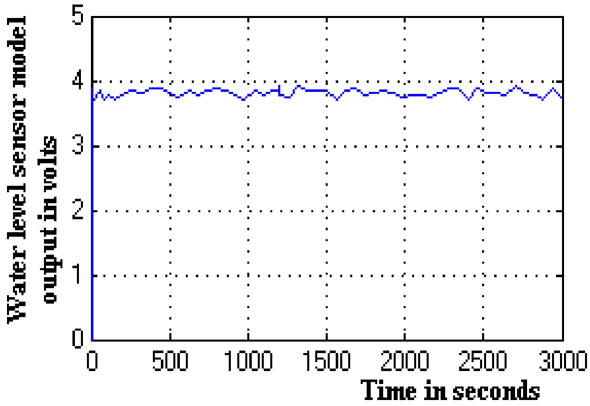

Fig. 7. Water level sensor model output in volts in no failure case.

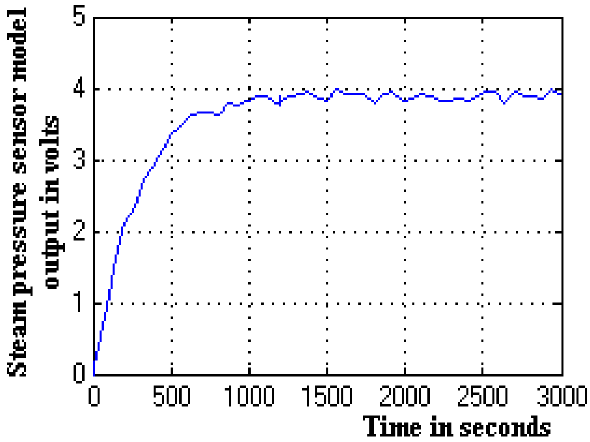

Fig. 5. Steam pressure sensor model output in volts in no failure case.

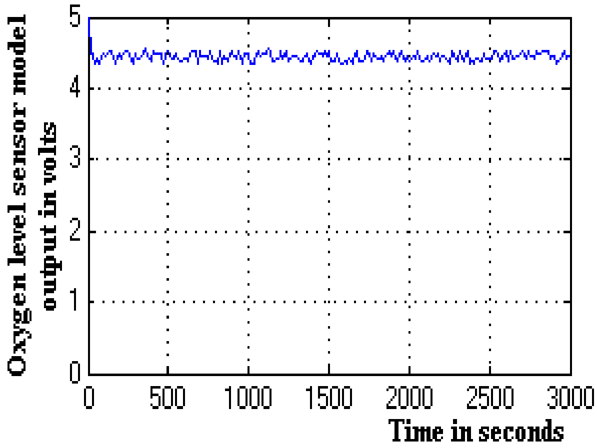

Fig. 8. Oxygen sensor model output in volts in no failure case.

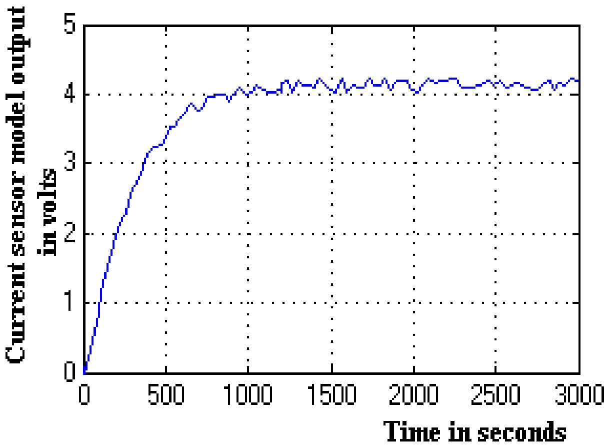

Fig. 6. Current sensor model output in volts in no failure case.

Abrupt and incipient failure simulations of different sensors with their related residual values are shown in figs. 9-16.

