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The design of field-oriented control system with artificial neural network to control faulty induction motor

***Abstract**. The paper deals with development neural network controller to ensure safe and reliable operation of damaged induction motor. It was chosen field-oriented control algorithm as a basis for neural controller aimed to provide reliable control signals both for healthy and damaged motor. It was investigated different compositions of neural network model. It was received simulation results for modified field-oriented control algorithm with neural network regulator, which showed similar results comparing to original model for healthy motor, which confirms correctness of developed model.*

Streszczenie.** Opisano zastosowanie sterownika wykorzystującego sieci neuronowe do stabilnej i niezawodnej pracy zdrowego lub uszkodzonego silnika indukcyjnego. **Projekt systemu sterowania zdrowym lub uszkodzonym silnikiem indukcyjnym a wykorzystującego sieci neuronowe

Keywords: induction motor, field-oriented control, artificial neural network.
Słowa kluczowe: sterownik, silnik indukcyjny, sieci nmeuronowe.

Introduction

Nowadays there is a problem to enhance operational quality of electric drive systems with induction motor. Another relevant problem is to ensure safe and reliable operation of faulty induction motor. To enhance quality of operation the electric drive system which includes faulty induction motor (asymmetrical, with broken rotor bars or winding short-circuits) it is necessary to use combined hardware and software system [1–8]. Last decades to solve such problems the field-oriented control (FOC) methods are widely used [9, 10]. This approach shows good results. However, it could be enhanced applying theory of artificial neural networks (NN) and methods for synthesis control systems based upon NN.

Traditional control methods could not ensure desired quality in tasks of control non-linear object, objects with unpredictable noises and interferences, and objects influenced by others factors, which makes control process more complicated.

The efficiency of artificial neural networks (ANN) implementation in control systems is determined by the following factors: universal approximation features, high learning ability and parallel processing of discrete and analogue values. Described features allows adaptive neural control (ANC) systems automatically form effective control algorithms, which are highly available for parametric and structural adaptation to environment and variable parameters control [11]. ANN showed up as reliable tool to solve complex non-linear control tasks when traditional methods could not afford desirable results for practical solutions [12]. The main ANN advantages to use them for control tasks are following:

- ANN are able to learn any functions, while it is provided relatively large volume of information about control object as well as correct type and model of NN are chosen;
- the use of sigmoid activation functions in hidden layers of multi-layer NN ensures possibility of nonlinear mappings;
- due to ability of ANN for self-learning and data compilation, it doesn't need huge volume of a prior information about control object, which is mandatory for traditional methods of optimal and adaptive control.

Previously mentioned advantages led to popularity of ANN for development and research control systems with ANC. Thus, these solutions worth to be implemented and investigated for tasks aimed to afford energy effective and reliable control of electric drive with faulty motors under fault progress, when it is not possible to acquire prior information for effective operation under traditional control methods.

Theoretical theses

The base of proposed control system is field-oriented control (FOC) algorithm. The choice is explained by its following advantages:

– the motor torque and flux are directly and separately controlled;
– precise transient and sustainable control;
– high speed control accuracy;
– smooth start and motor rotation for all possible frequencies;
– fast reaction on load change. Motor speed remains almost constant;
– increased regulation range and accuracy;
– decrease heat and magnetization losses, motor efficiency increases.

Another FOC advantage is the possibility to create control system without use of any additional sensors, which is highly important especially when it is not possible to use additional wiring, critical with increasing size of electric drive system due to aggressive medium, high temperatures, contact corrosion etc. In addition, FOC requires less energy consumption, comparing to other traditional solutions. This feature ensures higher energy efficiency, decreases both maintenance costs and electric drive components cost.

Under sensorless FOC motor speed and/or shaft position measured not directly, these values computed basing on other parameters, such as phase currents and voltages directly measured.

The advantages of this control method could be extended by implementing ANN into the control circuit. Multilayer neural network could be represented as a tool to shape control functions, which meet target conditions, object models and environment influence. The sigmoid functions are included into the hidden layers of the network, which makes it able generally represent any type of continuous functions and allows one to create specific types of control systems, for example, to control multiply connected nonlinear control objects. In addition, it is possible to use NN as alternative to traditional regulators implemented for linear control objects models. The use of ANN does not depend on control object type considering its mathematical model. Determining factor to choose control method using NN is information about object condition and environment influence available for creation control/learning model. These data are necessary for formation generalized network learning error used for back propagation algorithm. As a basis, it was taken FOC scheme, which is represented in fig. 1, which was modified via replacement PI control blocks used to form currents in d and q axis separately.

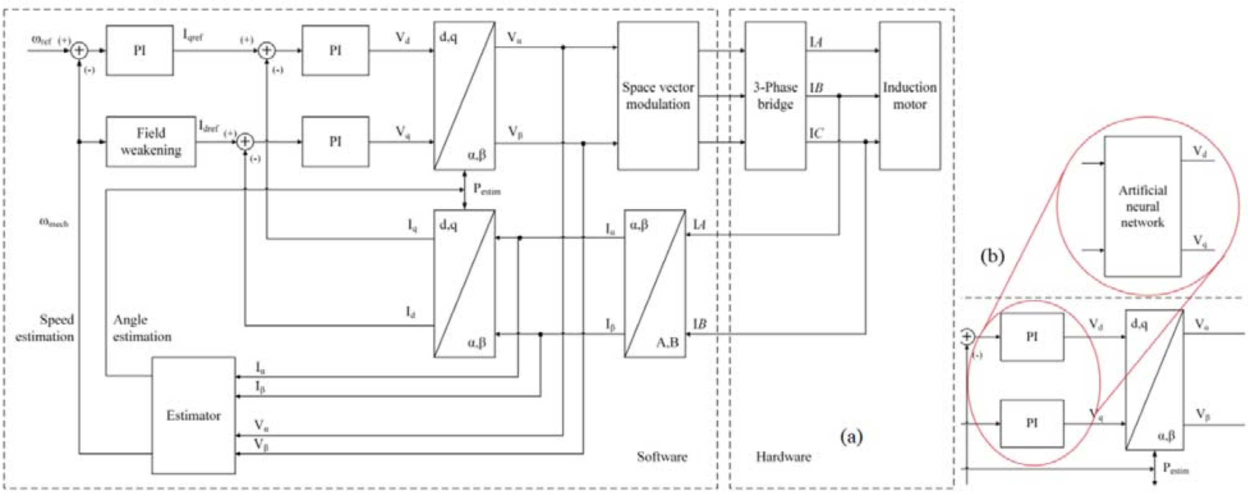


Fig. 1. Induction motor FOC control: a – traditional scheme; b – replaced blocks

In this scheme, Estimator computes speed and angle values and as inputs, it receives fixed stator coordinates, voltage and current values for two axes. Counter-EMS is used to estimate speed and position values, and it is computed as follows:

$$E_a = V_a - R_s I_\beta - \delta L_s \frac{dI_a}{dt}$$
$$E_\beta = V_\beta - R_s I_\beta - \delta L_s \frac{dI_\beta}{dt} \quad (1)$$

Space-vector modulation block is used to generate switch signals for three-phase bridge keys. Three independent switch signals are being generated in this block. Three-phase bridge is considered as a single device, which could generate eight different switching conditions: three-dimensional Cartesian product, two conditions for A phase, two conditions for B phase and two conditions for C phase. Among them, two conditions, (A, B, C) = (0, 0, 0) and (1, 1, 1), represents zero instantaneous values of linear voltage, and they often called as “zero condition” or “zero vectors”. Other six conditions represent not-zero vector voltages on motor terminals. Space-vector modulation is being implemented according to the following advantages. First, it appears increased linear voltage (up to 15% higher) in linear operational range. This leads to lower current values for constant rated power. The lower current means, on one hand, lower expenses for power conversion, and, on another hand, lower power loss during commutation. Second, as module input is represented as vector, determined in fixed stator coordinates system, this allows one to control generation of three-phase sinusoidal waves, using only one parameter, which leads to decrease need in computation capacity.

