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Neuro-Fuzzy Sensor Fault Diagnosis of an Induction Motor

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نموذج عصبوني ضبابي لاكتشاف الخطأ المتحسس للمحرك الحثي.

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الخلاصة: يقدم هذا البحث نموذج عصبوني -ضبابي لاكتشاف الخطأ وفحصه في المتحسس للمحرك الحثي. ان طريقة اكتشاف الخطا تعتمد على تقنيات هجينة مابين الخلايا العصبية وتقنيات المنطق الضبابي والتي يمكنها التعامل بشكل كفوء مع الحالات الديناميكية اللاخطية والحالات المحيرة.يعتمد النموذج المقدم على طريقة متكونة من مرحلتين تستخدم المرحلة الاولى الخلايا العصبية لتوليد الدالة المتبقية للخطا والثانية تستخدم طريقة هجينة عصبونية ضبابية لتخمين الدالة المتبقية للخطا. نتائج المحاكاة للنموذج مقدمه في البحث لدراسة كفاءة النظام.

الكلمات المفتاحية: المنطق الضبابي- المحرك الحثي- الخلايا العصبية- اكتشاف الخطا للمتحمسس وعزله

Abstract: In this paper, a neuro-fuzzy fault diagnosis scheme is presented and its ability to detect and isolate sensor faults in an induction motor is assessed. This fault detection and isolation (FDI) approach relies on a combination of neural modelling and fuzzy logic techniques which can deal effectively with nonlinear dynamics and uncertainties. It is based on a two step neural network procedure: a first neural network is used for residual generation and a second fuzzy neural network performs residual evaluation. Simulation results are given to demonstrate the efficiency of this FDI approach.

Keywords: Fuzzy logic, Induction motor, Neural networks, Sensor fault detection and isolation

1. Introduction

The problem of fault detection and isolation (FDI) is a crucial issue for the safety, reliability and performance of industrial processes.

The usual approach to fault diagnosis is based on hardware redundancy (multiple sensors, actuators and components) and uses a voting technique to decide if a fault has occurred and to locate it among the redundant system elements (Frank 1990). Instead, the analytical redundancy FDI approach, also referred to as the model-based FDI approach, makes use of a mathematical model of the monitored system [(Frank 1990). The task of model based diagnosis methods consists of detecting faults that may occur in the system and which can be additive or multiplicative in nature.

Basically the FDI procedure consists of two main steps: generation of residuals which should be useful fault indicators, and residual evaluation which involves decision making. The model-based FDI approach which has received intensive attention uses mainly state and parameter estimation techniques (Frank 1990). Model based FDI performance is directly related to the accuracy of the mathematical model of the monitored system. The effect of model uncertainties, disturbances and noise is therefore a key issue in model based fault diagnosis.

The main design requirements of model based fault diagnosis procedures are thus concerned with the problems of robustness with respect to model uncertainties and enhancement of sensitivity to faults. These requirements are contradictory so a trade off is needed to cope with sources of false alarms and missed detections. Two strategies may be used: an active strategy consisting in robust residual generation and a passive one through robust residual evaluation. Most of the

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existing model based FDI techniques rely on the use of linear system models (Benloucif and Staroswiecki 2002 and Frank 1990). Often, nonlinear systems are described by linear models with additive disturbances. Robust residual generation based on unknown input observers to achieve disturbance decoupling may provide an efficient solution to fault detection and isolation problems. As far as linear systems are concerned the problem of robust residual generation may be considered to be mature ((Benloucif and Staroswiecki 2002, Frank 1990 and Patton and Chen 1997) whereas the FDI problem for nonlinear dynamic systems has been investigated to a lesser extent (Benloucif and Balaska 2006; Garcia and Frank 1997 and Jiang *et al.* 2001).

Alternatively, FDI can be performed using qualitative techniques such as expert systems, fuzzy logic, neural networks (Al;exandru *et al.* 2000; Benloucif and Mehennaoui 2002; Benloucif and Mehennaoui 2005; Chen and Lee 2002; Evsukoff *et al.* 1999; Frank 1990; Isermann 1998; Schneider and Frank 1996; Simani and Fantuzzi 2002; Takagi and Sugeno 1985, Theilliol *et al.* 1997 and Uppal *et al.* 2002). To overcome the limitations of the analytical FDI approach, the actual trend integrates model based (analytical) and knowledge based (non analytical) methods in order to take advantage of their respective performances. Residual generation and residual evaluation for decision making may be achieved by using appropriate combinations of different techniques such as state estimation, parameter estimation, neural networks, fuzzy logic inference.