The proposed failure identification and classification stage is simulated through the development of lower, medium, and upper levels as described in section 3. The lower level is a FFMNN that receives four residual signals (R_1, R_2, R_3, and R_4) and produces signals (Y_1, Y_2, Y_3, and Y_4), each ranging from 0 to 1 and classifies the failure type of faulty sensor (sensors). The lower level FFMNN is trained using Levenberg Marquardt algorithm, the structure of such a network is shown in fig. 17.

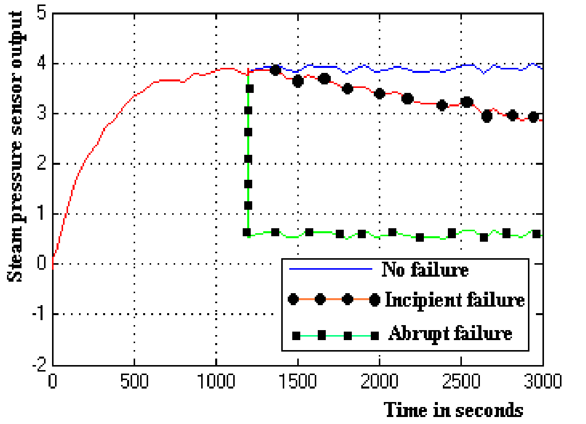

Fig. 9. Simulation of abrupt and incipient failures for steam pressure sensor at instant 1200.

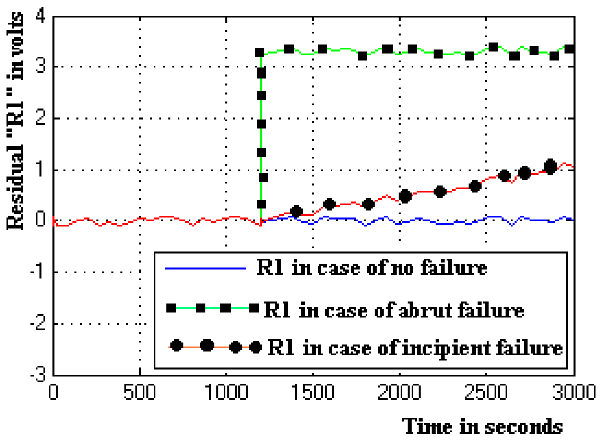

Fig. 10. Residual "R_1" in case of abrupt and incipient failures of steam pressure sensor.

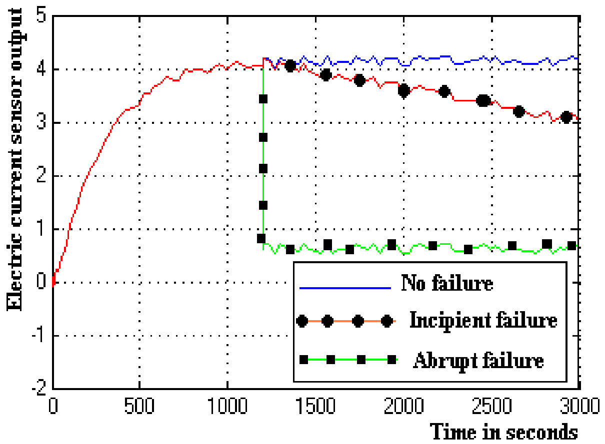

Fig. 11. Simulation of abrupt and incipient failures for electric current sensor at instant 1200.

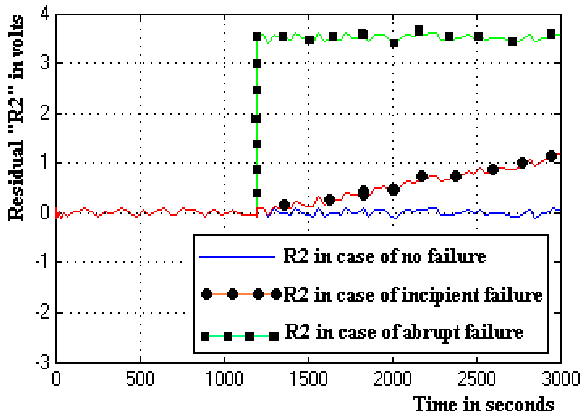

Fig. 12. Residual "R_2" in case of abrupt and incipient failures of electric current sensor.

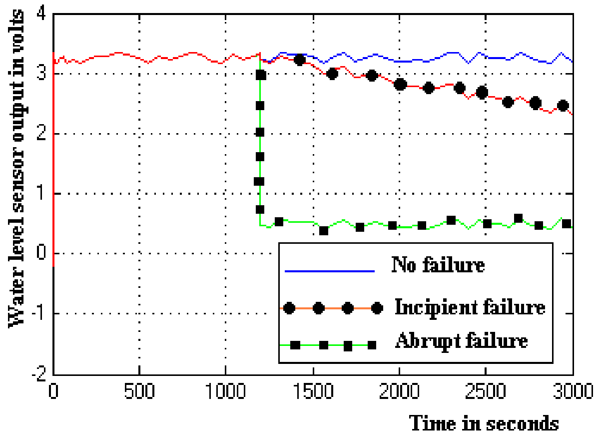

Fig. 13. Simulation of abrupt and incipient failures for water level sensor at instant 1200

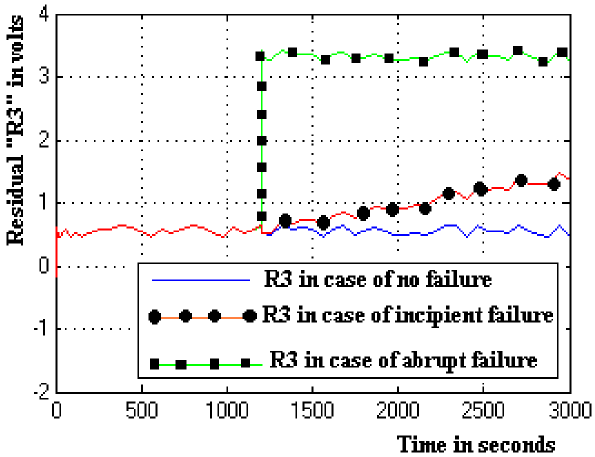

Fig. 14. Residual "R_3" in case of abrupt and incipient failures of electric current sensor.

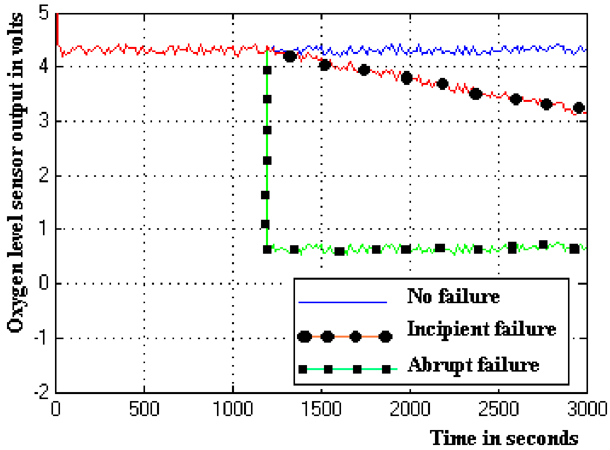

Fig. 15. Simulation of abrupt and incipient failures for oxygen level sensor at instant 1200.

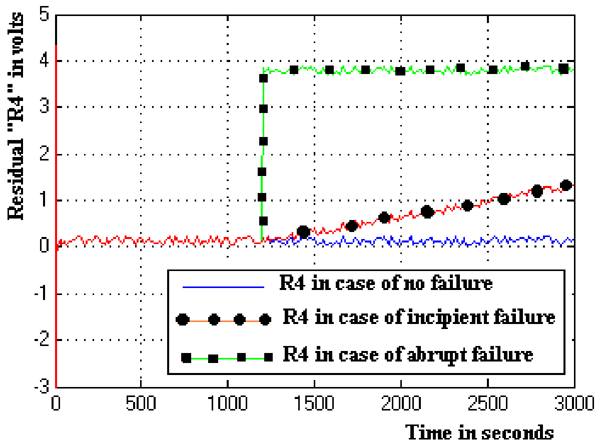

Fig. 16. Residual "R4" in case of abrupt and incipient failures of oxygen level sensor.

