Robust analytical redundancy relations and artificial neural networks for fault detection and isolation in electric drives

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***Abstract*— In this paper, a fault diagnostic system in electric drives using a robust analytical redundancy relations and perceptron multilayer artificial neural network based on classifier method. The ARRs and ANN design process are clearly described. For this purpose, we have treated the signals of the measured parameters (current and speed) to use them firstly. The simulation model of the electric drives is studied under normal and different fault mode (short-circuit and open faults of switching device in inverter) in electric drives are considered for fault detection and diagnosis. Robustness of classifier load torque is verified. Analysis, modelling and simulation results are presented to demonstrate the validity of the proposed method.**

Key-Words— Electric drive, ARRs, MLP NN, Fault, RMS.

I. INTRODUCTION

Physical systems are often subjected to unexpected changes, such as component failures and variations in operating condition, that tend to degrade overall system performance. We will refer to such changes as “failures,” although they may not represent the failing of physical components. In order to maintain a high level of performance, it is important that failures be promptly detected and identified so that appropriate remedies can be applied. Over the past decade numerous approaches to the problem of failure detection and isolation (FDI) in electric drives have been developed [1, 2]. The electric drives use more and more the asynchronous motors because of their robustness, specific power and low construction cost. However, it happens that these machines present electric or mechanical defects. Our objective is to detect these failures during their appearance and evolution. The different faults on induction machines may yield drastic consequences for an industrial process. The main problems are related to increasing costs, and worsening of process safety conditions and final product quality. Many of these faults show themselves gradually. Then the detection of incipient faults allows avoiding unexpected factory stops and saving a great deal of money [3, 4].

The kinds of faults of these machines are varied. However the most frequent are [5]:

- Opening or shorting of one or more of a stator phase winding,
- Broken rotor bar or cracked rotor end-rings,
- Static or dynamic air-gap irregularities, and
- Bearing failures.

In other way, with the development of power electronics and microprocessor, induction motors are predominantly fed from pulse width modulation (PWM) inverters for variable-speed operation. However, the power semiconductor device and control circuit are frail part of the inverter, and its reliability has not been resolved [6]. The recent research shows that the faults occurred in the power converter is about 82.5 percent of faults occurred in the inverter fed motor drives [7]. The faults are open-circuit and short-circuit of semiconductor device. A voltage-fed inverter induction motor drive system, as shown in Fig. 1, can develop various types of faults that can be classified as follows:

- Open-circuit fault of semiconductor device,
- Short-circuit fault of semiconductor device,
- Two semiconductor device of one leg open-circuit fault.

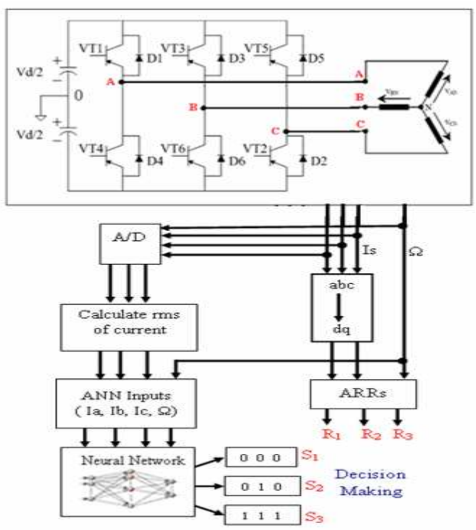


Fig.1 Block diagram of developed model

In this paper we present an investigation on the use of robust residual generation and Perceptron Multilayer Artificial Neural Network (MLP ANN) based classifier method. These approaches are applied an electric drive.

A. ARRs design and generation for electric drive

The basis for robust residual generation is analytical redundancy relation (ARR), which essentially takes two forms: 1) direct redundancy-the relationship among instantaneous outputs of sensors; and 2) temporal redundancy-the relationship among the histories of sensor outputs and actuator inputs. It is based on these relation-ships that outputs of (dissimilar) sensors (at different times) can be compared. The residuals resulting from these comparisons are then measures of the discrepancy between the behavior of observed sensor outputs and the behavior that should result under normal conditions. Consider the following system [8,9]:

$$\begin{cases} \dot{x} = f(x,\ z,\ \theta) \\ y = f(x,\ z,\ \theta) \end{cases} \tag{1}$$

Where $x \in R^n$ is the state vector, $z \in R^m$ is the input vector, $y \in R^m$ is the measurement vector and $\theta \in R^l$ is some constant parameter vector. f and h are assumed to be polynomial functions in their arguments and $z = (u^t, v^t, \varphi^t, \varepsilon^t)^t$

Where u presents control inputs, v unknown inputs, φ faults and ε noise.