Transition between coordinate systems is done using Clark and Park transformations.

Neural network development

Experiments for choosing NN type were provided using mathematical simulation. As a basis, it was taken straight forward network – multilayer perceptron. Another possible NN type could be recurrent network, but it needs more precise tuning of its parameters.

Another important factor after network architecture is the presence delay elements in network structure. Delay elements could be used to implement network dynamic memory, which, theoretically, could increase network operation; however, it needs higher equipment performance.

In this part of work, it was investigated influence of neuron numbers in hidden layers on its performance. For the straight forward NN structure with input layer, two hidden layers and output layer, the following hidden layer constructions were considered:

– first layer with 50 neurons, second layer with 75 neurons;

– first layer with 100 neurons, second layer with 150 neurons;

– first layer with 25 neurons, second layer with 45 neurons.

Along with this, input and output layers contain two neurons each, which determined by number of input and output parameters. Other features are tuned in the following way:

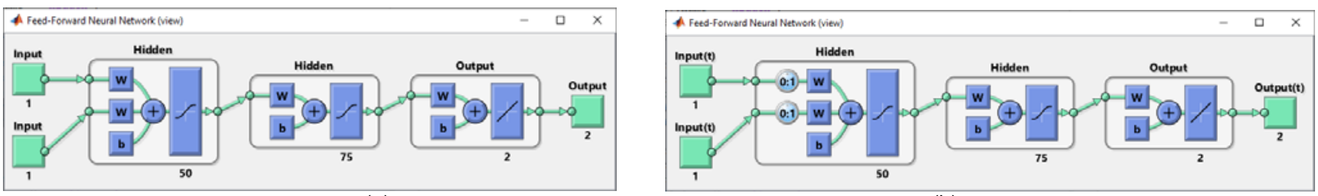
– hidden layers activation function is Hyperbolic tangent (tansig); linear activation function is used for output layer;

– learning rate is 0.001;

– perceptron weight and bias learning function – learnp;

– stop condition for deviation from the reference – 0.0001;

– error function – msereg (mean squared error with regularization performance function).



(a) (b)

Fig. 2. Simulation models of developed neural network: a) without delay element; b) with delay element

Basing on these parameters it was created two neural networks: with and without delay elements in input neurons (fig. 2).

NN teaching is done by tuning neurons weight coefficients aiming to minimize learning criteria. As result, control signal $u(t)$ is formed. Network is taught to reach zero error, and it behaves as control object inverse model. In [12, 13] such connection of NN with dynamic control object is called common customizing object (CCO) in control system. General representation of general customizing object is shown if (2):

(2) $$\frac{dy(t)}{dt} = F\left(y(t);u(t);r(t);w^{(\ell)};\theta;t\right), t>0, \ell=\overline{1,K},$$

where *F*() is functions class, *r*(*t*) is reference path for control system open-looped relative to its input, *u*(*t*) is control signal, *w* is a weight vector for coefficients should be set, *ℓ* is a network layer number, θ is CCO parameters vector, and, if needed, environment model parameters (disturbance model).

To teach the network it is used error back propagation method, which implements gradient from the speed of change of learning quality functional in accordance with CCO equation.

Back propagation algorithm consists in applying correction $\Delta w_{ji}(n)$ to synaptic neuron wieght in proportion to partial derivative $\partial E(n)/\partial w_{ji}(n)$:

(3) $$\frac{\partial E(n)}{\partial w_{ji}(n)} = \frac{\partial E(n)}{\partial e_j(n)} \cdot \frac{\partial e_j(n)}{\partial y_j(n)} \cdot \frac{\partial y_j(n)}{\partial v_j(n)} \cdot \frac{\partial v_j(n)}{\partial w_{ji}(n)},$$

where derivative $\partial E(n)/\partial w_{ji}(n)$ *is* sensitivity factor, which determines search direction for synaptic weight $w_{ji}(n)$ in weights space:

(4) $$\partial E(n)/\left(\partial e\_j(n)\right) = e\_j(n).$$

Tab.1 represents results of teaching ANN depending on its structure.