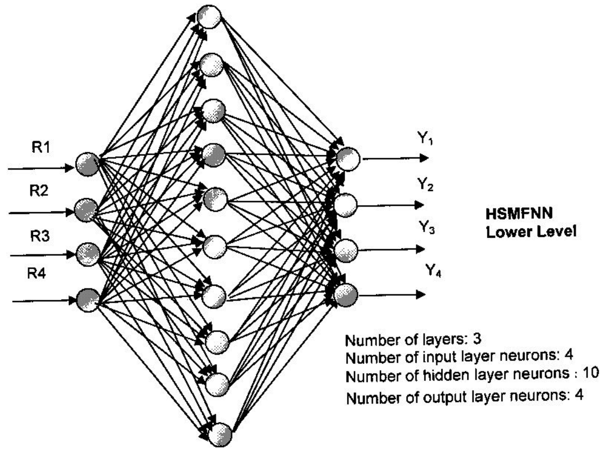

Fig. 17. The structure of lower level FFMNN.

The maximum values of residuals of faulty sensors don't exceed 5 volts, and the minimum values of residuals at no failure cases are not less than -0.5 volt therefore input training data to the lower level of the proposed HSMFNN is ranging from (-0.5 to 5). The maximum values of residuals at no failure case are not more than 0.5 volt therefore the threshold value of failure occurrence is designed as 0.7 volt. Input-output training data and failure classification of HSMFNN lower level are summarized in table 5. The lower level is trained on no failures as well as abrupt and incipient failures of single and double faulty sensor (sensors) using Levenberg Marquardt algorithm.

Table 5
Input-output training data and failure classification of HSMFNN lower level

Input	Output (target)	Failure classification
$-0.5 \leq R_i < 0.7$	$Y_i = 0$	No failure
$0.7 \leq R_i < 1.5$	$0.5 \leq Y_i < 0.9$	Incipient failure
$1.5 \leq R_i \leq 5$	$0.9 \leq Y_i \leq 1$	Abrupt failure

Table 6
Inputs to FFMNNs in the medium level

FFMNN	Inputs			
$FFMNN_1$	min (R_1, Y_1),	min (R_2, Y_1),	min (R_3, Y_1),	min (R_4, Y_1)
$FFMNN_2$	min (R_1, Y_2),	min (R_2, Y_2),	min (R_3, Y_2),	min (R_4, Y_2)
$FFMNN_3$	min (R_1, Y_3),	min (R_2, Y_3),	min (R_3, Y_3),	min (R_4, Y_3)
$FFMNN_4$	min (R_1, Y_4),	min (R_2, Y_4),	min (R_3, Y_4),	min (R_4, Y_4)

Detection, identification and classification of failures accomplished by the lower level are not enough; therefore HSMFNN is proposed.

The medium level contains four identical FFMNNs. Each medium level neural network is identical to the lower level FFMNN. Based on "fuzzy AND" operators between lower and medium levels, the inputs to different medium level neural networks are summarized in table 6.

Each FFMNN in the medium layer is trained on no failure as well as incipient and abrupt failures of single and double faulty sensor (sensors) using Levenberg Marquardt algorithm. The input-output training data for each FFMNN in the medium level is summarized in table 7; proposed failure classification is also given in table 7.

Four "fuzzy OR" operators are used as an upper level of the HSMFNN that specify the faulty sensor (sensors) and classify the failure (failures) type. If we assume the signals coming out from each FFMNN of the medium level are (Z_1, Z_2, Z_3, and Z_4) respectively, the four final outputs produced from the upper level are given by:

F_1 = Max (Z_1 of FFMNN_1, Z_1 of FFMNN_2, Z_1 of FFMNN_3, Z_1 of FFMNN_4)
F_2 = Max (Z_2 of FFMNN_1, Z_2 of FFMNN_2, Z_2 of FFMNN_3, Z_2 of FFMNN_4) (16)
F_3 = Max (Z_3 of FFMNN_1, Z_3 of FFMNN_2, Z_3 of FFMNN_3, Z_3 of FFMNN_4)
F_4 = Max (Z_4 of FFMNN_1, Z_4 of FFMNN_2, Z_4 of FFMNN_3, Z_4 of FFMNN_4)

The detailed MAT-LAB Simulink simulation of HSMFNN for the case study is shown in fig. 18.

