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Adaptive neural speed control of the induction motor drive

Abstract*. In this paper adaptive neural controllers implemented in the speed and flux control loops of the induction motor drive are presented. Feed-forward networks with sigmoidal neurons in the hidden layer are applied. Parameters of the neural network structure are updated on-line according to the Backpropagation algorithm. Described adaptive controllers provide the accurate control with fast response of the drive system to the reference speed signal. Important advantage of the proposed controllers is its simplified structure, reduced number of parameters adjusted in the design process (without direct dependency on parameter of the motor). In this paper results of tests showing correct work of the described control structure of the induction motor are presented.*

Streszczenie. *W artykule przedstawiono adaptacyjny neuronowy regulator zastosowany w pętli sterowania prędkością oraz strumieniem wirnika silnika indukcyjnego. Zastosowany regulator bazuje na sieci neuronowej bez sprzężeń zwrotnych z sigmoidalnymi funkcjami aktywacji w warstwie ukrytej. Parametry (współczynniki wagowe) sieci neuronowej są aktualizowane on-line zgodnie z algorytmem wstecznej propagacji błędu. Opisane regulatory adaptacyjne umożliwiają precyzyjne sterowanie i szybkie odpowiedzi układu na zadane trajektorie prędkości. Istotną zaletą proponowanego rozwiązania jest uproszczona struktura regulatorów oraz zredukowana liczba parametrów wyznaczanych w procesie projektowania (niezależnych bezpośrednio od parametrów silnika). W artykule zamieszczono wyniki badań prezentujących poprawną pracę opisywanych regulatorów. (****Adaptacyjny neuronowy regulator prędkości silnika indukcyjnego****).*

Keywords: induction motor drive, speed control, flux control, adaptive neural network, on-line backpropagation,
Słowa kluczowe: napęd elektryczny, silnik indukcyjny. regulacja prędkości, regulacja strumienia, adaptacyjna sieć neuronowa, algorytm wstecznej propagacji błędu,

Introduction

Electrical drives with induction motors are currently one of the most common structures found in the industrial solutions. Observed trend is related to the low costs of such machines. A large number of applications lead to increased demands for control systems of the induction motor drives. Many applications require precision in tuning the reference trajectory of velocity or position, while reducing influence from disturbances and parameter changes. Therefore, robust control methods are intensively developed.

In order to meet mentioned requirements, application of the adaptive control systems is recommended. On-line calculation of the control system parameters during the drive operation can give the possibility of adjustment of the controller to an actual state of the object. It leads to robustness against uncertainty in measurement signals and parameter fluctuations.

Neural control is very powerful tool capable of achieving very good results in the control of complex systems. It is preferred to use neural networks (NNs) for control when requirements for precision are high and system is not identified precisely or its parameters are changing. Application of control systems based on NNS can improve work of the industrial systems. Many of different structures of the control systems with NNs were developed. The most often presented in publications are: Direct Inverse Control, Additive Feedforward Control, Internal Model Control, Optimal Control, Predictive Control. The task of NNs in such control structures is related to object modeling, parameter identification, estimation of state variables, error compensation or direct calculation of the control signal. NNs can be trained of-line based on previously prepared database or on-line – for each sample of the measured input signal. It should be noticed that also different type of NNs can be applied in control systems [1].

Recently the increase of NNs applications in electrical drives is observed [2]. The most often presented applications concern: control [1],[3],[4],[5],[6], parameter identification [7], state variable estimation [8],[9] and diagnostics. The neural model reference adaptive controller is one of the most often found applications of NNs in drives' control structures. Simulations of three different solutions for speed control are presented in [3]. Also the combination of such structure with PI controller is described in the literature [4]. In the Direct Torque Control structure NN can perform two main tasks. The first is its application as a speed controller in the external speed control loop. The NN controller is trained on-line based on an error signal and historical samples, and thus the control signal is calculated [5]. The second task of NN in DTC structure is its operation as a voltage vector selector based on output signals of the hysteresis flux and torque controllers [6].

As it was mentioned above, in technical literature few examples of application of various neural speed controllers are presented. In this paper full Field Oriented Control structure with neural network controllers trained on-line is presented. One-hidden-layer neural networks are applied directly in speed and rotor flux control loops. *Backpropagation* algorithm is used for on-line adaptation of these two controllers.

This paper contains five chapters. After a short introduction, the general concept of the control structure is presented. Then neural adaptive controllers with on-line weights calculation are described. In the next part of the paper the results of research, presenting the work of the drive system, are shown. The last chapter includes conclusions on the results achieved for the tested control structure.

Speed control structure

The Direct Field Oriented Control (DFOC) structure is analysed in the paper. A characteristic feature of this type of control strategy is possibility to obtain two independent control circuits of stator current vector components, corresponding respectively to the rotor flux and electromagnetic torque. The decoupling module is required in a case of SVM inverter used for the IM control. In the structure four controllers are used. The most often, in classical solutions, the PI type controllers are applied. In this paper the PI controllers in the current control loops are optimized for fast response of the electromagnetic part of the drive. In speed and flux control loops neural networks controllers (NNC), trained on-line are implemented. The tested control system is presented in Fig. 1.

In the simulation model the voltage inverter with Space Vector Modulation (SVM) and decoupling modules were created. Simulated control structure in the described case assume the full availability of all required state variables, thus influence from estimators can be eliminated in the presented test results.

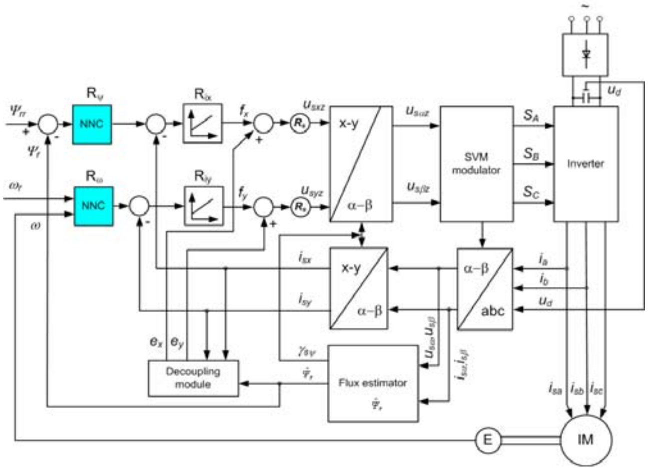


Fig.1. The block diagram of the control structure

The voltage inverter system (in the stationary α–β coordinates) is often modeled by the following equations describing the output voltage:

(1) $$U_{s\alpha} = \frac{2}{3} U_d \left(S_A - \frac{1}{2}\left(S_B + S_C\right)\right),$$

(2) $$U_{s\beta} = \frac{1}{\sqrt{3}} U_d \left(S_B - S_C\right).$$

where: S_A, S_B, S_C – switches of the inverter, U_d – voltage at the DC link.

Neural adaptive controllers

The main part of the presented speed and flux controllers is a feedforward network, without feedbacks inside the structure. Due to the assumption of on-line training, only one hidden layer in the network is applied. The NNs with structure: {2-10-1} are applied (which means: 2 inputs, 10 neurons in the hidden layer and 1 neuron in the output) as the speed and flux controllers. For the hidden layer the nonlinear sigmoidal activation functions are applied. The linear activation function is selected as the output function of the neural controller. Calculations in NN can be described by the following expression:

(3) $$\mathbf{Y} = \mathbf{f_o}\left(\mathbf{W_o}\mathbf{f_I}\left(\mathbf{W_I}\mathbf{X}\right)\right),$$

where: $\mathbf{f_o}$, $\mathbf{f_I}$ – activation functions of output and hidden layer, $\mathbf{W_o}$ – output weights matrix, $\mathbf{W_I}$ – input weights matrix, $\mathbf{X}$ – processed input vector. The input vector in both cases is defined by the equation presented below:

(4) $$\mathbf{X} = [x_r - x, G(x)],$$

where: x_r – is a reference value of controlled state variable, x – is an actual value of the controlled signal, G is an element with transfer function:

(5) $$G(s) = \frac{1}{Ts + 1},$$

with time constant T=1ms. Described structure is presented in Fig. 2.

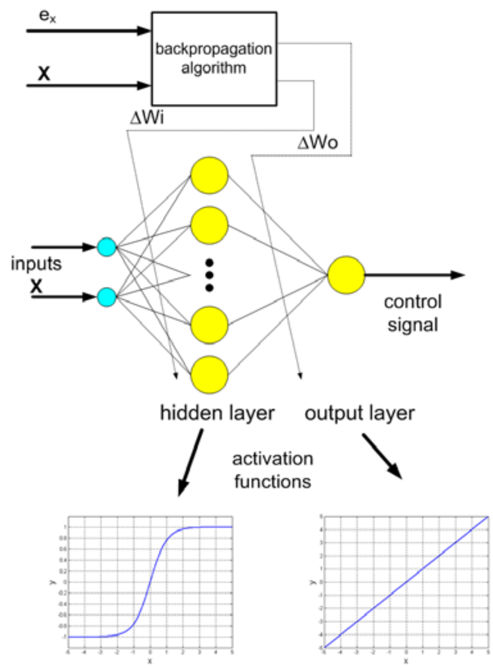


Fig. 2. Structure of the neural network trained on-line

In the technical literature on neural networks many methods for neural network weights update are presented. Most of them require gradient information, exactly – the calculation of derivative of the cost function according to several weights. One of the most effective and often used is *backpropagation* algorithm [10]. The general goal of training procedure is related to minimization of the cost function defined as mean square error between the NN output and the real value (training patterns). The cost function is often defined in the following way:

(6) $$E = \frac{1}{2}\sum_{n=1}^{P}\sum_{o=1}^{M}\left(d_o^n - y_o^n\right)^2,$$

where: P – number of training patterns, M – dimension of the output layer, $\mathbf{d}$ – required output vector, $\mathbf{y}$ – actual output vector of the network. For this purpose weights of neural network are updated as:

(7) $$w_{ij}\left(k+1\right) = w_{ij}\left(k\right) - \Delta w_{ij},$$

where: w_{ij} – weights between node i and j in k-th iteration. According to applied algorithm weights are updated according to following equations:

(8) $$\Delta w_{ij} = \eta\, \delta x_j,$$

where: η – learning rate, x_j - input of j-th neuron.
For output layer we have:

(9) $$\delta_o = f_o^{'}\left(d_o - y_o\right),$$

where: $f_o{}'$ -derivative of the activation function in the output layer.

Weights between the input and hidden layer are calculated using the following expression:

(10) $$\delta_I = f_I^{'}\sum_i \delta_o w_{jo},$$

where: $f_I^{'}$ - derivative of activation function in input layer, w_{jo} – weights between nodes in next layer.

The learning rate η determines rapidity of the algorithm.

Analyzed control structure can be considered as a series connection between the controller and the object (for several control loops). In the training algorithm, for calculation of the error in Eq. (6), the difference between the desired value and actual value of the suitable state variable is assumed. It is unlike in theoretical training of neural networks, when the net output is used for error calculation. Here the object (voltage converter and the induction motor) can be treated as a kind of disturbance of this back-propagation algorithm, thus the system output is used as a net output. Weights values of the NN are calculated in parallel to the main processing path. It is realized on-line during work of the drive system, according to the Eq. (7).

Results

In this section chosen simulation results obtained for the presented control structure with the described speed and flux NNCs are presented. Calculations are realized in Matlab/Simulink. