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AN ARTIFICIAL NEURAL NETWORKS APPROACH TO STATOR CURRENT SENSOR FAULTS DETECTION FOR DTC-SVM STRUCTURE*

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Abstract: In the paper, an analysis is made of the stator current sensor fault detector based on artificial neural network for vector controlled induction motor drive system. The systems with different learning algorithms and structures are analyzed and tested in different drive conditions. Simulation results are ob-tained in direct torque control algorithm (DTC-SVM) and performed in MATLAB/SimPowerSystem software.

Keywords: *DTC-SVM, current sensor, induction motor, detector, fault tolerant drive, neural network*

1. INTRODUCTION

During the last few years, fault-tolerant control systems (FTCS) [1] for electric motor drives became a very active research field for many research groups [1], [2], [7], [9]. The FTC aims to ensure the continuous system functionality even after the occurrence of fault of one of the components. The proper choice of the fault tolerant control algorithm and topology depends on the drive system requirements and components used. To ensure the proper work of complex systems, it is necessary to take account of diagnostic techniques that within a reasonable period of time will allow a failure to be detected and an appropriate response of the control structure [2], [8], [9].

In the electric motor drives these systems can be generally classified to passive (PFTCS) and active (AFTCS) systems [4]. The first group is designed to provide the optimum performance of the faulted drive without the necessity of identifying the type and location of the fault [10]. Passive fault tolerant control uses robust control techniques to ensure that the closed loop system remains insensitive to certain faults so that the impaired system continues to operate with the same controller and system structure [10]. In contrast to passive FTC, instead of relying on a fixed controller for all possible faults,

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an active FTC reacts to the diagnosed failure by redesigning control system with chosen level of performance. The main goals of AFTC may be obtained by additional control loops, redundant elements or by adjusting the parameters of controllers and/or estimators as a result of the identification of a new control object [4], [10].

The proper choice of the fault tolerant control algorithm and topology depends on the drive system requirements and components used [2], [9]. There are several methods for sensor fault identification that depend on hardware redundancy, analytical redundancy, or both [4], [9], [10]. One of the most popular and rapidly developing methods are software redundancy algorithms which are based on the relations between the measured and analytically calculated values of the state variables. The most commonly used fault detection and isolation (FDI) methods are knowledge-based fault-model methods, such as observer methods or parity space approach [4], [10].

The advanced control structures of Induction Motor (IM) drives use additional signals in the internal loops like stator and/or rotor flux, electromagnetic torque, rotor speed [5], [6] which may be applied in more advanced fault detection algorithms. One of such solutions are artificial neural networks [1], [2], [8]. However, the designing process of these diagnostic systems is difficult due to the lack of precise rules and norms which can be related to. Thus, in the paper an analysis of the current sensor fault detection systems based on neural networks is presented.

The main goal of the paper is selection of the most appropriate neural network intended for the detection and identification of stator current sensor faults. Different network structures and learning algorithms were tested. The simulation results were carried out in MATLAB/SimPowerSystem software.

2. MATHEMATICAL MODEL OF THE DTC-SVM DRIVE

Simulation tests were conducted in the well-known control structure of the induction motor – the Direct Torque Control DTC-SVM (Fig. 1) [5], [6]. In this structure, the classical PI controllers are used. The incremental encoder is applied to the rotor speed measure (resolution is equal to 5000 imp/rev). Stator voltage is calculated from DC bus voltage. For the stator current measurement, the closed-loop Hall-effect current sensors are used. Simulation and experimental tests were also conducted for other control structure – DFOC (Direct Field Oriented Control) but results of such a system were presented in detail in [11]. This system works properly in different drive conditions.

In Fig. 2, simulation results for DTC-SVM drive system with totally broken current sensor in phase B are presented. In this test only two current sensors were used in a control loop. Current components $i_{s\alpha}$ and $i_{s\beta}$ were calculated from the equations

$$i_{s\alpha} = i_{sA}, \quad i_{s\beta} = \frac{\sqrt{3}}{3}(i_{sA} + 2i_{sB}) . \tag{1}$$

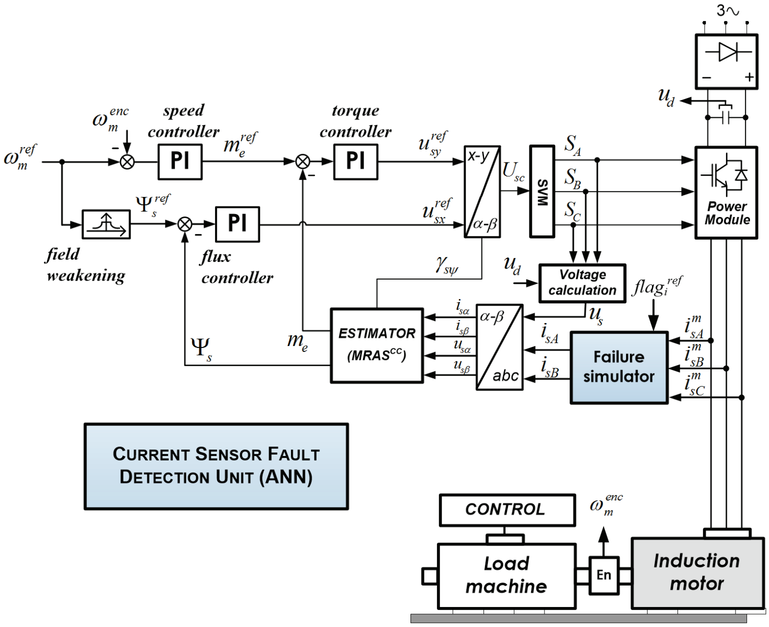

Fig. 1. Scheme of the Direct Torque Control structure for induction motor drive [6]

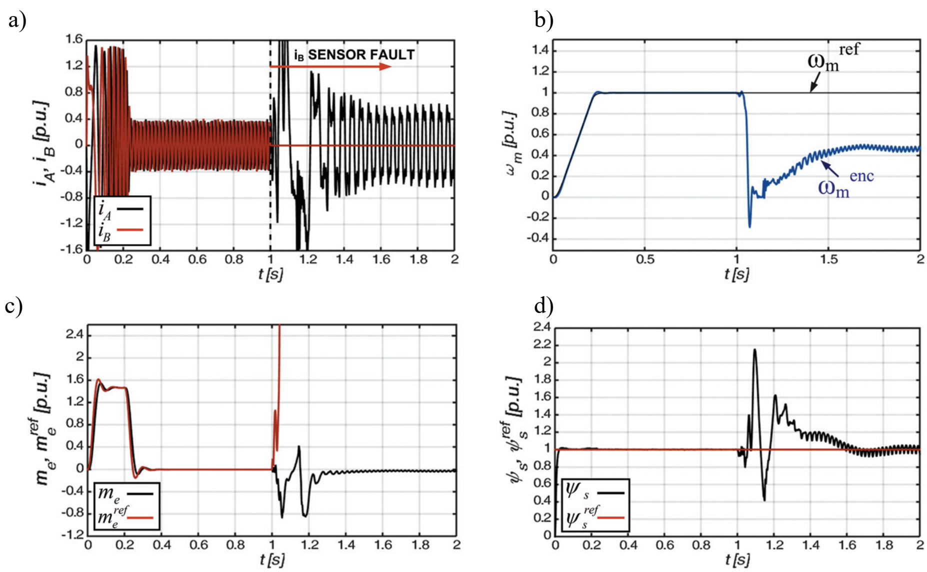

Fig. 2. Faulted operation of DTC-SVM drive system with totally broken current sensor in phase B: measured stator currents (a), measured and reference speed (b), estimated electromagnetic torque (c) and stator flux (d) (simulation results)

In the situation analysed current sensor was broken in t = 1s. After the fault occurrence the symptoms are visible on the current and other state variable transients. Control structure compensates some incorrect behaviours of the current which may be noticed in phase A current transient. The total failure of the current sensor is the most dangerous for the vector controlled induction motor drive, thus only this type of failure is analysed in the paper.

3. CHOSEN NEURAL NETWORK LEARNING METHODS

In this section, the neural network learning algorithms used in the paper are presented and described. The learning algorithm is the specific mathematical method that is used to update the network weights during each training iteration to achieve the best fit of the input data to output [3], [12]–[15]. One of the most traditional ways of solving multilayer neural networks learning problem is by an iterative gradient-based training algorithm which generates a sequence of weights [12], [13]. In each iteration the update of the network weights is performed based on minimization function gradient and its direction. The correction of weights is presented as follows [12]

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \eta \cdot \mathbf{p}(\mathbf{W}(k+1)), \tag{2}$$

where k is the current iteration usually called epoch, $\eta > 0$ is the learning rate, and $\mathbf{p}$ is descent search direction.

The direction of minimization function error $\mathbf{p}(\mathbf{W}(k))$ is obtained using the equation [12]

$$\mathbf{p}(\mathbf{W}(k)) = -[\nabla^2 \mathbf{E}(\mathbf{W}(k))]^{-1} \nabla \mathbf{E}(\mathbf{W}(k)). \tag{3}$$

A variety of approaches for improving the efficiency of the minimization error were suggested, such as the conjugate gradient methods [13]. The basic idea for determining the search direction in this method is the linear combination of the negative gradient vector at the current iteration with the previous search direction, which may be defined as [12], [13]

$$\mathbf{p}(\mathbf{W}(k)) = -[\nabla \mathbf{E}(\mathbf{W}(k))] + \sum_{j=0}^{k-1} \beta_k \, p(\mathbf{W}(j)). \tag{4}$$

Conjugate gradient methods differ in their way of defining the parameter β_k [14]. In the literature, there have been proposed several choices for β_k which give rise to distinct conjugate gradient methods [14]. In the paper, the Polak–Ribiere algorithm for β_k coefficient calculation is presented

$$\beta_k = \frac{[\nabla \mathbf{E}(\mathbf{W}(k))]^T (\nabla \mathbf{E}(\mathbf{W}(k)) - \nabla \mathbf{E}(\mathbf{W}(k-1)))}{[\nabla \mathbf{E}(\mathbf{W}(k-1))]^T \nabla \mathbf{E}(\mathbf{W}(k-1))}. \tag{5}$$

Despite the disadvantages the conjugate gradient methods represent an excellent choice for efficiently training large neural networks due to their simplicity and their low memory requirements [14].

One of the most effective ways of learning one-way neural networks is the Levenberg–Marquardt algorithm which is a modification of the Gauss–Newton algorithm, in which the direction of minimization function error $\mathbf{p}(\mathbf{W}(k))$ is obtained using equation (3) [13]. In the L–M method, the exact value of Hessian is replaced by the approximated value, determined on the basis of the information contained in the gradient with emphasis on the adjusting coefficient [3], [13]. Thus, the gradient vector and the approximated Hessian matrix corresponding to objective function are defined as [13]

$$\nabla \mathbf{E}(\mathbf{W}(k)) = \mathbf{J}^T(\mathbf{W}(k))\boldsymbol{\varepsilon}(\mathbf{W}(k)), \tag{6}$$

$$\nabla^2 \mathbf{E}(\mathbf{W}(k)) = \mathbf{J}^T(\mathbf{W}(k))\mathbf{J}(\mathbf{W}(k)) + \mathbf{S}(\mathbf{W}(k)), \tag{7}$$

where $\mathbf{J}(\mathbf{W}(k))$ is the Jacobian – the matrix of first partial derivatives of the error of each sample in individual neurons of the last layer with respect to all the weights in the network, and $\boldsymbol{\varepsilon}(\mathbf{W}(k))$ is the error vector for each sample in each neuron in the last layer of the network [13].

In the Gauss–Newton method the value of the $\mathbf{S}(\mathbf{W}(k))$ in formula (7) is assumed to be close to zero. In L–M algorithm it is presented as follows [13]

$$\mathbf{S}(\mathbf{W}(k)) \approx \mu \mathbf{I}, \tag{8}$$

where μ is adjusting coefficient.

After modification of equation (8) the correction of the weights in the Levenberg –Marquardt algorithm takes the form [13]

$$\mathbf{W}(k+1) = \mathbf{W}(k) - [\mathbf{J}^T(\mathbf{W}(k))\mathbf{J}(\mathbf{W}(k)) + \mu \mathbf{I}]^{-1}\mathbf{J}^T(\mathbf{W}(k))\boldsymbol{\varepsilon}(\mathbf{W}(k)). \tag{9}$$

The effectiveness of this algorithm determines the appropriate selection of the coefficient μ [3], [12]. The large initial value of this factor is to be reduced in the process of optimization and reach zero value in solution close to optimum [13].

Another approach to minimize the training error is using the more sophisticated optimization methods – the quasi-Newton algorithms [15]. These methods in each iteration use the derivatives of the error function with respect to the network weights to approximate the Hessian matrix required in the Newton optimization formulas. In literature there are many various solutions for Hessian approximation. Each of these modifications differs from the rest in the way of performing line search of the new point $\mathbf{p}(\mathbf{W}(k + 1))$ and update the Hessian approximation [15]. Among many methods the BFGS (named after its inventors Broyden, Fletcher, Goldfarb and Shanno) variant is used in the paper.

4. THE RESEARCH METHODOLOGY

The main goal of the paper is an analysis of the influence of the learning algorithm on the properties of the NN based stator current sensor fault detector. In the simulation studies four artificial neural network learning algorithms for one (chosen) network structure in configuration 4–9–4–1 were used. This specific set of neurons within two hidden layers was determined during experimental tests.

During the learning process the reference speed value was changed in the vector control system. At first, the drive runs at rated speed, which was reduced every 2 s by 20% until it reached $\omega_m = 0.02\omega_{mN}$ value. During the drive operation a total interruption of the current sensor loop occurred for each rotor speed level (Fig. 3a). On the input of the neural network four diagnostic signals from internal control loop were used, on which the current sensor failure has direct or indirect effect: absolute value of the difference between reference and estimated electromagnetic torque value (S_{D1}), absolute value of the stator flux error (S_{D2}), phase A (S_{D3}) and phase B (S_{D4}) of stator current. For current fault detector realized in Direct Field Oriented Control algorithm, similar signals may be used: absolute value of the stator current i_{sx} and i_{sy} components errors, phase A and phase B of stator current. Additionally, information about estimated torque may be applied for better results [11].

On the output of the NN detector is the binary signal connected with the current sensor failures (*flag$_i$*). A general scheme of the proposed neural network and input signals for DTC structure are presented in Fig. 3b. Transients of the chosen diagnostic signals during learning process are shown in Fig. 4.

a) b)

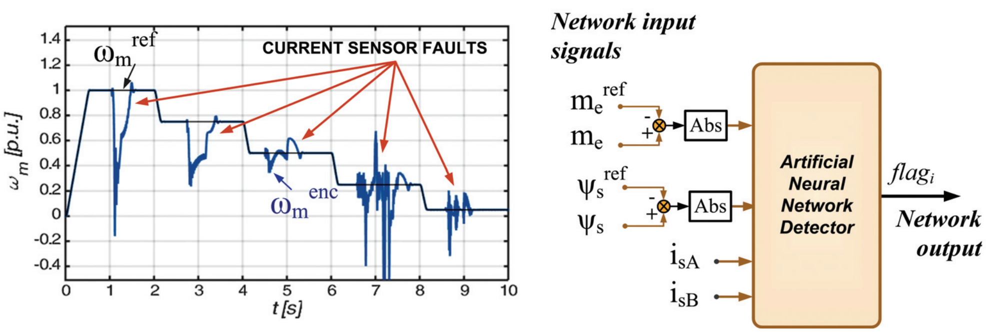

Fig. 3. Faulted operation of motor drive system with totally broken current sensor in phase A – measured and reference speed (simulation results) (a) and general scheme of proposed neural network as current sensor fault detector (b)

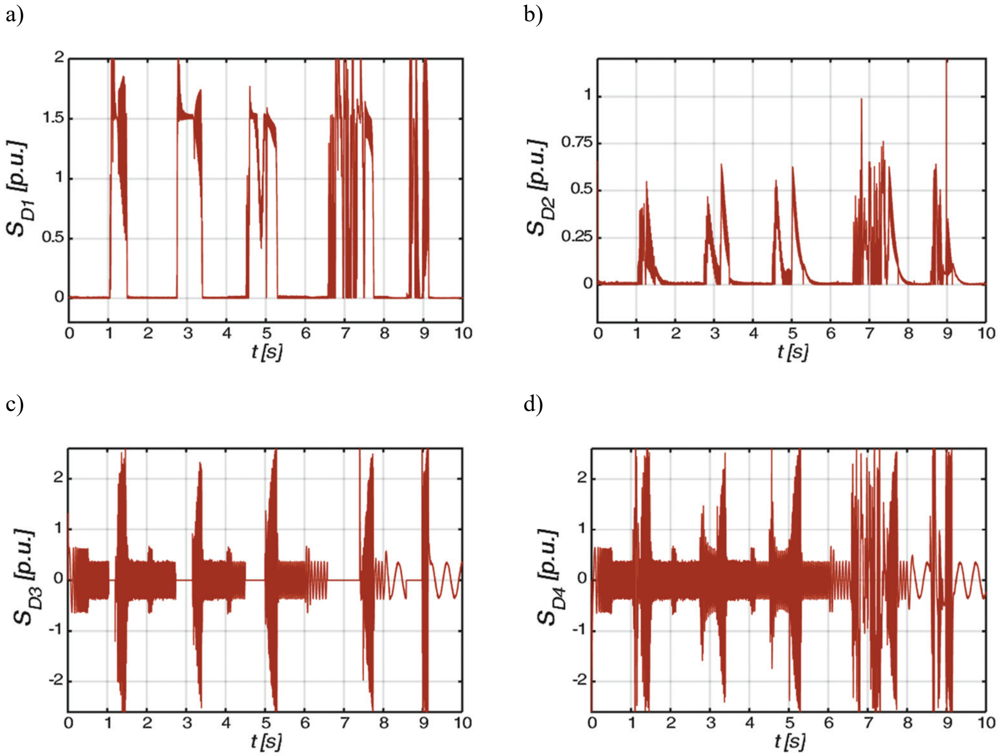

Fig. 4. Transients of diagnostic signals used in learning process: absolute value of the difference between reference and estimated electromagnetic torque value (a), absolute value of the stator flux error (b), phase A (c) and phase B (d) of stator current (simulation results)

To evaluate the quality of the selected NN current sensor fault detector learning algorithms the integral criteria: ISE, ITSE, IAE, ITAE and the failure detection time Δt_d were used in equations (10),

$$ISE = \frac{1}{n}\sum_{1}^{n}\int_{t=0}^{t=2s} e^2(t)dt \cdot 100\%, \quad ITSE = \frac{1}{n}\sum_{1}^{n}\int_{t=0}^{t=2s} t\cdot e^2(t)\,dt \cdot 100\%,$$
$$IAE = \frac{1}{n}\sum_{1}^{n}\int_{t=0}^{t=2s} |e(t)| \cdot 100\%, \quad ITAE = \frac{1}{n}\sum_{1}^{n}\int_{t=0}^{t=2s} t\cdot |e(t)|\,dt \cdot 100\%, \quad \Delta t_d = t_{fault} - t_{det}, \tag{10}$$

where: n – number of samples, $e(t)$ – error between fault occurrence time and neural network response, t_{fault} – fault occurrence time, t_{det} – fault detection time.

In the following part of the paper, an analysis of the simulation results for different drive operation conditions are presented. Further research for different number of hidden layers or neurons in each layer led in most cases to the misidentification of failure, lack of response at the time of failure occurrence or nonsignificant variations of the outcome. The best results were obtained for a set of neurons presented in the paper.

5. ANALYSIS OF RESULTS FOR ANN BASED DETECTOR

In the following part an analysis is made of the influence of the network learning algorithm and number of epochs on the properties of fault detector. Different learning algorithms, even those not dedicated to electric motor drive applications, were used. The main aim of these tests was to distinguish the best neural network, which may be used in fault detection unit, with the lowest values of criterion and detection time.

The simulation results of current sensor fault detector are shown in Tables 1–3 for different drive operation conditions:

(a) Nominal rotor speed value of induction motor $\omega_m = \omega_{mN}$ (Table 1).

(b) Low rotor speed value of induction motor $\omega_m = 0.02\omega_{mN}$ (Table 2).

(c) Nominal rotor speed value of loaded induction motor (Table 3).

The most popular and known learning algorithms (described in Section 2) and epoch quantity for each drive operation condition were used:

– the conjugate gradient method with the Polak–Ribi'ere algorithm (**CGP**),
– the quasi-Newton method with the BFGS algorithm (**BFG**),
– the backpropagation method with adaptive weights value selection (**GDX**),
– the Levenberg–Marquardt algorithm (**LM**).

Table 1. Neural networks results for $\omega_{m.} = \omega_{mN}$

Learning algorithm	Network structure	Epoch	ITSE [%]	ISE [%]	IAE [%]	ITAE [%]	Δt_d [ms]
CGP	4-9-4-1	200	1.25	1.02	5.03	5.52	12.59
CGP	4-9-4-1	400	0.84	0.67	2.96	3.36	3.46
BFG	4-9-4-1	200	1.97	1.48	5.19	7.15	2.56
BFG	4-9-4-1	400	0.50	0.37	0.87	1.78	2.24
LM	4-9-4-1	200	0.46	0.34	0.54	0.72	2.09
LM	4-9-4-1	400	0.46	0.34	0.66	0.77	2.12
GDX	4-9-4-1	200	37.26	26.13	53.60	70.65	–
GDX	4-9-4-1	400	23.65	18.77	58.99	51.75	149.7
Minimum			0.46	0.34	0.54	0.72	2.09

Best results (lowest values of criterion) were obtained for the Levenberg–Marquardt algorithm. In each of the proposed network structures the errors did not exceed 1%. Among the five different solutions the quickest response of fault detector was obtained for network with only two hidden layers. Increasing the number of epochs slightly decreased the quality of results. The worst outcomes were obtained for the neural network learned with backpropagation method. In this case the detector did not respond for failure occurrence in 4 out of 5 different network structures.

In Table 2, the results for low rotor speed value ($\omega_m = 0.02\omega_{mN}$) of induction motor are presented. The properly designed sensor fault detector should be able to detect failure in a wide range of motor drive speeds. Also in this case the worst results were obtained for backpropagation method. Similar criterion values and detection time, in comparison to previous drive conditions, were achieved by network learned with the Levenberg–Marquardt algorithm.

Last tests were performed for loaded motor and nominal rotor speed value (Table 3). It is clearly visible that also in these conditions the L-M method is the best choice for learning the neural network based current sensor fault detector. It should be noted that slightly worse results in all the cases presented were obtained for the quasi-Newton method with the BFGS algorithm, 2 hidden layers and 400 epochs. Therefore, this type of neural network training may be a good alternative to the Levenberg–Marquardt algorithm. It is shown that loading the motor does not significantly affect fault detector nor delays its response.

Table 2. Neural networks results for $\omega_m = 0.02\omega_{mN}$

Learning algorithm	Network structure	Epoch	ITSE [%]	ISE [%]	IAE [%]	ITAE [%]	Δt_d [ms]
CGP	4-9-4-1	200	5.20	3.56	9.70	13.40	5.68
CGP	4-9-4-1	400	7.10	4.72	9.24	13.35	5.30
BFG	4-9-4-1	200	4.91	3.28	4.42	6.27	2.21
BFG	4-9-4-1	400	8.88	6.20	4.91	6.57	2.12
LM	4-9-4-1	200	0.65	0.46	1.31	1.91	2.09
LM	4-9-4-1	400	1.01	0.70	4.83	2.87	2.11
GDX	4-9-4-1	200	29.74	21.08	39.01	51.10	–
GDX	4-9-4-1	400	28.99	20.53	36.68	46.91	–
Minimum			0.65	0.46	1.31	1.91	2.09

Table 3. Neural networks results for $\omega_m = \omega_{mN}$ and $m_o = m_{oN}$

Learning algorithm	Network structure	Epoch	ITSE [%]	ISE [%]	IAE [%]	ITAE [%]	Δt_d [ms]
CGP	4-9-4-1	200	3.15	1.93	5.83	7.74	3.66
CGP	4-9-4-1	400	1.92	1.20	3.70	5.12	2.62
BFG	4-9-4-1	200	4.39	2.56	6.64	10.51	2.32
BFG	4-9-4-1	400	1.29	0.81	1.12	3.09	2.15
LM	4-9-4-1	200	0.46	0.34	0.55	0.73	2.08
LM	4-9-4-1	400	0.46	0.34	0.77	0.78	2.10
GDX	4-9-4-1	200	37.69	24.87	52.45	71.28	–
GDX	4-9-4-1	400	25.30	17.89	58.78	53.88	–
Minimum			0.46	0.34	0.55	0.73	2.08

As a result of the studies conducted the neural network in 4–9–4–1 configuration was obtained. The solution presented may be used to successfully detect a fault of current sensor which was used in learning process. In order to implement the detection unit for both sensors, it is necessary to repeat the whole operation but during the learning process a second sensor failures must be simulated. As a result, the Fault Detection Unit based on two neural networks will be obtained.

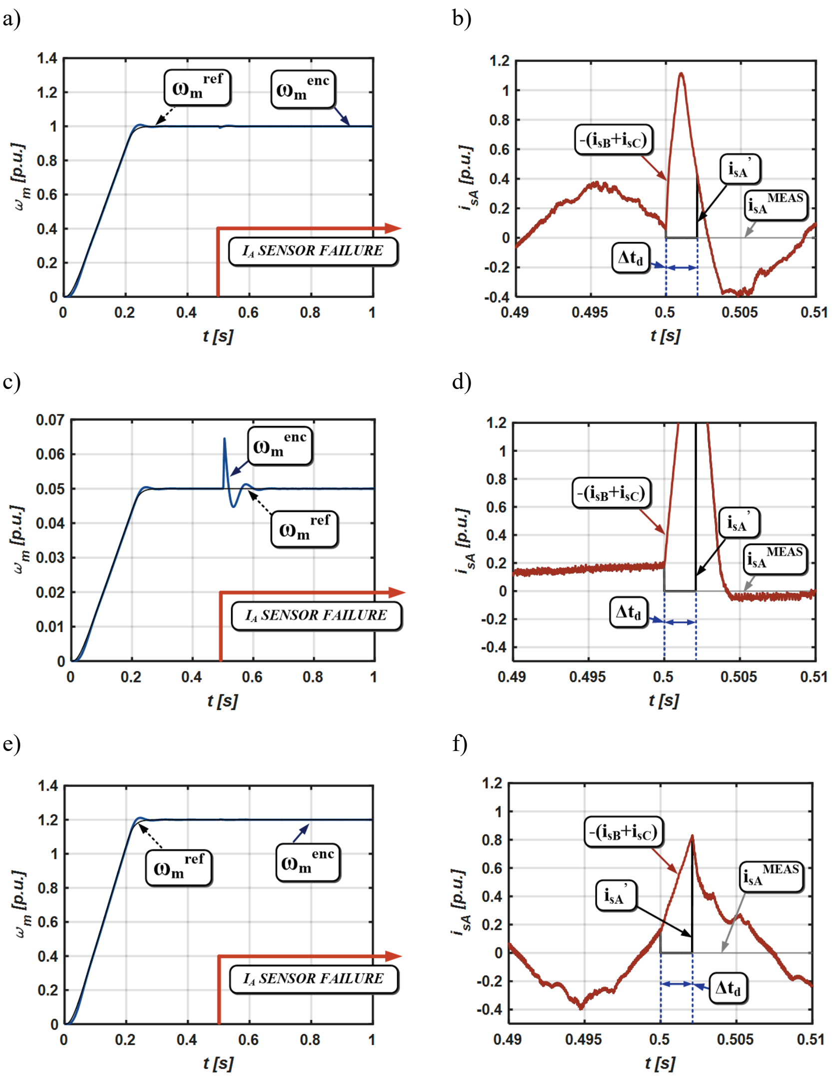

Fig. 5. Transients of measured and reference speed (a, c, e) and phase A current (b, d, f) during faulted operation of a current sensor for different rotor speed values: (a, b) nominal speed value, (c, d) low (5% ω_{mN}) speed value, field weakening operation (120% ω_{mN}) – simulation results

In Fig. 5, selected simulation results of the stator current sensor fault tolerant drive system for different rotor speed values are presented.

It was assumed that for $t = 0.5$ s the phase A current sensor was broken (total failure). After detection process (Δt_d) the disrupted measured signal is replaced by the sum of the remaining, properly measured phase currents ($-i_{sB} - i_{sC}$). Isolation of the faulted sensor allowed for further stable operation of the drive.

It is visible that during detection one of the most important advantages of the neural network based detector presented over other solutions is the possibility of using it for different sensor fault types (variable gain, phase shift, noise) even if the network has been taught only total failure occurrence. Moreover, this algorithm may properly work during various drive operation conditions (loaded and unloaded motor, field weakening operation) and also for different induction motors.

During the detection process an abnormal situation of the measured speed and phase current transients occurrs. It is also obvious that the estimated state variables like electromagnetic torque, rotor/stator flux are the most sensible since almost all of them depend on proper information about stator current.

6. CONCLUSION

In the paper, an analysis is made of stator current sensor fault detector based on artificial neural network for vector controlled induction motor drive system. Influence of this transducer faults on the performance of the induction motor drive was shown. Detectors based on neural networks with various learning methods and structures were presented and tested during different drive conditions. The tests and results obtained may be used in designing process of advanced detection algorithm for fault tolerant drives. It was proved that the lowest error values and quickest response of diagnostic unit were achieved for neural network with two hidden layers learnt by Levenberg –Marquardt algorithm. Similar results were obtained for the same network but trained by quasi-Newton method with the BFGS algorithm.

The solution put forward may be successfully used in FTC systems for induction motor drives ensuring short fault detection time and certain identification of faulted sensor.

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