The simulation proved that the proposed scheme is very active in diagnosis and classification of single/double abrupt/incipient failure (s), to assess the performance of the proposed HSMFNN scheme, double abrupt, double incipient and double abrupt-incipient failures of sensors are simulated. Tables 8-10 illustrate simulation results for some sample failures.

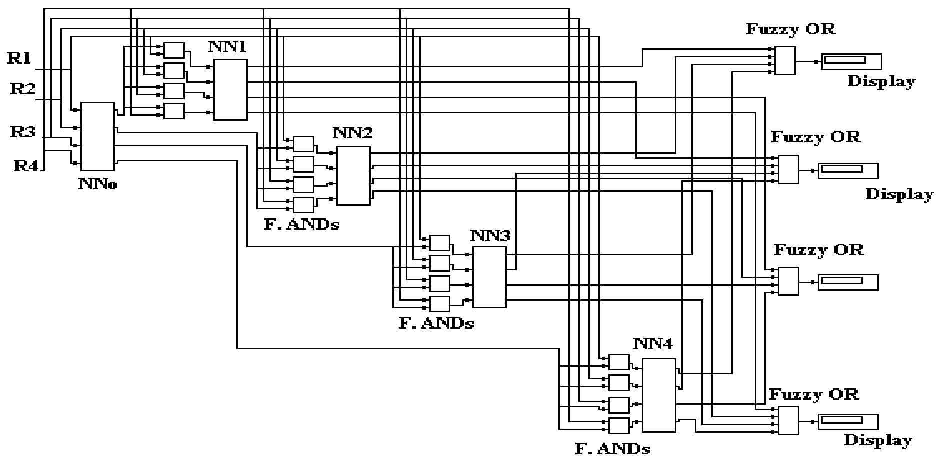

Fig. 18. Detailed Simulation simulation of HSMFNN for the case study.

Table 7
Input-output training data for each neural network in the medium level

Input	Output (target)	Failure classification
From 0 to 0.4	0	No failure
0.5	0.5	Incipient failure
0.7	0.7	Incipient failure
0..8	08	Incipient failure
0.9	0.9	Abrupt failure
1	1	Abrupt failure

Table 8
HSMFNN outputs for double abrupt failures

Double abrupt failures	Lower level outputs	Middle level outputs				Upper Level outputs	Class-ification
		FFMNN 1	FFMNN 2	FFMNN 3	FFMNN 4		
R_1 = 3	Y_1 =0.9741	Z_1=0.9994	Z_1=0.9956	Z_1= 0	Z_1= 0	F_1=0.9994	
R_2 = 4	Y_2= 1	Z_2=0.9969	Z_2=0.9953	Z_2= 0	Z_2= 0	F_2=0.9969	2 / 2
R_3 = 0	Y_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	F_3 = 0	
R_4 = 0	Y_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	F_4 = 0	
R_1 = 3	Y_1=0.9972	Z_1= 1	Z_1= 0	Z_1=0.9994	Z_1= 0	F_1= 1	
R_2 = 0	Y_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	F_2 = 0	2 / 2
R_3 = 4	Y_3= 1	Z_3=0.9995	Z_3= 0	Z_3=0.9999	Z_3= 0	F_3=0.9999	
R_4 = 0	Y_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	F_4 = 0	
R_1 = 3	Y_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	Z_1=0.9995	F_1=0.9995	
R_2 = 0	Y_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	F_2 = 0	
R_3 = 0	Y_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	F_3 = 0	2 / 2
R_4 = 4	Y_4=0.9931	Z_4= 0	Z_4= 0	Z_4= 0	Z_4=0.9997	F_4=0.9997	
R_1 = 0	Y_1= 0	Z_1= 0	Z_1 = 0	Z_1= 0	Z_1= 0	F_1 = 0	
R_2 = 3	Y_2= 0.07	Z_2= 0	Z_2 = 0	Z_2=0.9994	Z_2= 0	F_2=0.9994	2 / 2
R_3 = 4	Y_3= 1	Z_3= 0	Z_3 = 0	Z_3=0.9999	Z_3= 0	F_3=0.9999	
R_4 = 0	Y_4= 0	Z_4= 0	Z_4 = 0	Z_4= 0	Z_4= 0	F_4 = 0	
R_1 = 0	Y_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	F_1 = 0	
R_2 = 3	Y_2=0.9928	Z_2= 0	Z_2=0.9954	Z_2= 0	Z_2=0.9998	F_2=0.9998	2 / 2
R_3 = 0	Y_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	F_3 = 0	
R_4 = 4	Y_4= 1	Z_4= 0	Z_4=0.9968	Z_4= 0	Z_4= 1	F_4= 1	
R_1 = 0	Y_1= 0	Z_1= 0	Z_1= 0	Z_1=0	Z_1= 0	F_1 = 0	
R_2 = 0	Y_2= 0	Z_2= 0	Z_2= 0	Z_2=0	Z_2= 0	F_2 = 0	
R_3 = 3	Y_3=0.9992	Z_3= 0	Z_3= 0	Z_3=0.9993	Z_3=0.9998	F_3=0.9998	2 / 2
R_4 = 4	Y_4=0.9996	Z_4= 0	Z_4= 0	Z_4=0.9999	Z_4=0.9998	F_4=0.9998	

Table 9
HSMFNN outputs for double incipient failures

Double incipient failures	Lower level outputs	Middle level outputs				Upper level outputs	Classification
		FFMNN 1	FFMNN 2	FFMNN 3	FFMNN 4		
R_1= 0.85	Y_1=0.5681	Z_1=0.5995	Z_1=0.6908	Z_1= 0	Z_1= 0	F_1=0.6908	
R_2 = 0.9	Y_2=0.6891	Z_2=0.5994	Z_2=0.6907	Z_2= 0	Z_2= 0	F_2=0.6907	2 / 2
R_3 = 0	Y_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	F_3 = 0	
R_4 = 0	Y_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	F_4 = 0	
R_1 = 0.85	Y_1= 0.588	Z_1=0.5989	Z_1= 0	Z_1=0.592	Z_1= 0	F_1=0.5989	
R_2 = 0	Y_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	F_2 = 0	2 / 2
R_3 = 0.9	Y_3=0.5846	Z_3=0.5982	Z_3= 0	Z_3=0.5923	Z_3= 0	F_3=0.5982	
R_4 = 0	Y_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	Z_4= 0	F_4 = 0	
R_1 = 0.9	Y_1=0.5997	Z_1=0.5998	Z_1= 0	Z_1= 0	Z_1=0.6005	F_1=0.6005	
R_2 = 0	Y_2=0	Z_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	F_2 = 0	
R_3 = 0	Y_3=0	Z_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	F_3 = 0	2 / 2
R_4 = 0.9	Y_4=0.6006	Z_4=0.5998	Z_4= 0	Z_4= 0	Z_4=0.6005	F_4=0.6005	
R_1 = 0	Y_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	F_1 = 0	
R_2 = 0.85	Y_2=0.4613	Z_2= 0	Z_2=0.4293	Z_2=0.6527	Z_2= 0	F_2=0.6527	
R_3 = 0.9	Y_3=0.679	Z_3= 0	Z_3=0.4293	Z_3=0.6373	Z_3= 0	F_3=0.6373	2 / 2
R_4 = 0	Y_4= 0	Z_4= 0	Z_4=	Z_4= 0	Z_4= 0	F_4 = 0	
R_1 = 0	Y_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	F_1 = 0	
R_2= 0.85	Y_2=0.5181	Z_2= 0	Z_2=0.5165	Z_2= 0	Z_2=0.6249	F_2=0.6249	2 / 2
R_3 = 0	Y_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	Z_3= 0	F_3 = 0	
R_4= 0.9	Y_4=0.6266	Z_4= 0	Z_4=0.5185	Z_4= 0	Z_4=0.6253	F_4=0.6253	
R_1 = 0	Y_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	Z_1= 0	F_1 = 0	
R_2 = 0	Y_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	Z_2= 0	F_2 = 0	
R_3 = 0.85	Y_3=0.5837	Z_3= 0	Z_3= 0	Z_3=0.5909	Z_3= 0	F_3=0.5909	2 / 2
R_4 = 0.9	Y_4=0.3528	Z_4= 0	Z_4= 0	Z_4=0.5892	Z_4= 0	F_4=0.5892	

Table 10
HSMFNN outputs for double abrupt-incipient failures

Double abrupt-incipient failures	Lower level outputs	Middle level outputs				Upper level outputs	Classification
		FFMNN 1	FFMNN 2	FFMNN 3	FFMNN 4		
$R_1 = 3$	$Y_1 = 1$	$Z_1 = 1$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$F_1 = 1$	2 / 2
$R_2 = 0.75$	$Y_2 = 0$	$Z_2 = 0.7654$	$Z_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$F_2 = 0.7654$	
$R_3 = 0$	$Y_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$F_3 = 0$	
$R_4 = 0$	$Y_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$F_4 = 0$	
$R_1 = 3$	$Y_1 = 0.9834$	$Z_1 = 1$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$F_1 = 1$	2 / 2
$R_2 = 0$	$Y_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$F_2 = 0$	
$R_3 = 0.75$	$Y_3 = 0$	$Z_3 = 0.4754$	$Z_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$F_3 = 0.4754$	
$R_4 = 0$	$Y_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$F_4 = 0$	
$R_1 = 3$	$Y_1 = 1$	$Z_1 = 1$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$F_1 = 1$	1 / 2
$R_2 = 0$	$Y_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$F_2 = 0$	
$R_3 = 0$	$Y_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$F_3 = 0$	
$R_4 = 0.75$	$Y_4 = 0$	$Z_4 = 0.9977$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$F_4 = 0.9977$	
$R_1 = 0$	$Y_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$F_1 = 0$	1 / 2
$R_2 = 3$	$Y_2 = 1$	$Z_2 = 0$	$Z_2 = 0.9969$	$Z_2 = 0$	$Z_2 = 0$	$F_2 = 0.9969$	
$R_3 = 0.75$	$Y_3 = 0$	$Z_3 = 0$	$Z_3 = 0.9044$	$Z_3 = 0$	$Z_3 = 0$	$F_3 = 0.9044$	
$R_4 = 0$	$Y_4 = 0.1566$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0$	$F_4 = 0$	
$R_1 = 0$	$Y_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$F_1 = 0$	2 / 2
$R_2 = 3$	$Y_2 = 1$	$Z_2 = 0$	$Z_2 = 0.9942$	$Z_2 = 0$	$Z_2 = 0.9955$	$F_2 = 0.9955$	
$R_3 = 0$	$Y_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$Z_3 = 0$	$F_3 = 0$	
$R_4 = 0.75$	$Y_4 = 0.9987$	$Z_4 = 0$	$Z_4 = 0.3935$	$Z_4 = 0$	$Z_4 = 0.751$	$F_4 = 0.751$	
$R_1 = 0$	$Y_1 = 0.9983$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$Z_1 = 0$	$F_1 = 0$	1 / 2
$R_2 = 0$	$Y_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$Z_2 = 0$	$F_2 = 0$	
$R_3 = 3$	$Y_3 = 1$	$Z_3 = 0.2948$	$Z_3 = 0$	$Z_3 = 0.9957$	$Z_3 = 0.9528$	$F_3 = 0.9957$	
$R_4 = 0.75$	$Y_4 = 0.9997$	$Z_4 = 0$	$Z_4 = 0$	$Z_4 = 0.9975$	$Z_4 = 0.7068$	$F_4 = 0.9975$	

6. Conclusions

Simulation results of applying the proposed HSMFNN to the case study prove its validity, feasibility and high accuracy. Although the proposed technique considers training for single and double failures of the same type it achieves superior performance in detecting, identifying and classifying failures of different types.

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