In (Benloucif and Mehennaoui 2002) a fault diagnosis procedure for linear systems used a combination of an analytical residual generator based on Kalman filtering and a fuzzy neural network for residual evaluation. In this work, an extension of the neuro-fuzzy FDI scheme given in (Benloucif and Balaska 2006) is proposed. It is based on a two step neural network procedure: The first network which has the ability to model a wide class of nonlinear dynamic systems acts as an on-line residual generator. The second network performs the decision making which consists in detecting and isolating a fault when it occurs. This neural network coupled to a fuzzy inference block acts as an on-line fault classifier.

The paper is organized as follows. In section 2 the model of the induction motor is presented, starting from the classical Park transformation. The architecture of the neuro-fuzzy scheme used for residual generation and evaluation is discussed in section 3. Simulation results are given in section 4 to illustrate the performance of the proposed neuro-fuzzy FDI scheme for sensor fault diagnosis of the induction motor.

2. Model of the Induction Motor

Assuming linear magnetic circuits and a balanced three-phase system in the (a, b, c) frame, the electrical equations of the induction motor expressed in the two-phase stationary (d, q) reference frame (Benloucif and Balaska 2006) are:

$$\begin{bmatrix}\Phi_{sd}\\ \Phi_{sq}\\ \Phi_{rd}\\ \Phi_{rq}\end{bmatrix}=\begin{bmatrix}L_s & 0 & L_m & 0\\ 0 & L_s & 0 & L_m\\ L_m & 0 & L_r & 0\\ 0 & L_m & 0 & L_r\end{bmatrix}\begin{bmatrix}I_{sd}\\ I_{sq}\\ I_{rd}\\ I_{rq}\end{bmatrix} \tag{1}$$

$$\begin{aligned} V_{sd} &= R_s I_{sd} + \dot{\Phi}_{sd} - \Phi_{sq}\dot{\theta}_s\\ V_{sq} &= R_s I_{sq} + \dot{\Phi}_{sq} + \Phi_{sd}\dot{\theta}_s\\ V_{rd} &= 0 = R_r I_{rd} + \dot{\Phi}_{rd} - \Phi_{rq}\dot{\theta}_r\\ V_{rq} &= 0 = R_r I_{rq} + \dot{\Phi}_{rq} + \Phi_{rd}\dot{\theta}_r \end{aligned} \tag{2}$$

where Φ, I, V are the stator/rotor fluxes, currents and voltages expressed in the (d, q) reference frame. θ_s is the angle between the stator reference frames (a, b, c) and (d, q), and θ_r is the angle between the rotor reference frames (a, b, c) and (d, q). R_s, R_r, L_s, L_r are the stator/rotor resistances and inductances, respectively, and L_m is the magnetizing inductance. For a squirrel-cage IM the rotor voltages are zero. The mechanical equation is:

$$J\dot{\Omega} = T_e - f_v\Omega - T_L \tag{3}$$

and dthe electromagnetic torque T_e is given by:

$$T_e = pL_m(I_{sq}I_{rd} - I_{sd}I_{rq}) \tag{4}$$

Ω, J, f_v are the rotor speed, inertia and friction, respectively, p is the number of pole pairs and T_L is the load torque. Using the Park transformation with the reference frame (d,q) fixed to the stator (*ie* with $\theta_s = 0$ and $\dot{\theta}_r = -p\Omega$), Eq. (1),(2),(3) and (4) are transformed to the following nonlinear state space equations:

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$$\dot{x}=\begin{bmatrix}\xi(-L_rR_sx_1+L_m^2px_5x_2+L_mR_rx_3+pL_rL_mx_5x_4)\\ \xi(-L_m^2px_5x_1-L_rR_sx_2-pL_rL_mx_5x_3+L_mR_rx_4)\\ \xi(L_mR_sx_1-pL_sL_mx_5x_2-L_sR_rx_3-L_sL_rpx_5x_4)\\ \xi(pL_sL_mx_5x_1+L_mR_sx_2+L_sL_rpx_5x_3-L_sR_rx_4)\\ \frac{1}{J}(pL_mx_2x_3-pL_mx_1x_4-f_vx_5-T_L)\end{bmatrix}+\begin{bmatrix}\xi L_r & 0\\ 0 & \xi L_r\\ -\xi L_m & 0\\ 0 & -\xi L_m\\ 0 & 0\end{bmatrix}u \quad , \quad y=\begin{bmatrix}1&0&0&0&0\\0&1&0&0&0\\0&0&0&0&1\end{bmatrix}x \tag{5}$$

Where the state, input and output vectors are defined as:

$$x=\begin{pmatrix}I_{sd} & I_{sq} & I_{rd} & I_{rq} & \Omega\end{pmatrix}^T \; , \; u=\begin{pmatrix}V_{sd} & V_{sq}\end{pmatrix}^T$$
$$y=\begin{pmatrix}I_{sd} & I_{sq} & \Omega\end{pmatrix}^T \quad \text{and} \quad \xi=1/(L_rL_s-L_m^2)$$

The stator currents I_{sd}, I_{sq} and the rotor speed Ω are assumed to be measured since they are usually used for control purposes. As a matter of fact, measurements of stator currents and voltages are made in the (a, b, c) reference frame but they can be expressed in the (d, q) reference frame and vice-versa, thanks to the Park transformation:

$$\begin{bmatrix}V_{sd}\\ V_{sq}\end{bmatrix}=\sqrt{\frac{2}{3}}\begin{bmatrix}1 & -\frac{1}{2} & -\frac{1}{2}\\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2}\end{bmatrix}\begin{bmatrix}V_a\\ V_b\\ V_c\end{bmatrix} \tag{6}$$

In the next sections we present a particular neuro-fuzzy FDI procedure and its application for sensor fault diagnosis of an induction motor.

3. Neuro-Fuzzy Based Residual Generation and Evaluation

Neuro-fuzzy FDI systems can be designed as hybrid systems in which neural networks and fuzzy system modules may cooperate and interact to implement efficiently the required FDI tasks. Indeed, fuzzy logic systems can be combined with neural networks to design neuro-fuzzy structures whose successful applications rely on the ease of rule base design, linguistic modelling, applicability to complex uncertain and nonlinear systems, learning abilities, parallel processing.

A general FDI structure which uses any combination of neural, fuzzy and neuro-fuzzy methods for residual generation and evaluation is depicted in Fig. 1.

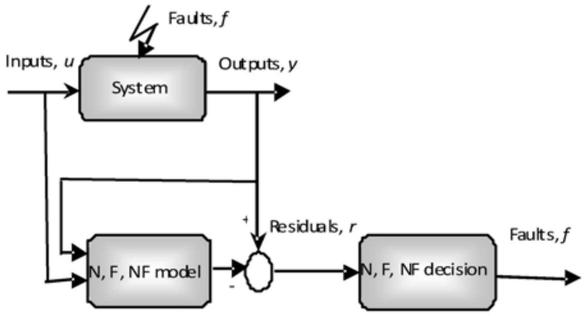

Figure 1. Neuro fuzzy FDI structure

3.1 Residual Generation

It is relevant to use the high potential of neural networks for nonlinear system modelling in the context of fault diagnosis of nonlinear dynamic systems. The neural network architecture most commonly used is the multilayer perceptron (MLP) network (Norgaard *et al*. 2000). The configuration for neural model identification is depicted in Fig. 2. Its implementation goes through the following steps.

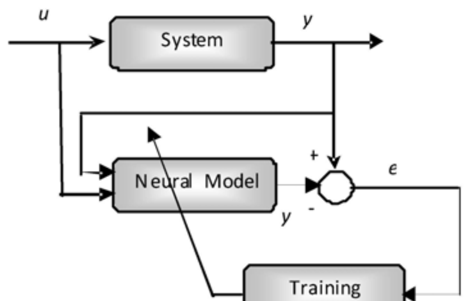

Figure 2. Neural network identification

3.1.1 Off-Line Construction of a Database

Expert knowledge of the process characteristics is used under different operating conditions.

3.1.2 Selection of the Neural Network Structure

Assuming that an input-output data set $\{u(k), y(k)\}$ $k = 1,...., N$ has been obtained, a nonlinear model structure is chosen in the general predictor form given by Eq. (7).

$$\hat{y}(k)=g(\varphi(k),\theta) \tag{7}$$

where the regression vector $\varphi(k)$ has to be selected and is the vector of adjustable parameters known as the weights of the network and g is the nonlinear function which must be realized by a suitable neural network architecture.

The NNARMAX model is obtained with the following regression vector definition, where $\varepsilon(k)=y(k)-\hat{y}(k)$:

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$\varphi^T(k)$ = $(y(k-1)...y(k-n),u(k-d)...u(k-d-m)\ \varepsilon(k-1)...\ \varepsilon(k-n'))$

The choice of this regressor form leads to a predictor with feedback which can be implemented as a recurrent neural network.

The NNARX model is recommended (Chen and Lee, 2002 and Norgfaard *et al*. 2000) when the system under consideration is deterministic or weakly noisy and this is the case for our application on an induction motor. The NNARX model is defined by the regression vector: $\varphi^T(k) = (y(k-1)...y(k-n),u(k-d)...u(k-d-m)$.

A multivariable NNARX model can be adequately implemented as a feedforward two-layer perceptron network having one hidden layer and an output layer as shown in Fig. 3.

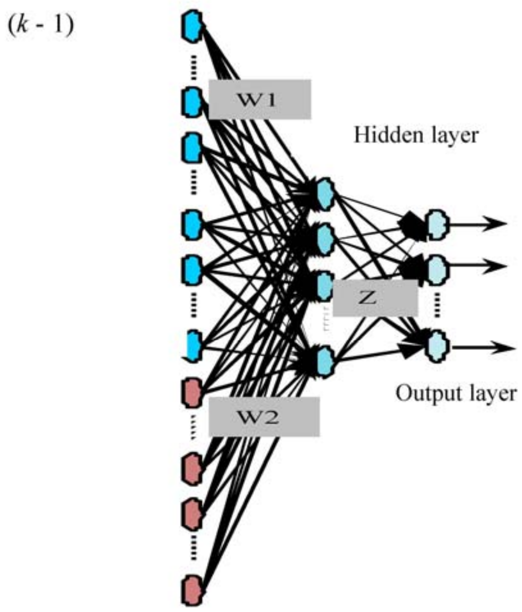

Figure 3. Two-layer neural network

The vector $\varphi(k)$ of delayed outputs and inputs of the system is applied to the network inputs. $(n_1...n_n,\ m_1...m_m,\ d)$ are the structural indices also referred to as the lag space of the neural model. The input delay d is generally taken as one. The hidden layer includes a sufficient number n_h of sigmoid units (n_h must be specified experimentally) and the output layer contains linear units.

$W = (W1\ \ W2) = (W_{ij})$ is the weight matrix relating the inputs to the hidden layer units and $Z = (Z_{if})$ is the weight matrix relating the hidden layer units to the output units.

The neural network outputs are given by:

$$\hat{y}_i(k) = \psi_i\left(\sum_{j=1}^{n_h} Z_{ij} h_j(k) + z_{i0}\right) \quad i = 1..n \tag{8}$$

$$h_j(k) = \phi_j\left(\sum_{l=1}^{n_\varphi} W_{jl}\varphi_l(k) + w_{j0}\right) \quad j = 1...n_h \tag{9}$$

where φ_j are sigmoïd type activation functions and Ψ_i are linear type activation functions and (w_{jo}, z_{io}) are the biases.

3.1.3 *Network Training*

The network weights and biases (randomly initialized) are adjusted using a suitable minimisation algorithm of the following mean square error criterion:

$$E_N = \frac{1}{N}\sum_{k=1}^{N}(y(k) - \hat{y}(k))^T (y(k) - \hat{y}(k)) \tag{10}$$

where N is the length of the training data set. The Levenberg-Marquardt algorithm is recommended to use as pointed out in (Norgaard *et al*. 2000).

3.2 Network Validation

In this stage the resulting neural model is evaluated to decide for its adequate representation of the system. This is done by testing the trained network using a data set different from the one used for training. If the trained network is judged unsatisfactory after the validation tests then it is necessary to go backwards in the procedure by retraining the network with different weight initializations, or by generating additional training data, or by modifying the network structure (by redefining the regression vector and the number of hidden units).

All these steps are accomplished off-line. When the neural network is validated, it may be utilized for on-line residual generation.

3.2.1 *Residual Evaluation*

The task of residual evaluation can be achieved by a neuro-fuzzy decision scheme as represented in Fig. 4.