Table 1. Neural network teaching results

NN type	#	Parameters	Number of teaching iterations	Teaching error	Correlation coefficient
Without delay elements	1	{50, 75}; 0.001; learnp	770	0.0157	0.91108
	2		524	0.0158	0.91047
	3		2331	0.0153	0.9132
	4	{100, 150}; 0.001; learnp	1022	0.0155	0.91205
	5		896	0.0152	0.91361
	6		506	0.0154	0.91205
	7	{25, 45}; 0.001; learnp	1009	0.0161	0.90857
	8		2500	0.0164	0.90681
	9		940	0.0158	0.91043
With delay elements	10	{50, 75}; 0.001; learnp	1561	0.0157	0.91076
	11		1555	0.0157	0.91102
	12		1837	0.0157	0.9113
	13	{100, 150}; 0.001; learnp	376	0.0158	0.91036
	14		777	0.154	0.9129
	15		637	0.0153	91.268
	16	{25, 45}; 0.001; learnp	1189	0.0159	0.90961
	17		647	0.0159	0.90911
	18		2097	0.0161	0.9085

First, it should be mentioned different iteration numbers for experiments. This is caused not because of different network quality, but because of catching local minimum in some cases. As expected, the worst learning results were derived for the smallest neuron number. However, some results for this case are quite close to cases with much bigger neuron numbers. Different, even very close, results, derived for repeated learning of same network type, complicates analysis. This could be explained by random choice of initial point for moving along gradient field during operation of error back propagation method using gradient descent method. In addition, it should be mentioned similarity of results for {50, 75} and {100, 150} neurons combination event under double difference in neuron numbers.

Tendency to use network with less neuron number could be explained, on one hand, by the fact, that for bigger neuron number structures the requirements to computation capacity of device, where NN will be implemented, increases. On another hand, network could be appeared in overfitting condition, when network could only normally work with data provided in learning, losing ability to adaptation and generalization of data. Basing on table 1, it was chosen network without delay element, with neuron numbers in hidden and input layer {50, 75}.

To verify ANN, it was created mathematical model showed in fig. 3, 4

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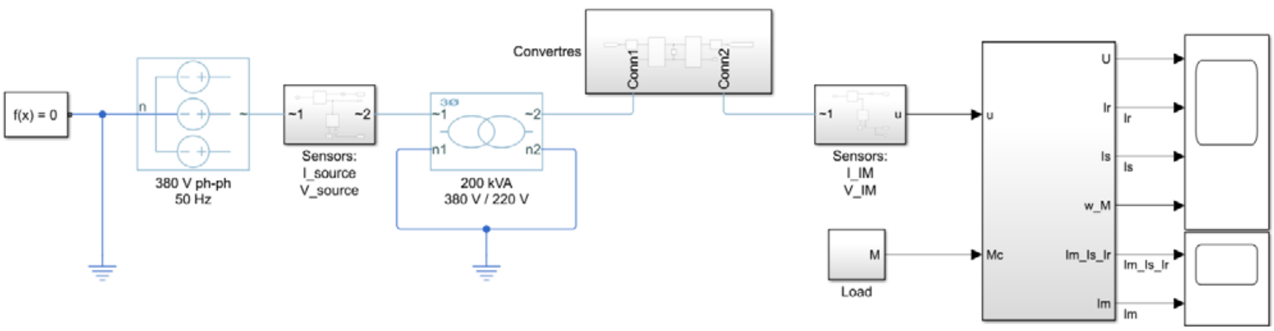

Fig. 3. Simulation model for electric drive control system

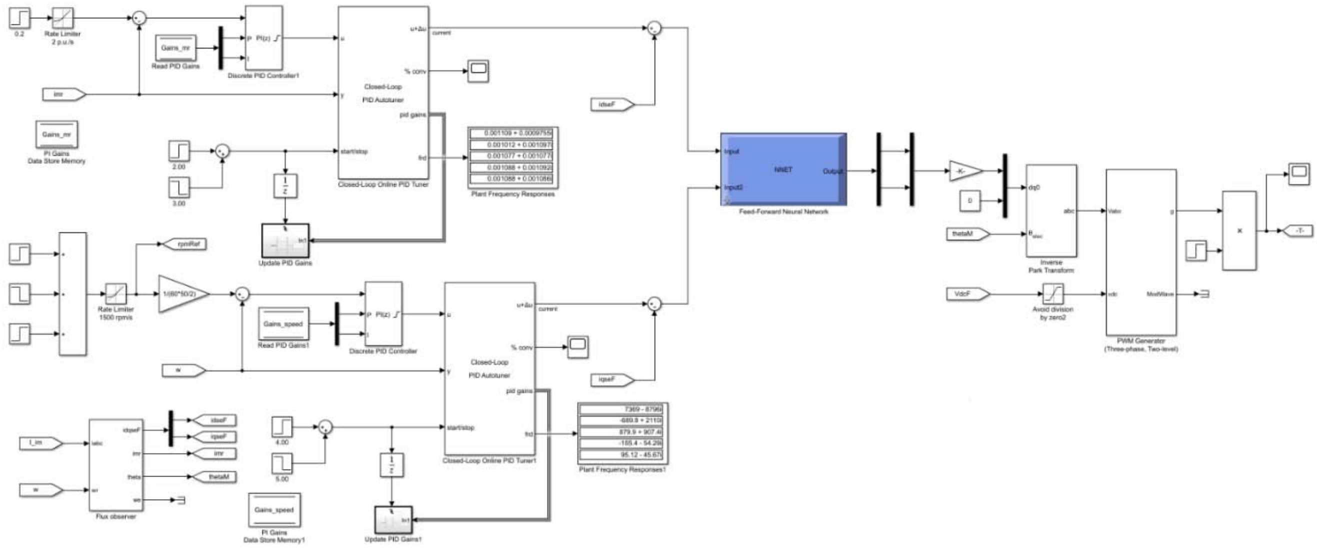

Fig. 4. Simulation model for control system of induction motor's inverter

Fig. 5 shows timewaves for motor speed under FOC (line 1) and modified neural network FOC (NN FOC, line 2) control algorithms for healthy 1.1 kW, 1400 rpm induction motor under idle start for 40 % of rated speed with further progress up to 85 % of rated speed. Simulation shows even better results for NN FOC algorithm. Thus, developed model could be used for further investigations for broken motor operation modes.

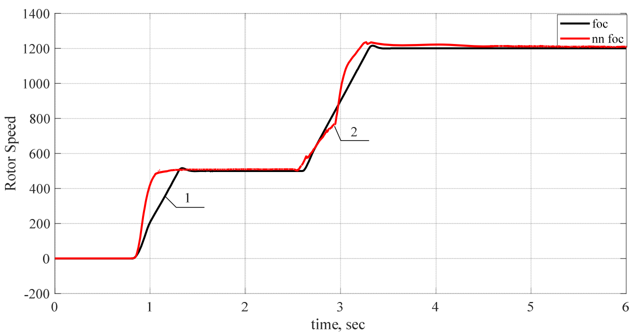

Fig. 5. Simulation results for motor speed: 1 – FOC; 2 – NN FOC

Conclusions

This paper proposes modification of vector FOC algorithm with replacement of traditional PI controllers used to control currents in *d* and *q* axes with ANN-based controllers aimed to enhance quality and reliability of control electric drive systems. Proposed approach allows one to adopt previously trained ANN to ensure desired behavior of damaged induction motor without need to re-calculate controller parameters. During research, it was analyzed two ANN variations: with and without delay elements in input layer. It was provided number of NN training and teachings, which revealed network structure with optimal neurons number. It was proposed a model of induction motor control system with modified FOC algorithm. Simulation results showed similar healthy motor characteristics both for FOC and NN FOC algorithms, which confirmed correctness of developed NN FOC model. Further research will be provided to reveal possibility of implementation NN FOC algorithm to ensure safe and reliable faulty motor operation.

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