Considering s_j successive time derivations of the j^{th} output one obtains:

$$\bar{y}_j^{(sj)} = G_j^{(sj)}\left(x, \bar{z}^{(sj)}, \theta\right) \tag{2}$$

where $y_j^{(sj)}\left(resp. \bar{z}^{(sj)}\right)$ stands for $y_j(resp. Z)$ and its time derivatives up to order S_j.

The concatenation of equation 3 for $j \in J = \{1, \ldots, p\}$ gives a system of $\sum (S_j + 1)$ equations:

$$\bar{y} = G_x(x, \bar{z}, \theta) \tag{3}$$

Where $S = (S_j,\ j \in J)$ and for simplicity $\bar{y}$ stands for

$$\left(y^{(S_1)t},\ y^{(S_2)t},\ \ldots\ y^{(S_p)t}\right) \tag{4}$$

ARR are input/output relations obtained by eliminating the unknown state x in equation 3.

ARR existence conditions are depend on the rank of the Jacobian matrix [10] $\dfrac{\partial G_s(x, \bar{z}, \theta)}{\partial x}$. Using symbolic computation algorithms a set of polynomial ARR is found.

$$\bar{y} = G_S(x, \bar{z}, \theta) \Rightarrow w(\bar{y}, \bar{z}, \theta) = 0 \tag{5}$$

Since each component of $w(\bar{y}, \bar{z}, \theta)$ is a polynomial in its arguments, the following decomposition holds:

$$w(\bar{y}, \bar{z}, \theta) = w_c(\bar{y}, \bar{u}, \theta) - w_e(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta) \tag{6}$$

Where $w_e(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta)$ is of degree at least one in some components of $\bar{v}$, $\bar{\varphi}$ and $\bar{\varepsilon}$ (thus it equals zero in the absence of faults, noise and unknown inputs).

Let $r = w_c(\bar{y}, \bar{u}, \theta)$ be the calculable part of the ARR. r is the non linear parity space residual vector, $w_C(\bar{y}, \bar{u}, \theta)$ is its computation form and $w_e(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta)$ is its evaluation form.

Considering the unknown inputs, $w_e(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta)$ can be decomposed into two parts:

$$w_e(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta) = w_{rob}(\bar{y}, \bar{u}, \bar{\varphi}, \bar{\varepsilon}, \theta) + w_{r\bar{o}b}(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta) \tag{7}$$

with $w_{r\bar{o}b}(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta) = 0$

Considering the noise, $w_{rob}(\bar{y}, \bar{u}, \bar{\varphi}, \bar{\varepsilon}, \theta)$ can further be decomposed:

$$w_{rob}(\bar{y}, \bar{u}, \bar{\varphi}, \bar{\varepsilon}, \theta) = w_{robd}(\bar{y}, \bar{u}, \bar{\varphi}, \theta) + w_{robs}(\bar{y}, \bar{u}, \bar{\varphi}, \bar{\varepsilon}, \theta) \tag{8}$$

with $w_{rob,d}(\bar{y}, \bar{u}, 0, \theta) = 0$ and $w_{rob,S}(\bar{y}, \bar{u}, \bar{\varphi}, 0, \theta) = 0$ suppose the ARR are such that $w_{r\bar{o}b}(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta) = 0$ then a FDI algorithm is built using the residuals:

$$r = w_c(\bar{y}, \bar{u}, \theta) = w_{rob,d}(\bar{y}, \bar{u}, \bar{\varphi}, \theta) + w_{rob,s}(\bar{y}, \bar{u}, \bar{\varphi}, \bar{\varepsilon}, \theta) \tag{9}$$

and testing the two hypotheses $H_0: \varphi = 0 (i.e.\ w_{rob,d} = 0)$ against $H_1: \varphi \neq (i.e.\ w_{rob,d} \neq 0)$ note that a possible definition of non detectable faults is $w_{rob,d}(\bar{y}, \bar{u}, \bar{v}, \bar{\varphi}, \bar{\varepsilon}, \theta) = 0$ in spite of $\bar{\varphi} \neq 0$.

Consider the (d, q) model of the induction motor. The state variables are the rotor angular speed Ω and the (d, q) projections of the stator current and rotor flux: i_{sd}, i_{sq}, ϕ_{rd} and ϕ_{rq}. The control inputs are the (d, q) projections of the stator voltage: v_{rd} and v_{rq}. The load torque T_l is unknown. The outputs are the only state variables that can be measured i.e. Ω, i_{rd} and i_{rq}. Under usual hypotheses the equations are [10]:

$$
\begin{cases}
\dot{x}_1 = \dfrac{pM}{L_r J}\left(x_2 x_5 - x_3 x_4\right) - \dfrac{B}{J} x_1 - \dfrac{T_l}{J} \\
\dot{x}_2 = \beta\left(M x_4 - x_2\right) - p x_1 x_3 \\
\dot{x}_3 = \beta\left(M x_5 - x_3\right) + p x_1 x_2 \\
\dot{x}_4 = \dfrac{1}{\sigma}\left(\gamma x_4 + \delta\left(\beta x_2 + p x_1 x_3\right) + \dfrac{v_{S_d}}{L_s}\right) \\
\dot{x}_5 = \dfrac{1}{\sigma}\left(\gamma x_5 + \delta\left(\beta x_3 - p x_1 x_2\right) + \dfrac{v_{Sq}}{L_s}\right)
\end{cases}
\tag{10}
$$

With state vector $x=(x_1,x_2,x_3,x_x,x_5)^t=(\Omega,\phi_{rd},\phi_{rq},i_{sd},i_{sq})^t$, and measurement vector $y=(y_1,y_2,y_3)^t=(x_1,x_4,x_5)^t$.

R_s , L_s are the stator resistance and inductance.

R_r , L_r are the rotor resistance and inductance,

M is the mutual inductance between stator and rotor, p is the number of pole pairs, B is the damping coefficient, J is the moment of inertia, T_l is the load torque an unknown input,

$\sigma = 1 - \dfrac{M^2}{L\ L_s}$ and $\gamma = -\dfrac{1}{\sigma}\left(\dfrac{R_s}{L_s} + (1-\sigma)\dfrac{R_r}{L_r}\right)$.

This Works deals with the ARRs approach. The mathematical equations of the system are manipulated to derive diagnostic signals (called ARRs, residuals, or consistency relations), which are based only on measurable and fault variables and their time derivatives. The capability of isolating different faults requires the simultaneous evaluation of multiple ARRs, each one being ideally zero in fault-free conditions and different from zero after the occurrence of a failure. Three residuals are generated as follows:

$$
R_1 = p^2 L_s \sigma A_1\left(p y_1 y_2 - \beta y_3\right) + p^2 L_s \sigma A_2\left(p y_1 y_3 - \beta y_2\right) + \left(\beta^2 + (p y_1)^2\right)\left(\left(J(p\dot{y}_1) + Bpy_1\right) + pT_l\right) = 0 \tag{11}
$$

$$
R_2 = \left[\beta^2 + (py_1)^2\right]\left[\dot{A}_1 - \frac{1-\sigma}{\sigma}\left[\beta^2 y_2 + \beta\ py_1 y_3\right]\right] - \left(\beta A_2 + A_1 py_1\right)\left(-2\beta py_1 + p\dot{y}_1\right) - \left(\beta A_1 - A_2 py_1\right)\left((py_1)^2 - \beta^2\right) = 0 \tag{12}
$$

$$
R_3 = \left[\beta^2 + (py_1)^2\right]\left[\dot{A}_2 - \frac{\beta(1-\sigma)}{\sigma}\left[\beta y_3 + py_1 y_2\right]\right] - \left(\beta A_1 + A_2 py_1\right)\left(2\beta py_1 + p\dot{y}_1\right) - - \left(\beta A_2 - A_1 py_1\right)\left((py_1)^2 - \beta^2\right) = 0 \tag{13}
$$

With:

$A_1 = \dot{y}_2 - \gamma y_2 - \dfrac{v_{sd}}{\sigma L_s}$, $A_2 = \dot{y}_3 - \gamma y_3 - \dfrac{v_{sq}}{\sigma L_s}$, $\beta = \dfrac{R_r}{L_r}$, $\alpha = \dfrac{R_s}{L_s}$

It can be seen that only the first residual is robust to the load disturbance. It can be used to estimate load torque.

$$
T_l = -\frac{pL_s\sigma A_1\left(py_1 y_2 - \beta y_3\right) + pL_s\sigma A_2\left(py_1 y_3 + \beta y_2\right)}{\beta^2 + (py_1)^2} - J\dot{y}_1 - By_1 \tag{14}
$$

Robust analytical redundancy relations based residuals are indicators of behaviors and thus may be used for FDI: they are equal to zero in normal (no-fault) situation and different from zero when the faults they are sensitive to, occur. A structured set of residual, i.e. a set of residuals that are not sensitive to the same subsets of faults, may be used to isolate the faults [10, 11]. These residuals can also be used, when hybrid systems are considered like our case of application (asynchronous machine associated to electronic converter). Therefore this technique detects all the faults but it can't localize them as open or short circuit fault of semiconductor device what leads us look for another technique that enables us to localize all those faults of our system, the artificial neural networks technique can do so .

II. Methodology of Neural Network Fault Classification

Neural networks provide the ability to recognize anomalous situations because of their intrinsic capacity to classify and generalize. The stages of neural network fault classification are explained as follows:

A. Strategy adopted for identification of the defects

Before the ANN block construction system for the failure detection of the electromechanical systems (identification of the acquired signals), one must first of all reach the phase of data acquisition (training bases) from which the ANN will be able to learn. This one can be always put in the form of file or of table. To build a nonparametric model (ANN) describing the behaviour of the electromechanical system (normal and abnormal operations), one must build a data base as detailed as possible. The training base the ANN is put in the form of file or table (matrix). This last is represented by vector classes, where each class represents an operation type, and each vector is represented by the effective values. In this case each vector is consisted of the 3 parameters as quoted above (Ids, Iqs and Ω). The latter represent the ANN input layer. In fact, to pass to the classification stage, we dispose for each parameter, 7 operating types, including normal operation (see table 1) [12,13].

B. Neural network training

Each network is trained with one set of normal data and six sets of abnormal data, thus the size of the input matrix is seven input data rows. The neuron network: its inputs are the effective values (Isa, Isb, Isc and Ω), which means that the umber of input of this network is equal to 4 (Fig.1). The digital output from the A/D converter is converted into suitable linguistic values. In addition, standardization will be carried out to bring back all the values of the inputs in the interval [0, 1]; this operation is carried out to adapt to the input neurons. The retro propagation algorithm is utilised in this research. It is the most algorithm used paradigm of the ANN. The term refers to an algorithm to adjust the weights in a multi layer ANN. Under these conditions the ANN was trained with the learning algorithm. Figure 2 shows the performance of a training session (Best validation performance is 8.7343e-012 at epoch 100).

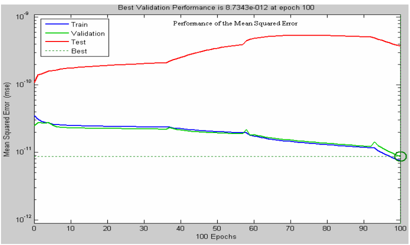


Fig. 2 Performance of the network, during training

C. Neural network architecture design

The architecture of the proposed fault diagnostic neural network is illustrated in Fig. 3. The NN is a three layered. The numbers of nodes in the input (X), in the hidden (Hi), and the output layers (Y) are 4, 4 and 3 respectively. Logsig functions were selected in the hidden and output layers. The sigmoid activation function is used. A logsig activation function is used for an output node because the target output is between (0) and (+1).

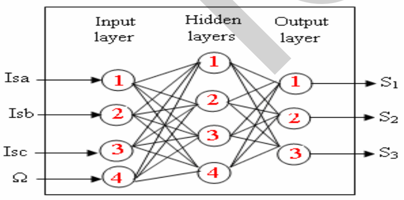


Fig.3. Proposed neural network architecture

Firstly, the analogical measurements are converted in digital data through an A/D converter. Then, the root mean square (RMS) of each phase current is calculated over a period of time using the standard formula:

$$rms\ (I(t)) = \sqrt{\left| \left(\frac{1}{T} \int_{t}^{(t+T)} I(t)^2 \right) \right|} \tag{15}$$

I(t): input current , T=1/fundamental frequency. In this layout, the motor currents and speed are considered as input variables of the ANN system, these variables have vague information.

D. Neural network testing

The networks are examined with the test data sets, as mentioned above, when the proposed networks have trained to the desired error goal. Testing the network involves presenting the test set to the network and calculating the error. If the error goal is met, the training is complete.

III. Simulation Results and Discussion

A. Simulation parameters

The parameters are: Rs=1.2Ω, Ls=0.1554H, Rr=1.8Ω, Lr=0.1568H, p=2, M=0.15H, J=0.07 kg/m², P=4kW, f=50Hz.

The simulation sampling period is equal 1ms and it is performed during 2s. The load torque is constant and equal 25N.m this torque is supposed to be unknown. Based on the SPWM technique, the control strategy can be shown in fig.4 and Fig.5 respectively.

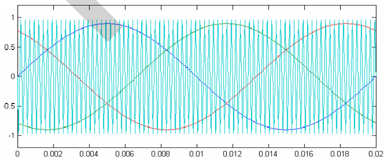


Fig. 4 SPWM control strategy

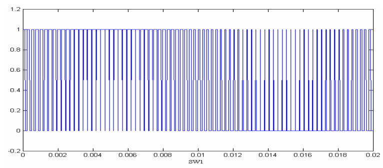


Fig. 5 Switch function

Figure 6 shows the time evolution of residuals R1 to R3 when no fault acts on the system.

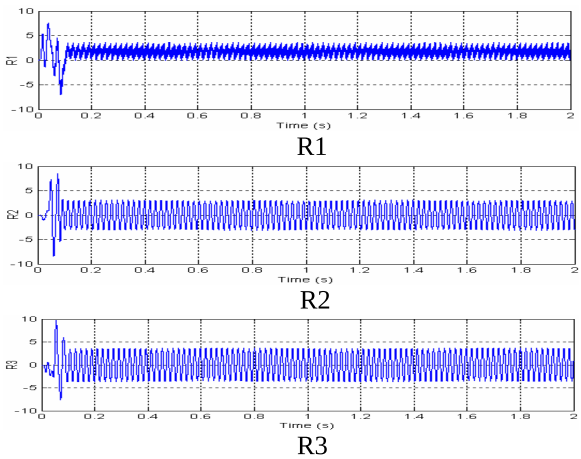
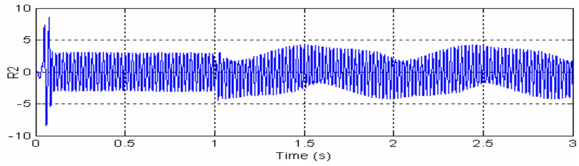
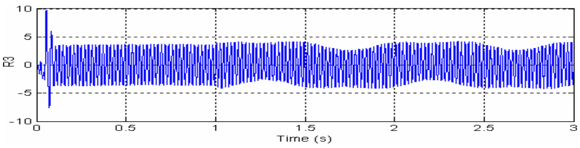


Fig. 6 Residual evolution

Fig 7.a) and the two robust residuals R2 and R3 when semiconductor device VT1 open-circuit fault occurred. The difference in the mean values between the no faulty and the faulty cases are significant enough.



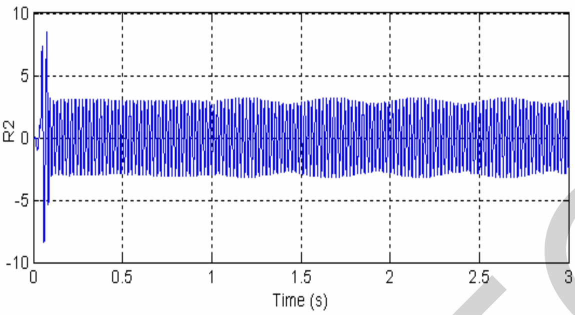
R2



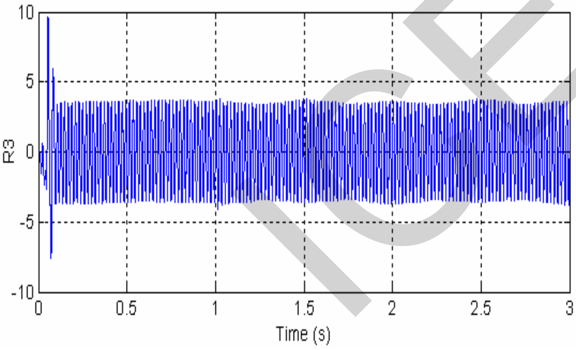
R3

Fig.7 Residual evolution

Figure 8 displays the time evolution of the corresponding residuals in the faulty case, stator resistance is abrupt change at t= 1 s.



R2



R3

Fig.8 Residual evolution

The simulation data by using the neural networks which we have collected were separated into two parts: the training datasets and the testing datasets. They consisted 7 operating mode for monitoring, 1 no fault (NF) and 6 faults (see table1).

Table 1

Defect classification

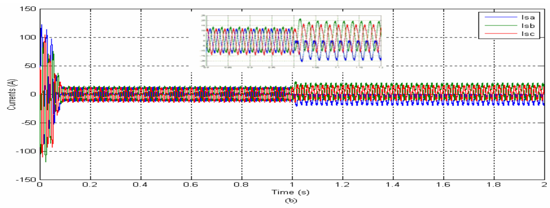
N°	Defect type	Symbol
1	Without fault	NF
2	VT1 Open circuit fault	FVT1
3	VT5 Open circuit fault	FVT5
4	VT2 and VT6 Open circuit faults	FVT2-6
5	Stator resistance fault (A)	SRFA
6	Stator resistance fault (B)	SRFB
7	Stator resistance faults (B) and (C) phases	SRFBC

Table 2: Outputs of the network for testing the studied system

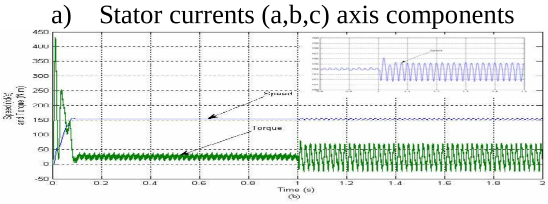
Classification	Desired output			Actual output		
	S1	S2	S3	S1	S2	S3
NF	0	0	0	6.156 e-07	1.221e-06	-4.054 e-08
FVT1	0	0	1	-1.950 e-06	-7.613 e-07	0.9999976
FVT5	0	1	0	5.156 e-07	0.9999651	8.475 e-09
FVT2-6	0	1	1	3.093 e-07	0.9999976	1.0000000
SRFA	1	0	0	1.0000003	-2.354 e-07	1.060 e-06
SRFB	1	0	1	0.9999999	-1.442 e-06	1.0000020
SRFBC	1	1	0	0.9999990	1.0000003	-8.442 e-07

B. Interpretation of the results

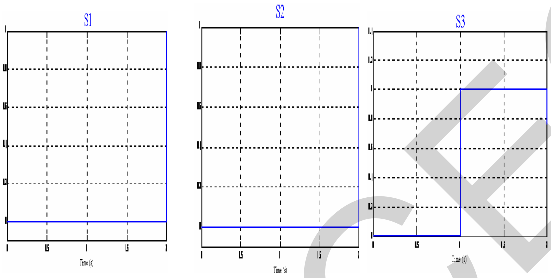
From the representation on line of the ARRs and ANN inputs, we notice that the graphs change their characteristics at the moment of the application of the defect. In our case the defect is created at the moment t =1s. At this moment, for example, inputs: [S1, S2, S3], indicate respectively the values: [0, 0, 1], therefore the defect corresponding is: semiconductor device VT1 open-circuit fault (See figure 9).



a) Stator currents (a,b,c) axis components



b) Speed and Torque



c) ANN output (S1S2 S3)

Fig. 9 ANN test performance under VT1 open circuit fault condition

The networks are examined with the test data sets, as mentioned above, when the proposed networks have trained to the desired error goal (Table 2).

V. Conclusion

This paper presents a method to use a robust analytical redundancy relations and artificial neural networks to detect and localize faults in electric drives. The analytical redundancy is an alternative approach to physical redundancy. Physical redundancy means that redundant signals are generated by means of a set of equal redundant sensors through which the failed ones can be detected. Analytical redundancy uses mathematical models and observers to generate redundant signals. Computations use those signals and present and / or previous measurements of other variables. The resulting differences, called residuals, are indicative of the presence of faults in the system. But this technique still be incomplete what leads us to look for another technique witch enable us to complete this work. A study of a fault diagnosis system in electric drives using neural networks has been proposed. The choice of this last is justified by its robustness, ability to localize all the faults especially as open or short circuit fault of semiconductor device, in addition to the simplicity because the of the neuron network inputs come directly from the current rotation speed sensors.

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