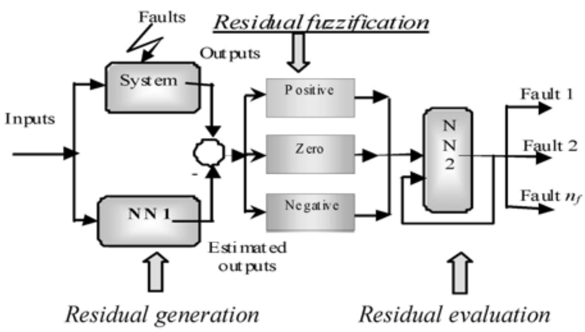

Figure 4. Fuzzy neural diagnostic scheme

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A neuro-fuzzy network is based on the association of fuzzy logic inference and the learning ability of neural networks.

The neuro-fuzzy approach is a powerful tool for solving important problems encountered in the design of fuzzy systems such as: determining and learning membership functions, determining fuzzy rules, adapting to the system environment.

The main points of the residual evaluation procedure are described below.

3.2.2 Residual Fuzzification

It consists in converting the numerical values of residuals into linguistic variables. Each input (residual) may be described by three linguistic variables (Negative, Zero, Positive). Each linguistic variable is represented by a membership function which has generally a triangular or trapezoidal shape. The linguistic variable Zero defines the range where the residual may be considered to be unaffected by a fault. The linguistic variables Negative and Positive define the residual amplitude ranges indicating the presence of a fault. The corresponding membership functions give the extent to which a residual is or is not affected by a fault.

3.2.3 Neural Network Structure

For fault diagnosis it is desirable to use a neural network to model the nonlinear relationship between the fuzzified residuals and the fault decision functions. A multilayer perceptron network is therefore a good candidate. Moreover, to account for memory in the decision process it is necessary to use a recurrent neural network (RNN). The RNN may be implemented as a neural model described by:

$$D_k(f_i) = g_i(\varphi(k)) \tag{11}$$

where $D_k(f_i)$, $i = 1 \ldots n_f$, are the fault decision functions also referred to as fault indicators and f_i are the faults acting on the process. The regression vector contains the fuzzy residuals $R_i(k)$, $i = 1 \ldots n_r$, and the delayed decisions $D_{k-1}(f_i)$, $i = 1 \ldots n_f$. Because of the feedback introduced, the recurrent neural model may be realized by a three-layer MLP.

This is illustrated by the example given in Fig. 5 which shows a residual evaluation scheme processing three residuals (r_1, r_2, r_3) to diagnose three faults (f_1, f_2, f_3).

The corresponding neural network has the following architecture: an input layer with 12 units representing all possible states of the fuzzy residuals together with the past decisions, a hidden layer having 4 units, and an output layer with 3 units each assigned to a decision function. The use of this RNN architecture ensures reliable dynamic decision making (Alexandru *et al*. 2000; Benloucif and Mehennaoui, 2005 and Chen and Lee 2002).

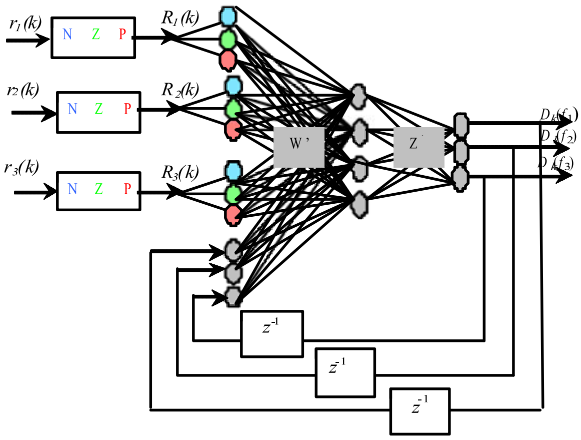

Figure 5. Example of a RNN used for residual evaluation

3.2.4 Training

Prior to on-line use, network training is performed for all possible fault scenarios. During training a residual pattern corresponding, *eg*. to fault f_1, is applied to the network input and a one is assigned to the corresponding output. The network weights are then adjusted by an appropriate algorithm thus enabling the neural network to learn the imposed input-output pattern. The use of the backpropagation algorithm is recommended (Benloucif and Mehennaoui 2005). The ultimate goal of the training is to achieve the extraction and selection of the necessary parameters defining the «If-Then» inference rules

4. Numerical Results

Results using MATLAB simulation are next presented to assess the ability of this diagnosis approach based on neural and fuzzy techniques to detect and isolate sensor faults in an induction motor. Its model expressed in the two-phase reference frame (d, q) is given by the nonlinear state space Eq. (5).

The squirrel-cage induction motor considered here has power rating of 1 kW and its electrical and mechanical parameters are as follows:

$$R_s = 10\ (\Omega),\ R_r = 5\ (\Omega),\ L_s = 500\ (mH),$$
$$L_r = 430\ (mH)\ L_m = 430\ (mH),\ J = 0.08\ (kg.m^2),$$
$$T_L = 1\ \ (N.m),\ f_v = 0.025\ (N.m.s/rad),\ p = 2.$$

Simulation is carried out with a sampling period of 1 *msec*, with 400 V and 50 Hz sinusoidal inputs. In normal operation, the outputs (I_{sd}, I_{sq}, Ω) and the electromagnetic torque T_e are shown in Fig. 6.

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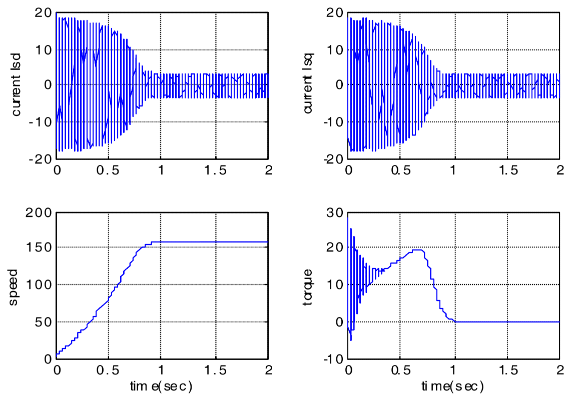

Figure 6. Stator currents (I_{sd}, I_{sq}), rotor speed Ω, torque T_e (normal operation)

4.1 Residual Generation:

A NNARX model having the architecture shown in Fig. 3 has been used with the following parameters: $n_1 = n_2 = n_3 = n_l = m_1 = m_2 = 1, d = 1$. Training of this MLP network was achieved by the Levenberg-Marquardt algorithm for different numbers of hidden neurons. For $n_h = 4$, the output error cost reached at 36 iterations is E = 1.528e-002. After validation this NNARX model is used to generate the residuals:

$$r_i(k) = y_i(k) - \hat{y}_i(k), \quad i = 1...3 \tag{12}$$

4.2 Residual Evaluation

The linguistic variables describing the fuzzified residuals are defined by the following membership functions (MF): « N: negative residual with trapezoidal MF», «Z: zero residual with triangular MF», «P: positive residual with trapezoidal MF ».

After many tests on residuals for different fault sensor situations to achieve a good trade off between missed detections and false alarms, the following membership functions for each residual were selected:

Residual 1: N1= [-1,-1,-0.005,-0.002]
Z1= [-0.0025,0 , 0.0045] , P1= [0.0035, 0.006, 1, 1].
Residual 2: N2= [-1, -1, -0.04, -0.015]
Z2= [-0.02, 0, 0.005], P2= [0.004, 0.009, 1, 1].
Residual 3: N3= [-1, -1, -0.018, -0.015]
Z3=[-0.016,-0.0135,-0.012],P3=[-0.0125,-0.0115,1,1].

The RNN used in this simulation study is shown in Fig. 5. Its training is based on the rules summarized in Table 1 which have been obtained after many simulation tests. The learning operation realized by the back-propagation algorithm converged after 3600 epochs with a sum of squared error E=0.025.

Each row of the Inference table represents a rule. For example, rule 2 is expressed as:

IF {residual 1 is positive and residual 2 is negative and residual 3 is zero} THEN sensor 1 is faulty.

Table 1. Inference table

N°	N1	Z1	P1	N2	Z2	P2	N3	Z3	P3	D1	D2	D3
1	0	1	0	0	1	0	0	1	0	0	0	0
2	0	0	1	1	0	0	0	1	0	1	0	0
3	0	0	1	0	0	1	0	1	0	0	1	0
4	0	1	0	0	1	0	0	0	1	0	0	1
5	0	0	1	1	0	0	0	0	1	1	0	1
6	0	0	1	0	0	1	0	0	1	0	1	1
7	0	0	1	0	0	1	0	1	0	1	1	0

4.3 Sensor Fault Diagnosis of the Induction Motor

Various simulation tests have been performed in order to validate the efficiency of this diagnosis scheme and the results are quite conclusive. Bias and drift type sensor faults are introduced during steady state conditions of the system. For illustrative purposes only a few fault scenarios summarized in Tables 2 to 4 are discussed.

Table 2. Case 1

Sensor N°	Fault time	Bias fault
1	2.5	0.2

Table 3. Case 2

Sensor N°	Fault time	Bias fault
2	2	0.8
3	3	3

Table 4. Case 3

Sensor N°	Fault time	Drift slope
2	2	0.001
3	3	0.0025

4.3.1 Case 1

A bias type fault is injected on sensor 1 as described in Table 2.

The corresponding residuals are shown in Fig. 7. Although a single fault may induce changes in several residuals (here a fault on sensor 1 affects positively the first residual and negatively the second residual at time t=2.5 sec) the decision functions ensure successful detection and isolation of the fault on sensor 1 as shown in Fig. 7. The neuro-fuzzy classifier has been trained to recognize the faulty situations from the fuzzified residual patterns according to the rule base given in Table 1.

4.3.2 Case 2

This fault scenario of bias faults on sensors 2 and 3 is described in Table 3.

The residuals and the corresponding decision functions are shown in Fig. 8. The faulty sensors are promptly detected and correctly isolated.

4.3.3 Case 3

This fault scenario uses drift faults on sensors 2 and

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3 as described in Table 4. Drift faults are modelled as ramp functions with given slopes.

The diagnosis effectiveness in the presence of sensor drift faults is illustrated in Fig. 9. We notice a detection delay for fault sensor 2. This delay, which is dependent on the slope of the drift, gives rise to a temporary false alarm on sensor 1.

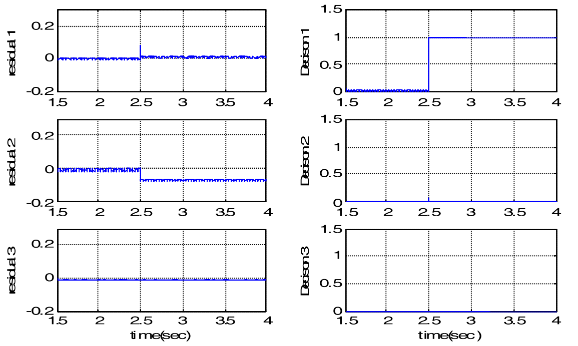

Figure 7. Faculty residuals and corresponding decisions (Case 1)

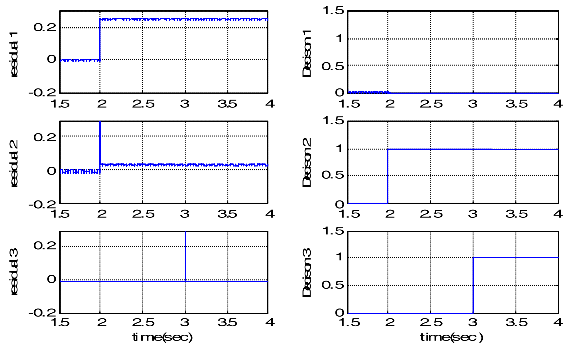

Figure 8. Faculty and corresponding decisions (Case 2)

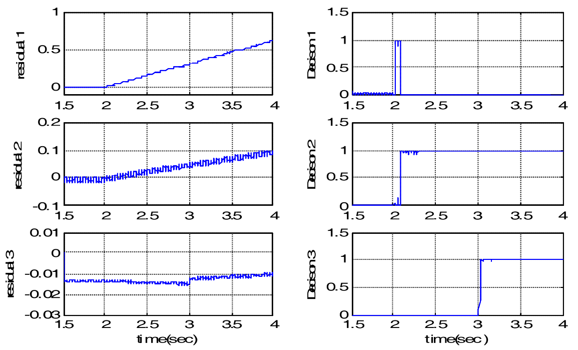

Figure 9. Faculty residuals and corresponding decisions (Case 3)

5. Conclusions

In this paper, a neuro-fuzzy scheme for on-line fault diagnosis was applied to the induction machine. This FDI approach relies on combinations of neural modelling and fuzzy logic which can deal effectively with nonlinear dynamics and uncertainties.

The proposed neuro-fuzzy FDI scheme is based on a two step procedure: a neural NNARX model is used for residual generation and a recurrent fuzzy neural network performs the residual evaluation task. Fault diagnosis is achieved by training the network to recognize the fault signatures from the patterns of the fuzzified residuals. The successful results obtained in simulation demonstrate the efficiency of this neuro-fuzzy diagnosis scheme to detect and isolate bias and drift sensor faults in an induction motor.

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