Sensor Fault Detection and Isolation Based on Artificial Neural Networks and Fuzzy Logic Applicated on Induction Motor for Electrical Vehicle

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ABSTRACT

Recently, research has picked up a fervent pace in the area of fault diagnosis of electrical vehicle. Like failures of a position sensor, a voltage sensor, and current sensors. Three-phase induction motors are the “workhorses” of industry and are the most widely used electrical machines. This paper presents a scheme for Fault Detection and Isolation (FDI). The proposed approach is a sensor-based technique using the mains current measurement. Current sensors are widespread in power converters control and in electrical drives. Thus, to ensure continuous operation with reconfiguration control, a fast sensor fault detection and isolation is required. In this paper, a new and fast faulty current sensor detection and isolation is presented. It is derived from intelligent techniques. The main interest of field programmable gate array is the extremely fast computation capabilities. That allows a fast residual generation when a sensor fault occurs. Using of Xilinx System Generator in Matlab/Simulink allows the real-time simulation and implemented on a field programmable gate array chip without any VHSIC Hardware Description Language coding. The sensor fault detection and isolation algorithm was implemented targeting a Virtex5. Simulation results are given to demonstrate the efficiency of this FDI approach.

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1. INTRODUCTION

Development and research in the field of electric vehicles appeared with the collective awareness on global warming. Indeed, the transport sector is one of the main causes in the emission of greenhouse gas emissions. This context that manufacturers are facing the challenge of reducing Carbon Dioxide not rejected combustion vehicles [1]. To address these environmental constraints, the most promising technological solution is the substitution of the engine with an electric motor. However, the electrical propulsion chain is built around a large number of components (electrical machine, sensors, converters power electronics ... etc.) which may be the site of a high number of defects. The detection and location of these defects are essential but not sufficient to ensure the safety and operation in degraded mode.

Much work has been done in order to limit the impact of these defects in power plant [2]-[4]. A numbers of approaches for fault detection and isolation are developed, but most of them focused on the stator windings of a motor and power semiconductor of an inverter. Sudden severe faults of a current sensor result in the over current malfunction of the system, and if there is no proper protection scheme in the gate-drive circuit, it leads to irrecoverable faults of power semiconductors in the inverter. The largely used approach for sensor FDI is based on residuals generated by comparison between measured sensor output and reconstructed sensor output, using other system sensors. It could be classed into two categories: one based free model methods and the second based analytical model. The method used the model of system to generate a residual which becomes small in the absence of defect and large in the case of fault. Sensor fault is detected and identified using analytical redundancy as presented in the different works [5]-[8]. Unfortunately, the analytical model could be imprecise and uncertain that's why the residual could indicate a false alarm. For this reason these techniques are well-suited for deterministic models. To solve this problem, intelligent techniques are used. This category has many advantages: uncertainty, complex and disturbance system modeling. Therefore, these techniques are required in this problem type, where the detection and the isolation of the fault for the sensors of specifying system will be guaranteed with desired performances. Many works have used intelligent techniques to adopt the detection sensor failures for various systems as presented in [9]-[11]. Authors developed this approach taking advantages on the one hand of digital control implementation hardware and software specifications and on the other hand, of electrical systems specifications. The simplicity of the final algorithm leads to low execution time and low consumed resources for digital implementation.

To successfully implement on the FPGA board the FDI algorithm for the induction motor and realized an embedded system. There are three methods: the first is to directly program our FPGA using VHDL, the disadvantage of this method it is that we cannot visualize the behavior of real-time of the control. The second is to use the toolbox added to Matlab / Simulink HDL coder, the disadvantage of this method that the toolbox missing a lot and we are obliged to make several approximations and the resulting program is not optimized. And the last consists to use the toolbox added to Simulink Xilinx System Generator (XSG), the advantage of this programming method is the resolution of all problems of display. We can also take advantage of Simulink and visualize the actual behavior of the machine before implementation.

This paper gives detailed information on a new current sensor FDI algorithm, which is developed using intelligent techniques (Neuro Fuzzy). After this introductory section, the problem statement is presented, with a description of the machine model and its control system. The architecture of the Neuro Fuzzy schema used for 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. SYSTEM OVERVIEW

2.1. Presentation

Automotive application drives (EV) has some major requirements that are summarized as follows [3]-[4]:

1. high torque at low speeds for starting, as well as high power at high speed for cruising;
2. fast torque response;
3. high power density and high instant power;
4. high efficiency for regenerative braking, over wide speed and torque;
5. reasonable cost.

The traction of an electric vehicle can subdivide in three parts: a power source, an inverter and a receiver (see Figure 1). The source is the battery and the receiver is the mechanical chain. The powertrain composed of the inverter (and its control) and the motor is the electromechanical power converter.

Faults can affect all the components of the system: induction motor, power converters, connectors and sensors. The failures in the electric motor can have various origins:

a. Failures related to the exploitation that can lead to faults and also a premature degradation ;
b. Failures related to wrong weak dimensioning and design which lead to a premature degradation

It is very important to detect a sensor failure on a real-time basis for structural health monitoring and vibration control. Many fault detection and isolation FDI techniques for current sensors have been discussed over the past decades Frank 1990, Gertler 1991. The two major sensor failure detection methods can be distinguished:

a. Direct pattern recognition of sensor readings that indicate a fault and an analysis of the discrepancy between the sensor readings and expected values, derived from some model. In the latter case, it is typical that a fault is said to be detected if the discrepancy or residual goes above a certain threshold.
b. In signal processing based FDI, some mathematical or statistical operations are performed on the measurements, or some intelligent technique is trained using measurements to extract the information about the fault.

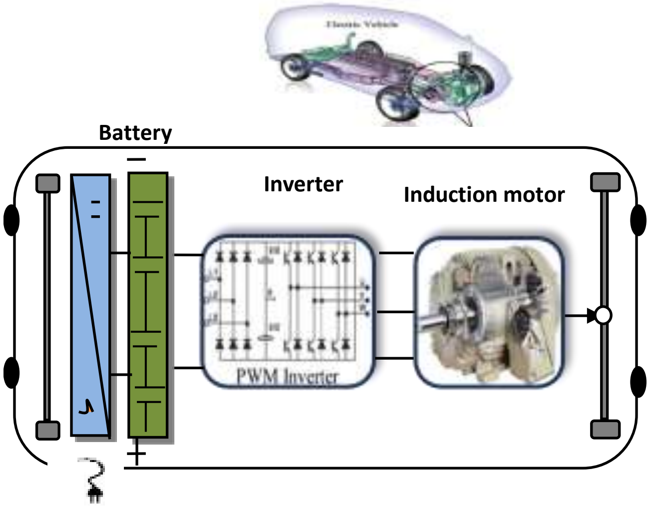

Figure 1. Main components of an EV traction drive.

2.2. Basic Principle of DTC SVM

The conventional DTC strategy is a developed drive control technique of the IM. This type of torque and flux control was first proposed as direct self-control by Depenbrock [17] and DTC by Takahashi and Noguchi [18]. The DTC method is characterized by its simple implementation, fast dynamic response, and robustness to the rotor parameter variation essentially. The main idea of DTC SVM is to recover the reduction of the ripples of torque and flux, and to have superior dynamic performances. Figure 2 present a possible schematic of Direct Torque Control by using Space Vector Modulation. There are two different loops corresponding to the magnitudes of the stator flux and torque. The error between the estimated stator flux magnitude φ_s and the reference stator flux magnitude φ_s^* is the input of a bloc SVM.

Knowing that in the graduation phase voltages (V_a, V_b, V_c) are represented in the plane by a vector V_s. Each modulation period Tmod of the inverter, the projected vector Vs on the two adjacent vectors assures the switching time of calculation. The values of these projections provide the desired commutation times. The key step of the SVM technique is the determination of T_i and T_{i+1} during every modulation period T_{mod}. To illustrate the methodology we consider the case where V_s can be compounded by the active voltage vectors V_1 and V_2.

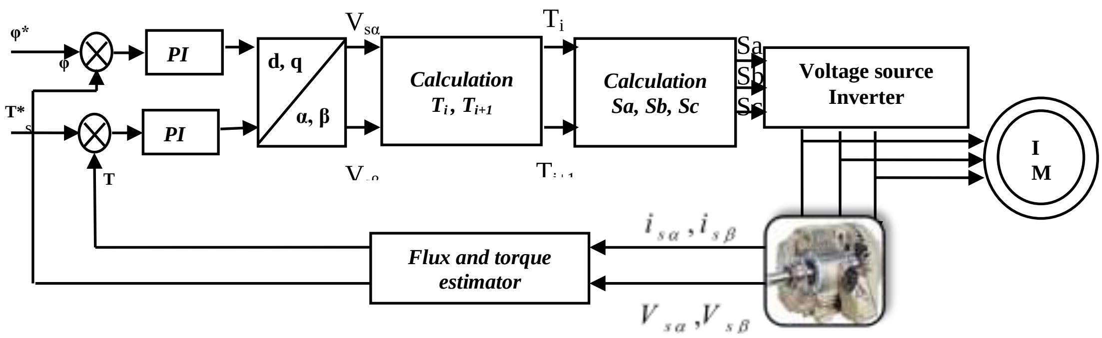

Figure 2. Bloc diagram of DTC

The stator voltage and stator current are calculated from the state of three phase (S_a ,S_b ,S_c) and measured currents (i_a, i_b, i_c).

$$V_s(S_a,S_b,S_c)=\sqrt{\frac{2}{3}}E_0(S_a+S_b e^{j\frac{2\pi}{3}}+S_c e^{j\frac{4\pi}{3}})$$
$$i_s(i_a,i_b,i_c)=\frac{2}{3}(i_a+i_b e^{j\frac{2\pi}{3}}+i_c e^{j\frac{4\pi}{3}}) \qquad (1)$$

Expressing the voltage vector Vs in the graduation (α, β) we have:

$$\overrightarrow{V_s}=V_{s\alpha}+jV_{s\beta}=\frac{T_1}{T_{\text{mod}}}\overrightarrow{V_1}+\frac{T_2}{T_{\text{mod}}}\overrightarrow{V_2} \qquad (2)$$

Expanding this equation it is possible to express the time T_1 and T_2 in terms of $V_{s\alpha}$ and $V_{s\beta}$. The conduction time will be expressed as follows:

$$T_1=(\sqrt{\frac{3}{2}}V_{s\alpha}-\sqrt{\frac{1}{2}}V_{s\beta}).\frac{T_{\text{mod}}}{E}$$
$$T_2=\sqrt{2}V_{s\beta}.\frac{T_{\text{mod}}}{E} \qquad (3)$$

Consequently, the duties expressions are given as follows:

$$D_1=\frac{\sqrt{3}}{\sqrt{2}}.\frac{\mathrm{V}_{s\alpha}}{\mathrm{E}}-\frac{1}{\sqrt{2}}\frac{\mathrm{V}_{s\beta}}{\mathrm{E}}$$
$$D_2=\frac{\mathrm{V}_{s\beta}}{\mathrm{E}}\sqrt{2} \qquad (4)$$
$$D_0=1-D_1-D_2$$

The space vector in sector 1 is shown in figure 3.The time duration of zero vectors is divided equally into (V0, V1, V2, V7, V2, V1, V0), whereas the time duration of each nonzero vector is distributed into two parts. This sequence can ensure that is one phase switches when the switching pattern switches, thus can reduce the harmonic component of the output current and the loss of switching devices. The duties of each phase of the inverter are presented as follows:

$$S_a=0.5(1+D_1+D_2)$$
$$S_b=0.5(1-D_1+D_2) \qquad (5)$$
$$S_c=0.5(1-D_1-D_2)$$

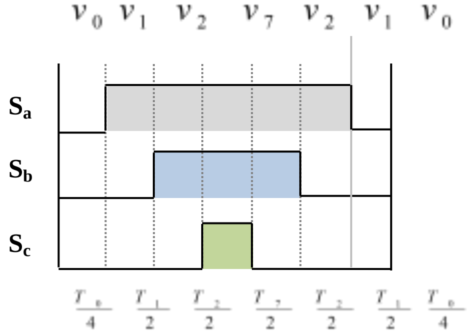

Figure. 3 Sequences of the switches states in sector N1

3. FAULT DETECTION and ISOLATION (FDI)

FDI system is designed as a hybrid system in which fuzzy system and neural networks may cooperate and interact to implement efficiently the required FDI tasks. The structure of Neuro Fuzzy is successful applications rely on the ease of rule base design, applicability to complex, uncertain and nonlinear systems, linguistic modeling, learning abilities, parallel processing. The FDI scheme is divided into two steps (detection step and localization step). The first step is based on generating a signal called residual. It's used like indictor of the occurrence of the fault. If the difference is equal to zero, then the equipment system operate in healthy case, otherwise (residual ≠0) they are affected by a fault which should be isolated. The role of the second step is to determine the time of the default application. In order to get the adequate decision, this phase requires a technique deals with uncertain data. The most appropriate technique is the Neuro Fuzzy logic. It needs an expert system. The Figure 4 shows the different stages of the adopted strategy.

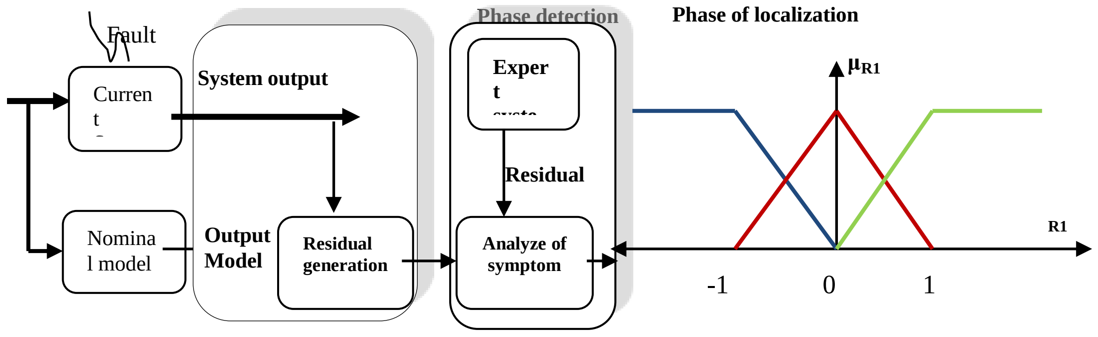

Figure 4. Adopted strategy

3.1. Phase Detection

In the case of nonlinear systems, a residue generator by conventional quantitative methods is not an easy task. It would be better to use neural networks to generate residues functions, using their ability to model nonlinear functions. Beforehand, a database must be performed offline with expert knowledge. It must include the main characteristics of the process (operating point, stability, noise ...). In order to make the neural network describe the behavior of the system, it should be learned with data base rich in information. Once this base is realized, a structure of the neural network must be chosen.

3.2. Phase of localization

The role of the residual Fuzzification\ Evaluation step is to identify the element (current sensors) attached by the fault. In order to get the adequate decision, this phase requires a technique deals with uncertain data. The most appropriate technique is the fuzzy logic. It needs an expert system. The Figure 5 shows the different stages of the adopted strategy.

An NF generally consists of two principal units: (a) a fuzzifie which converts analog inputs into fuzzy variables. These variables are produced by using membership functions (MF); (b) the residual evaluation step is based RNN. The inputs of the network are the fuzzifier residues (three membership functions for each residue) and in the outputs we have the decisions.

3.2.1. Fuzzy variables

Each residual (R_1, R_2, R_3) could be described with three memberships (N= Negative, Z= Zero and P=Positive). For each residue three membership functions are selected: two functions type trapezoidal and one function type triangular as shown in Figure 6. For the choice of parameters, many tests are affected. The linguistic variables describing the fuzzifie residuals are defined by the following membership functions: ''N: negative residual with trapezoidal MF", ''Z: zero residual with triangular MF", ''P: positive residual with trapezoidal MF". The universe of discourse has been normalized to [−1, 1] band.

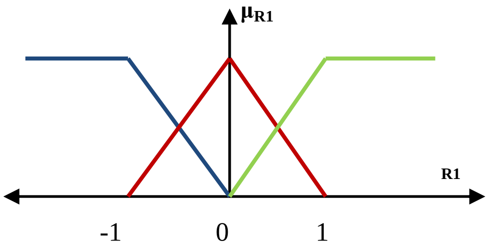

Figure 5. Fuzzy MF of the input R_1

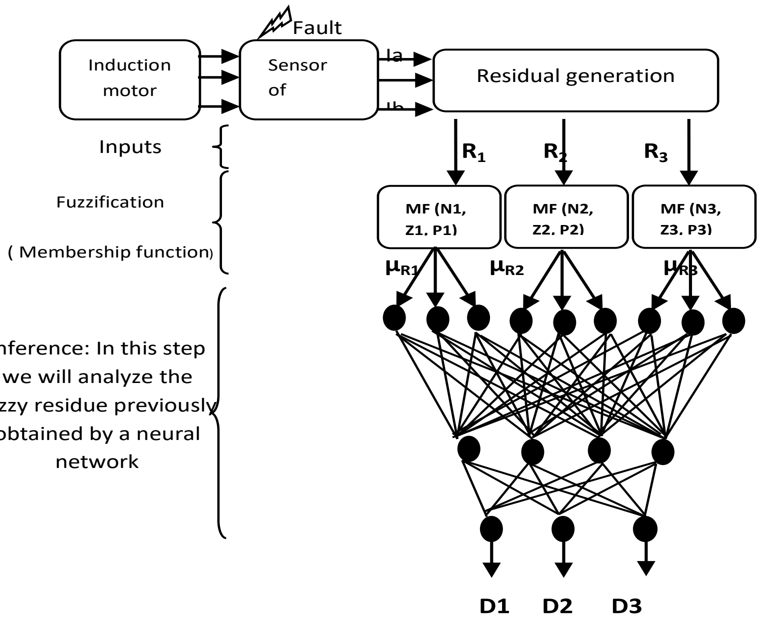

Figure 6. Neuro Fuzzy diagnostic scheme

3.2.2. Inference

The residual evaluation step is based RNN. The inputs of the network are the fuzzifie residues (μ_{R1}, μ_{R2}, μ_{R3}) and in the outputs we have the decisions (D_1, D_2, D_3). The network RNN is consists of: nine neurons in the input layer representing the inputs of the various possible states of residues at a time (k) (after fuzzification), four neurons in the hidden layer and three neurons in the output layer. The RNN used in this simulation study is based on the rules summarized in Table 1 which have been obtained after many simulation tests. Each row of the inference table represents a rule. Each control rule from Table 1 can be described using the input variables R_1, R_2 and R_3, and the outputs variables D_1, D_2 and D_3. For example rule 3 is expressed as follow: If {residual 1 is Positive and residual 2 is Positive and residual 3 is Zero} THEN sensor 2 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

The mathematical model of a neuron is given by:

$$D(i) = \mu(\sum_{i=1}^{N} w_i * R_i + b) \tag{6}$$

Where (R_1, R_2, R_3) are inputs signal of the neuron, (w_1, w_2,… w_N) are the corresponding weights and b is the bias of the neuron, μ is the tangent sigmoid function and y is the output signal of the neuron. The most popular supervised training algorithm is the back-propagation [13], which consists of a forward and backward action. In the first, the free parameters of the network are fixed, and the input signal is propagated through the network layer by layer. The forward phase finishes with the computation of a mean square error. Once the ANN is trained properly, it should be adequately tested with intermediate data to verify that training is correct and complete.

4. DEVELOPMENT of the PROPOSED NEURO FUZZY LOGIC DIAGNOSIS ARCHITECTURE

4.1. Presentation of Xilinx System Generator

Xilinx System Generator Tool developed for Matlab Simulink package is widely used for algorithm development and verification purposes in Digital Signal Processors (DSP) and Field Programmable Gate Arrays (FPGAs). Xilinx System Generator (XSG) a high-level tool for designing high-performance DSP systems under Simulink environment, It is a highly desirable to have this simulation tool that can easily make the direct translation into hardware of control algorithms with no-knowledge of any Hardware Description Language (HDL). System Generator Tool allows an abstraction level algorithm development while keeping the traditional Simulink blocksets, but at the same time automatically translating designs into hardware implementations that are faithful, synthesizable, and efficient. For rapid prototyping, the choice of this tool is easily explained by the advantage to simulate the control algorithm is the possibility to generate code that can be used to program an FPGA directly from the simulation model. When the control algorithm design of the controller is completed in Matlab Simulink environment by using Xilinx System Generator, it can be translated automatically into VHDL programming language and then can be embedded into the Xilinx FPGA application board.

4.2. Fuzzification Block

To evaluate the rule premise, it is necessary to calculate the value of membership of each input to a specified MF. The residual R_1 is represented by three fuzzy set, as shown in Figure 6. For this input we have 2 mathematical functions depending: trapezoidal function and triangular function. The trapezoidal curve depends on four scalar parameters a, b, c, and d, as given by,

$$f(x,a,b,c,d)=\left\{\begin{matrix} 0 & x < a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & b < x < c \\ \frac{d-x}{d-c} & c < x < d \\ 0 & d < x \end{matrix}\right\} \tag{7}$$

This Equation is implemented in the hardware using substractors, multipliers and comparator as shown in Figure 7. The fuzzification process is performed using three fuzzifie units. The fuzzifie block of R_1, the fuzzifie block of R_2 and the fuzifie block of R_3 takes the input and produces three output values.

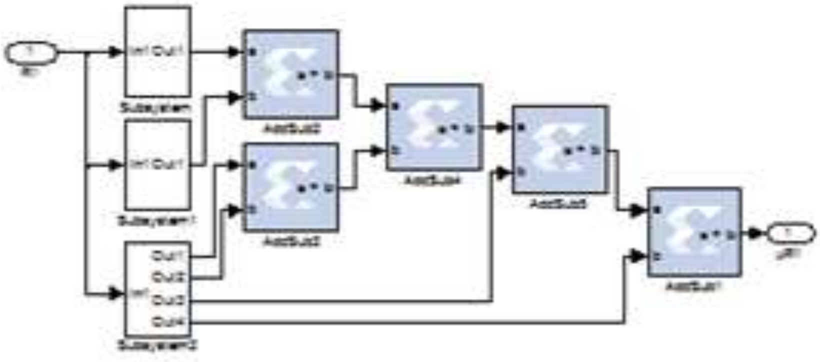

Figure 7. Fuzzifier unit of R1.

4.3. Inference

The hardware implementation of the inference block, as shown in Figure 8, accepts three inputs ($\mu_{R1,}$ $\mu_{R2,}\mu_{R3}$) from the fuzzification block. The neural processing propagates the inputs to outputs (D_1, D_2, D_3). Propagation occurs through the different layers of neurons, each neuron $N_{m,j}$ of the layer m calculates the output $X_{m,j}$. The layer module is made basic unit of the neuron. In effect, each layer is composed of several neurons operating in parallel. That is why our approach to description of the neuron module is designed in compliance with the constraint of reusability. In the case of this work we developed our three layers forming the neural network. The first hidden layer contains 9 neurons. The second layer comprises 4 neurons. The processing in this block is similar to that determined in the first layer. The internal structure of a neuron is composed of a set of adders, multipliers and comparator. The third layer contains only three neurons (the output layer). This last layer detrmine the sensor which is defected; The mathematical processing in this block is similar to that determined later.

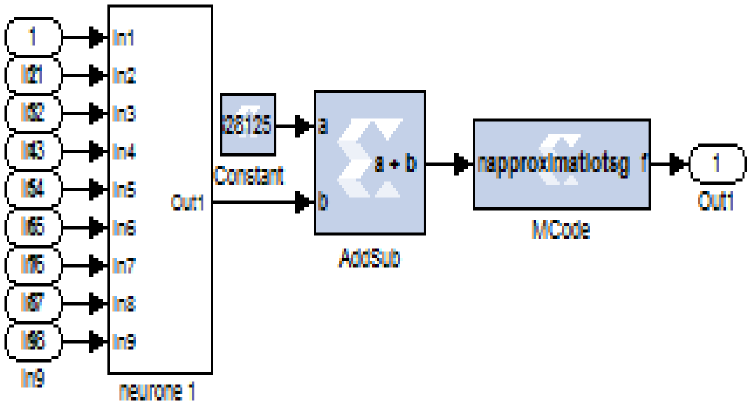

Figure 8. Structure of a neuron of the second layer.

5. Simulation and Interpretation Results

Figure 9 showed the model that uses the Xilinx blocksets for tolerant control. This model is used for co-simulation. Once the design is verified, a hardware co-simulation block can be generated and then it will be used to program the FPGA. The System Generator will first download the bit stream. When the download is complete, System Generators read the inputs from Simulink simulation environment and send them to the design on the board using the JTAG connection. System Generator then reads the output back from JTAG and sends it to Simulink for displayed.

To study the performance of this approach, the simulation of the system was conducted using MATLAB. Motors parameters for simulation are given in Table 2. The simulation results are shown in Figures 10-12. The torque and flux references that are used in the simulation results of the DTC-SVM strategy are 10 N · m and 0.91Wb, respectively. The sampling period of the system is 50 µs. Results using hardware co-simulation is presented to assess the ability of this diagnosis approach based Neuro Fuzzy technique to detect and isolate sensor faults in an induction motor. Simulation is carried out with 500 V and 50 Hz sinusoidal inputs. Figure 10 shows speed, torque and current.

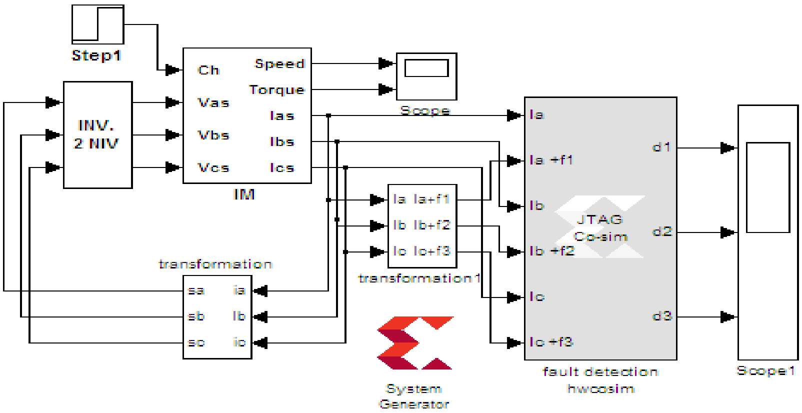

Figure 9. The hardware Co-simulation block.

The machine parameters used for simulation are given in Table 2. Various simulation tests have been performed in order to validate the efficiently 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 3 and 4 are discussed.

Case 1: A bias type fault is injected on sensor 1 as described in Table 3. The corresponding residuals are shown in Figure 11. Although a single fault may induce changes in several residuals. The decision functions ensure successful detection and isolation of the fault on sensor 1 as shown in Figure 11. The Neuro-Fuzzy classifier has been trained to recognize the faulty situations from the fuzzifie residual patterns according to the rule base given in Table 1.

Case 2: This fault scenario of bias faults on sensors 1 and 2 is described in Table 4. The residual and the corresponding decision functions are shown in Figure 12. The faulty sensors are promptly detected and correctly isolated.

Table 2. Induction machine parameters

Voltage	220/380 v
Stator resistance R_s	5.717 Ω
Rotor resistance R_r	4.282 Ω
Stator inductance L_s	0.464 H
Rotor inductance L_r	0.464 H
Mutual inductance M	0.441 H
Moment of inertia J	0.0049 Kg.m^2

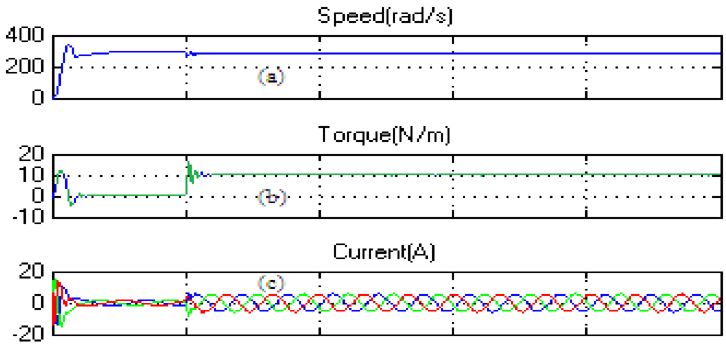

Figure 10. (a) Speed(rad/s),(b) torque(N/m) and (c) current(A)

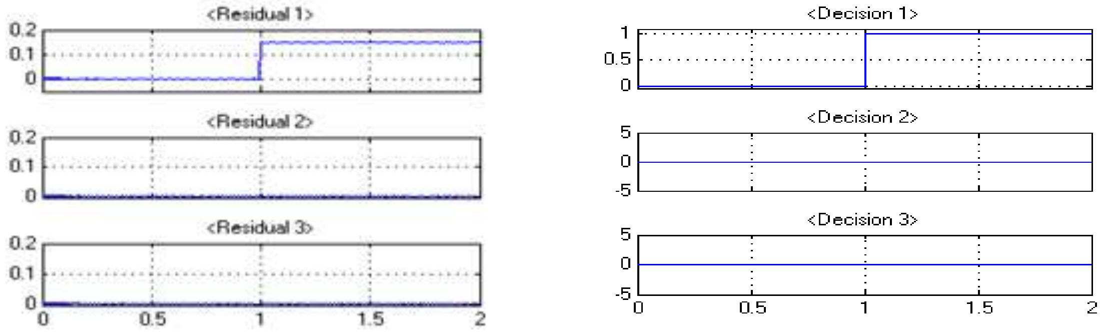

Figure 11. Faculty residuals and corresponding decisions using XSG

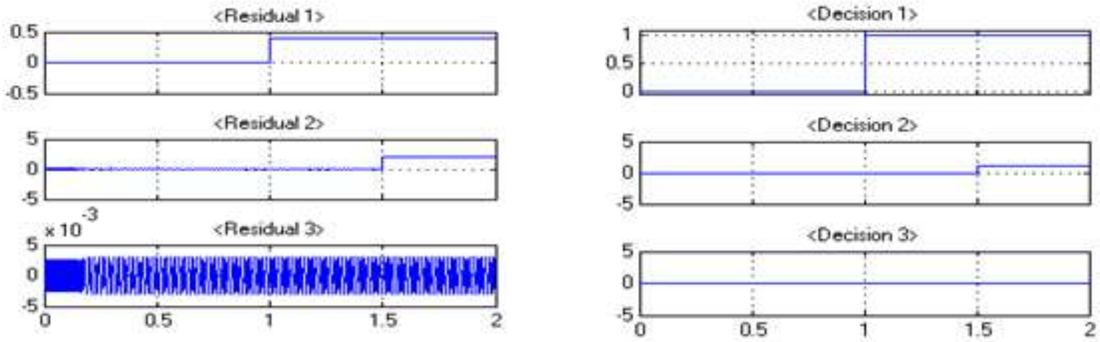

Figure 12. Faculty residuals and corresponding decisions using XSG

Table 3.CASE 1

Sensor N	Fault time	Bias fault
1	1	0.15

Table 4. CASE 2

Sensor N	Fault time	Bias fault
1	1	0.4
2	1.5	1

6. CONCLUSION

This paper proposed a new current sensor fault detection and isolation algorithm for electrical drives. The design was based on intelligent technique. The developed FDI algorithm is available for any current sensor in power converters or electrical drives. The innovative FDI algorithm proposed in this paper does not require the knowledge of the system model and only concerned sensor outputs are required. The proposed FDI scheme is based on a two step procedure: a Neural Network is used for residual generation and a fuzzy neural network performs the residual evaluation task. 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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