Computer Applications in Electrical Engineering

Vol. 13 *2015*

Concept of the speed sensor faults detector for DFOC drive based on the neural network

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In the paper the concept of safety vector controlled drive system with induction motor is presented. The speed sensor fault detector, based on the neural network, is described and tested in vector controlled (DFOC) induction motor drive. The fault tolerant algorithm using proposed neural network algorithm was applied and tested during different drive conditions. Simulation (obtained in MATLAB/SimPowerSystem) results are presented.

KEYWORDS: Fault Tolerant Control Drive (FTC); speed sensor faults; failure detection; speed estimator, neural network, DFOC

1. Introduction

Modern technological motor drives rely on sophisticated control methods to meet an increased performance and safety requirements. This approach resulted in application of much more complex systems which leads to increased probability of system main components failure [1, 6, 8]. During normal drive operation system components faults may result in deficient performance, instability of the whole process or even compromising the operating personnel safety [8]. To ensure the correct functioning of complex drive systems it is necessary to take into account diagnostic techniques and control which, in a timely manner will allow to detect fault and respond appropriately to control structure. It is said then about the Fault-Tolerant Control Systems - FTCS [3, 4].

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 to identification the type and location of the fault. 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, an active FTC reacts to the diagnosed failure by redesigning control system with chosen level of performance. The main goal of AFTC is stable operation of the drive, which can 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 [10].

During last decade, fault tolerant control systems (FTCS) became a very active research field for many research groups [2, 7, 10]. The FTC aims to preserve the stability of the overall system and to maintain an acceptable level of performance in the event of system component malfunctions. Therefore, these systems should be able to detect and identify faults and to cancel their effects or to attenuate them until an acceptable level [2, 10].

In this paper an analysis of the detection algorithm of the speed sensor failures (incremental encoder) is presented. Designed detector is based on artificial neural network. Included results refers to the Direct Field Oriented Control structure induction motor drive and were implemented in MATLAB/SimPowerSystem software.

2. Speed sensor faults detector based on neural network

In this chapter, the concept of detection algorithm for angular velocity sensor damage based on artificial neural networks is presented. Designed detector in the configuration 7-15-1 with one hidden layer is shown in Fig. 2 was applied in the DFOC algorithm (Fig. 1).

In the analyzed DFOC method a four sensors are used: voltage sensor in intermediate circuit, incremental encoder and two sensors to measure motor phase currents. A detailed description and analysis presented control structure shown in [3]. In the control structure the rotor flux can be calculated using the measured rotor speed value from the equation [6]:

$$\frac{d}{dt}\mathbf{\Psi}_r^i = \left[\frac{r_r}{x_r}(x_m\mathbf{i}_s - \mathbf{\Psi}_r^i) + j\omega_m\mathbf{\Psi}_r^i\right]\frac{1}{T_N} \tag{1}$$

Current estimator and current model used in MRAS^{CC} system, which is used in the Fault Tolerant System and in diagnostic process, [3, 6] can be obtained by the equations:

$$\begin{aligned}\frac{d}{dt}\mathbf{i}_s^e &= -\frac{r_r x_m^2 + x_r^2 r_s}{\sigma T_N x_s x_r^2}\mathbf{i}_s^e + \frac{1}{\sigma T_N x_s}\mathbf{u}_s + \frac{x_m r_r}{\sigma T_N x_s x_r^2}\mathbf{\Psi}_r^i - j\omega_{est}\frac{x_m}{\sigma T_N x_s x_r}\mathbf{\Psi}_r^i \\ \frac{d}{dt}\mathbf{\Psi}_r^i &= \left[\frac{r_r}{x_r}(x_m\mathbf{i}_s - \mathbf{\Psi}_r^i) + j\omega_{est}\mathbf{\Psi}_r^i\right]\frac{1}{T_N}\end{aligned} \tag{2}$$

where: ω_{est} – estimated rotor angular speed, r_s, r_r, x_s, x_r, x_m – stator and rotor resistances, stator and rotor leakage reactances, $\mathbf{u}_s$, $\mathbf{i}_s^e$, $\mathbf{\Psi}_r^i$ – stator voltage, estimated stator current and rotor flux vectors respectively, $\sigma = 1 - x_m^2/x_s x_r$. $T_N = 1/2\pi f_{sN}$.

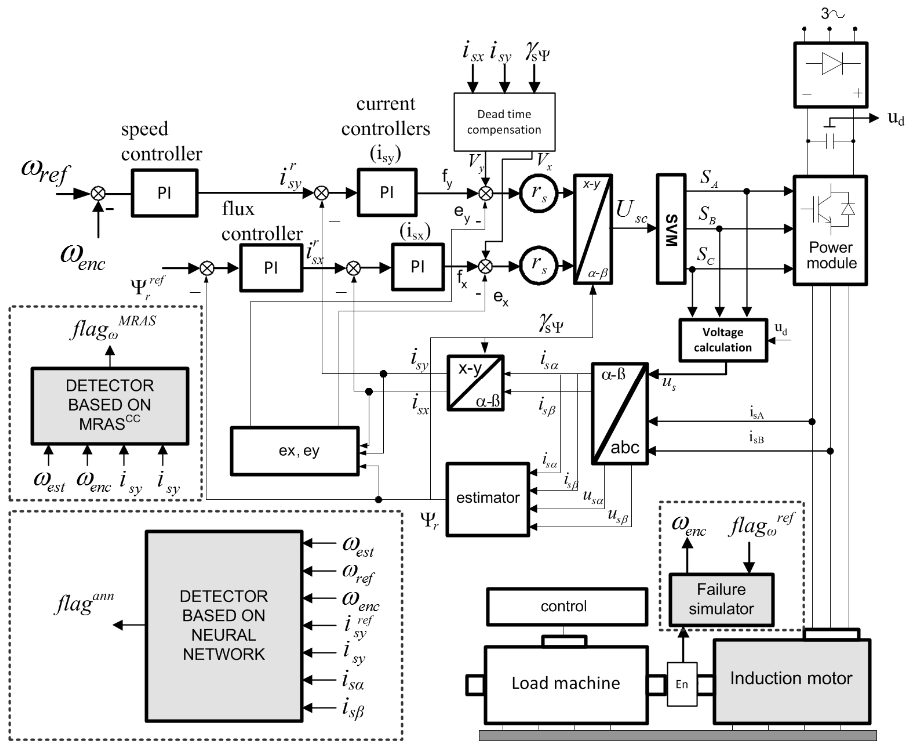

Fig. 1. Scheme of the Direct Field Oriented Control structure for induction motor drive

MRAS^{CC} estimator was presented in detail in [3, 6]. Both stator current estimator and rotor flux model (2) are adjusted by the estimated rotor speed [3]:

$$\omega_m^e = K_P\left(e_{i_{s\alpha}}\Psi_{r\beta}^i - e_{i_{s\beta}}\Psi_{r\alpha}^i\right) + K_I\int\left(e_{i_{s\alpha}}\Psi_{r\beta}^i - e_{i_{s\beta}}\Psi_{r\alpha}^i\right)dt \tag{3}$$

where: $e_{i_{s\alpha,\beta}} = i_{s\alpha,\beta} - i_{s\alpha,\beta}^e$ - error between the measured and estimated stator current components.

In proposed diagnostic system the neurons with nonlinear activation functions were used. The hidden layer consists of 15 neurons, and the output layer of 1 neuron. Input signals are defined by the vector: U = [ω_{ref}, ω_{enc}, ω_{est}, i_{sy}, i_{sy}^{ref}, $i_{s\alpha}$, $i_{s\beta}$]. On the output of the NN detector is the signal connected with the state of the speed sensor (with failures). The Levenberg-Marquardt algorithm was used for learning. Algorithm ends when the minimum gradient or a specified number of iterations is reached. Studies of designed detector was carried out in MATLAB libraries using Neural Network Toolbox.

During the learning process the value of the reference speed was changing. At first, the drive was operating at 80% of nominal value. The reference speed value was reduced every 2 seconds. During the drive operation rotor speed sensor failures occurred (Fig. 3). The symptoms of the fault were observed in the internal signals from the control structure (Fig. 4). The essential fact is that the neural network had been taught only for the total failures of speed sensor. The neural network detector was verified using a specific trajectory of rotor speed, load torque and a failure occurring.

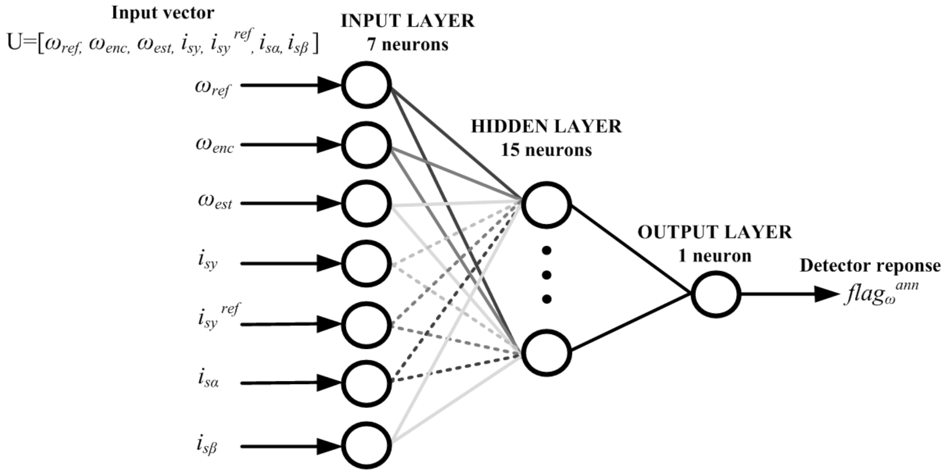

Fig. 2. Block diagram of the speed sensor fault detector based on neural network for DFOC algorithm

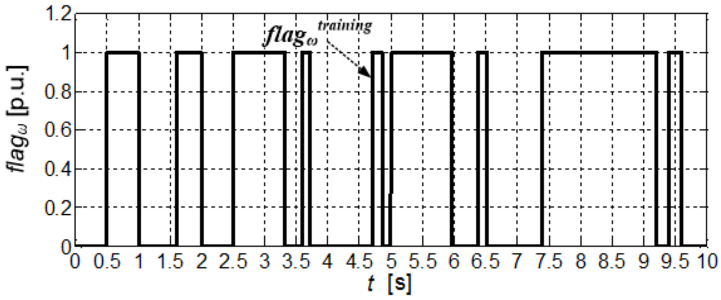

Fig. 3. Transient of the reference failure simulator signal

Speed sensor failure caused rapid growth of the real and estimated rotor speed value (estimated by the $MRAS^{CC}$ estimator [6]) and the amplitude of the stator currents. The real speed value is increasing, the control (PI speed controller) system sets maximum possible value of the i_{sy} stator current vector component. Thus the estimated state variables (e.g. electromagnetic torque, rotor flux) are disrupted which may lead to abnormal drive operation conditions, instability or even total drive devastation.

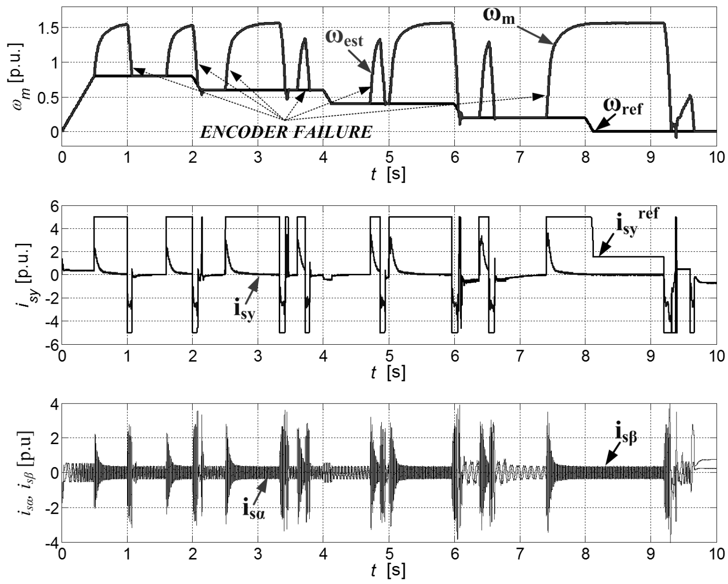

Fig. 4. Transients of learning signals for total failure of the encoder: measured, estimated and reference speeds, i_{sy}, $i_{s\alpha}$ and $i_{s\beta}$ stator current components (simulation results)

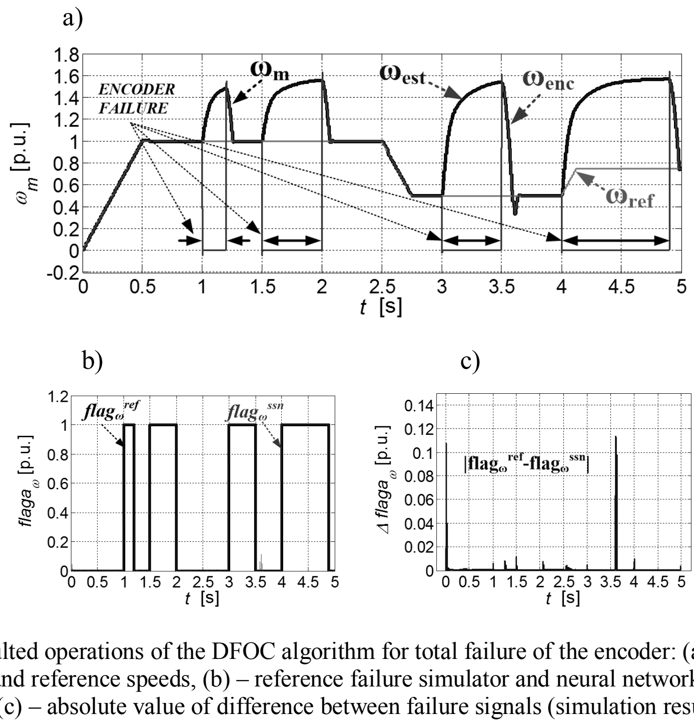

Fig. 5. Faulted operations of the DFOC algorithm for total failure of the encoder: (a) – measured, estimated and reference speeds, (b) – reference failure simulator and neural network output signal, (c) – absolute value of difference between failure signals (simulation results)

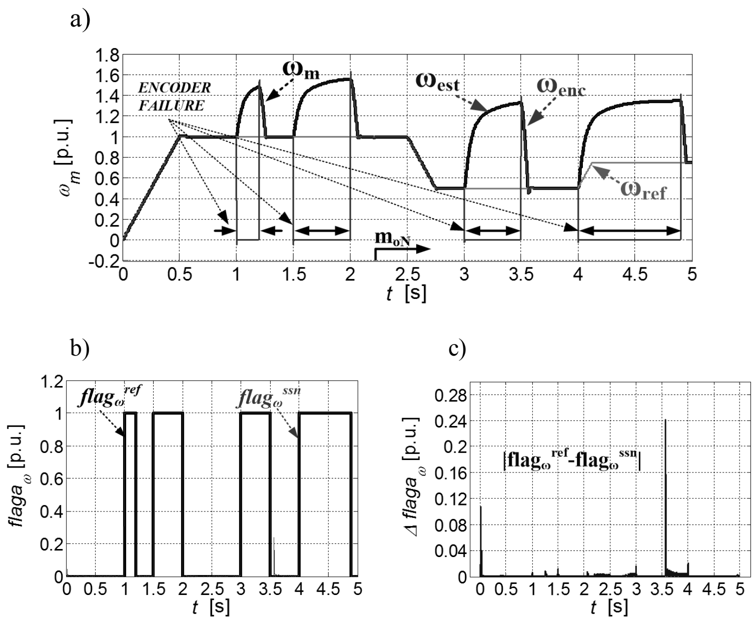

Fig. 6. Faulted operations of the DFOC algorithm for total failure of the encoder: (a) – measured, estimated and reference speeds, (b) – reference failure simulator and neural network output signal, (c) – absolute value of difference between failure signals (simulation results)

The estimated rotor speed (using an MRAS type speed estimator [6]) coincides with the actual speed value, which is different from the reference value. Based on the learning process of the neural network the weights on a connections between neurons have been calculated. Detection algorithm has been verified by forcing different values of angular velocity and failure occurring at different time samples. Moreover, the possibility of using this detector in drive system in which there are other types of encoder faults (those for which the network has not been trained) [4] was verified. In Fig. 5 and Fig. 6 the results of a drive operating with nominal speed value for the torque unloaded (Fig. 5) and loaded (Fig. 6) are presented. The first transients (Fig. 5) relate to the motor running at the nominal value of angular velocity and without load.

Figure 6 shows similar drive operation conditions, but motor is loaded with nominal torque value in t = 2.2 s. In both cases it is clearly visible that detection algorithm responds properly at the times of speed sensor failure occurrence.

Despite small differences between given results, it can be noticed that the loaded operation of the drive does not affect on neural detector efficiency. The only visible changes refers to rotor speed values during faulted drive operations. For unloaded motor an increase of 60% of rotor speed is observed and for loaded motor 40%. This is a result of saturation in a stator current vector components values in PI current controllers.

In Fig. 7 the simulation results for lower rotor speed values is presented. Drive is started from zero to the 20% of nominal speed value, for t = 2.2 s drive is loaded with nominal torque value m_{oN}. Presented results prove that detection algorithm is working properly for lower speed values and even with loaded drive operations. In Fig. 8 - 9 the simulation results for faulted operations of the DFOC algorithm for partial failure of individual pulses of the encoder are shown and in Fig. 10 results for cyclic interruption of specific pulses from the encoder are presented.

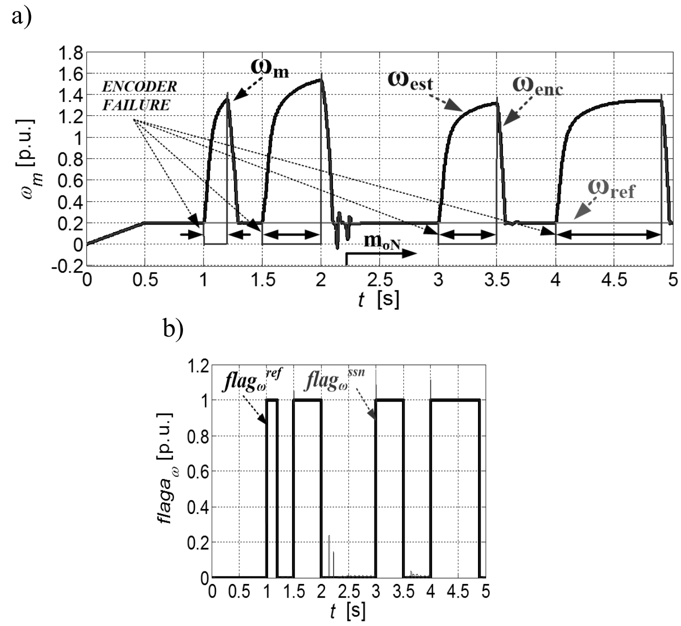

Fig. 7. Faulted operations of the DFOC algorithm for total failure of the encoder (ω_m = $0,2\omega_{mN}$): (a) – measured, estimated and reference speeds, (b) – reference failure simulator and neural network output signal (simulation results)

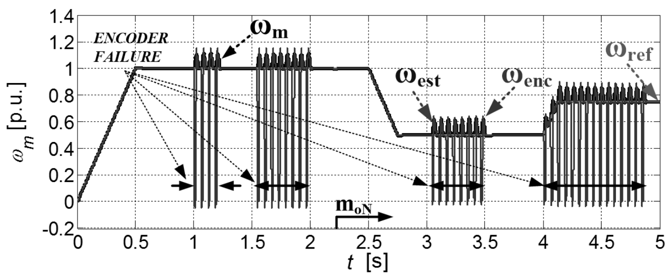

Fig. 8. Faulted operations of the DFOC algorithm for partial failure of individual pulses of the encoder – measured, estimated and reference speeds (simulation results)

Absolute values of difference between failure signals are higher than in previous conditions. However it does not decrease the performance and effectiveness level of the diagnostic system.

In next part of this paper the detection algorithm for different types of fault is presented.

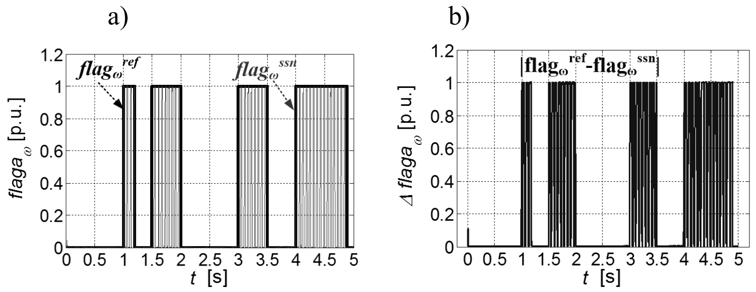

Fig. 9. Faulted operations of the DFOC algorithm for partial failure of individual pulses of the encoder: (a) – reference failure simulator and neural network output signal, (b) – absolute value of difference between failure signals (simulation results)

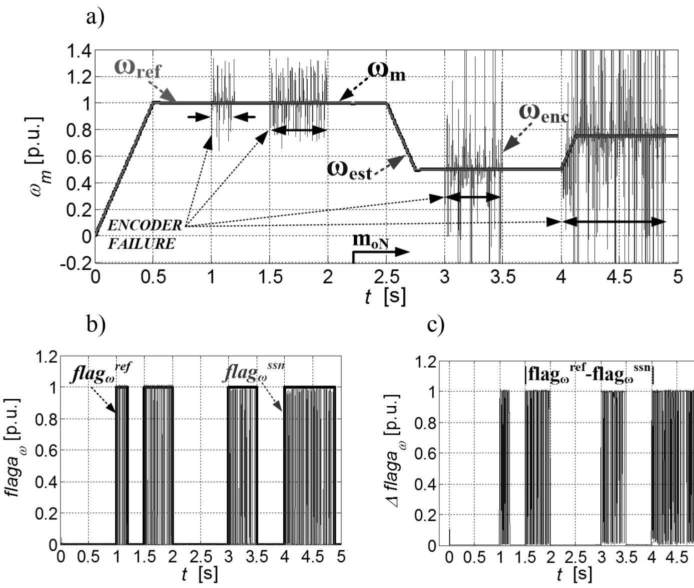

Fig. 10. Faulted operations of the DFOC algorithm for cyclic interruption of specific pulses from the encoder: (a) – measured, estimated and reference speeds, (b) – reference failure simulator and neural network output signal, (c) – absolute value of difference between failure signals (simulation results)

For both types of speed sensor faults the detection algorithm works properly even in loaded drive operation. Failures are detected in very short period of time (about 1 ms) after they occur. It is visible that the resulting output from the neural network detector is a cyclic signal. Thus, there is a necessity to use additional counter or bistable switch on the output of the diagnostic system. Such a modification will allow to identification of the failure in the first or specific number of time samples after fault occurrence.

It is therefore proved that presented detection system designed to identify total failure of the speed sensor based on artificial neural network can be used in Fault Tolerant Control drives.

In the final part of this paper the possibility of using analysed neural speed sensor fault detector in a fault tolerant motor drive is presented. After diagnostic process drive is switched to the sensorless mode with MRAS type speed and flux estimator [6] in the external control loop. Detection time for developed neuronal detector is much shorter than in the case of methods based exclusively on mathematical motor model. After fault detection the control topology is almost instantaneously switched to sensorless mode.

The first transients (Fig. 11) of FTC drive system are related to the motor running at the nominal value of rotor speed without load torque. Total failure of speed sensor occurred at $t = 3s$.

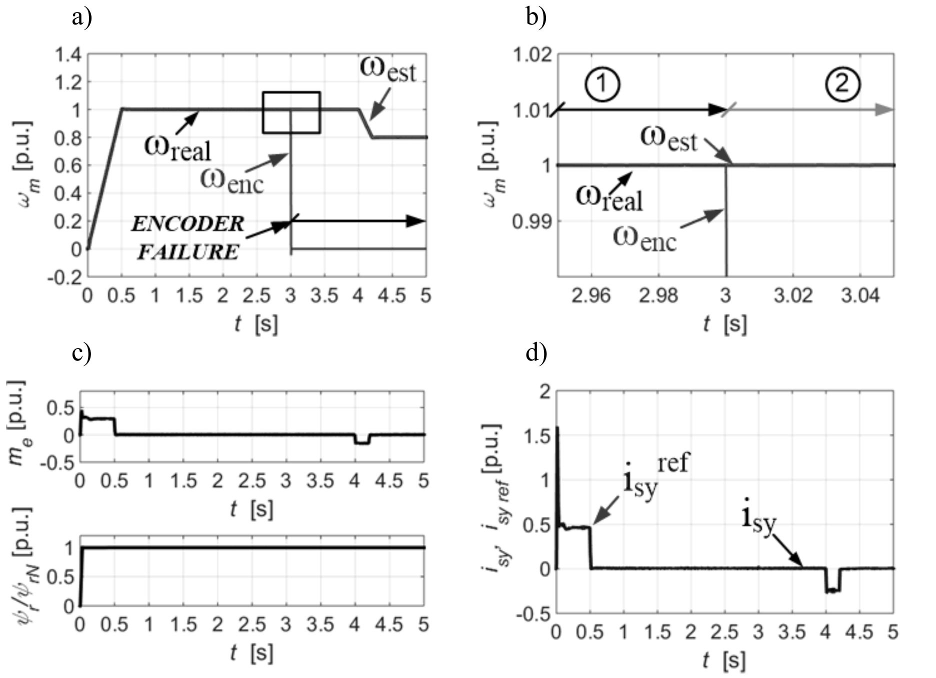

Fig. 11. Faulted operations of the FTDFOC algorithm for total failure of the encoder: (a, b) – estimated, real and measured rotor speed, (c) – electromagnetic torque and absolute value of rotor flux, (d) - stator current i_{sy} component, 1 – sensor mode, 2 – sensorless mode, $\omega_m = \omega_{mN}$ (simulation results)

In the sensorless mode the motor drive was able to perform stable operation. The presented neural system detect the speed sensor fault very fast. During the topology changes any fluctuation are not visible on the basic state variables.

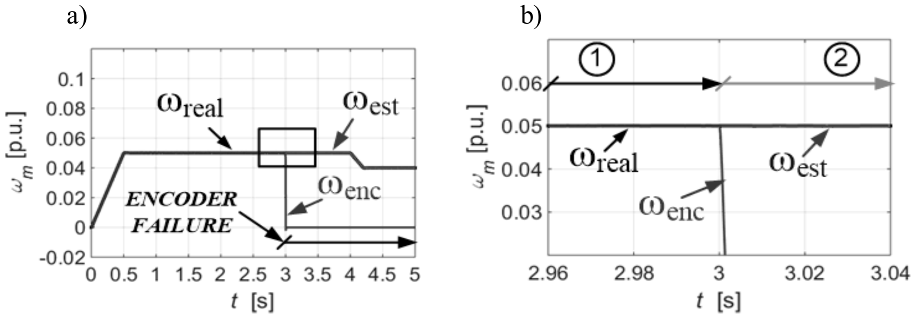

Fig. 12. Faulted operations of the FTDFOC algorithm for total failure of the encoder: (a, b) – estimated, real and measured rotor speed, 1 – sensor mode, 2 – sensorless mode, $\omega_m = 0{,}05\omega_{mN}$ (simulation results)

The drive with proposed detector was also tested in the small speed region ($\omega_m = 0{,}05\omega_{mN}$) - Fig. 12. Also in this case similar outcome in the transients of basic state variables can be observed. Detectors were tested for other types of the faults. Received results of simulations are presented in Fig. 13(a, b) for cyclic interruption of specific pulses from the encoder and in Fig. 14(a, b) for partial failure of individual pulses of the encoder. Cyclic interruption of specific pulses from the encoder is the least severe for the drive. However, as in other cases of failures - rapid and reliable identification is necessary to isolate the faulted component.

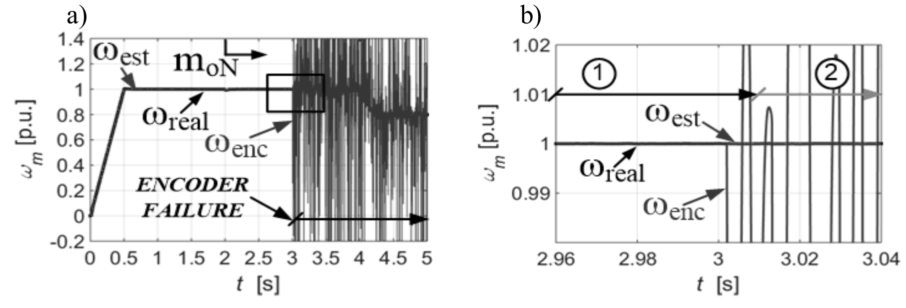

Fig. 13. Faulted operations of the FTDFOC algorithm for cyclic interruption of specific pulses from the encoder, 1 – sensor mode, 2 – sensorless mode, $\omega_m = \omega_{mN}$ (simulation results)

After the speed sensor fault at $t = 3\ s$, detection mechanism changes the topology of the drive to the sensorless structure. In all tested cases, the FTC system based on neural network has detected failure relatively promptly.

Implementation of neural network minimize detection time which is almost completely eliminate typical estimated speed oscillations and basic state variables overshoots.

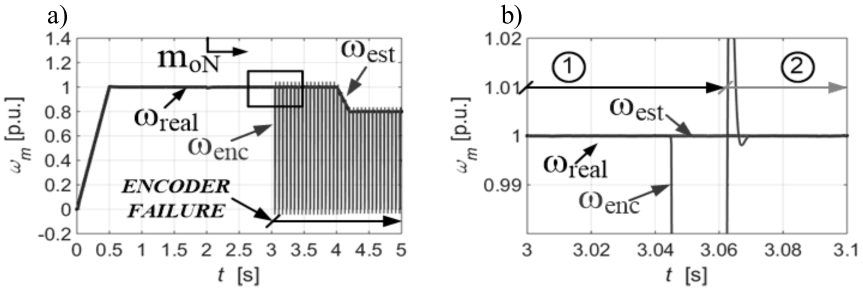

Fig. 14. Faulted operations of the FTDFOC algorithm for partial failure of individual pulses of the encoder, 1 – sensor mode, 2 – sensorless mode, $\omega_m = \omega_{mN}$ (simulation results)

3. Conclusions

In this paper the Fault Tolerant Direct Field Oriented Control (FTDFOC) system for induction motor drive was presented. The detection system based on neural network of the rotor speed sensor faults was presented and tested for different fault types and different drive operation conditions. It was proved that the speed sensor fault can be detected by the proposed detector and the control structure can be changed to the sensorless mode for post-fault operation, with the MRASCC speed estimator. Developed detection algorithm effectively detects the failure and may be used successfully in systems with an increased degree of safety.

This research work is supported by National Centre for Research (Poland) under grant DEC-2013/09/B/ST7/04199

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(Received: 30. 09. 2015, revised: 4. 12. 2015)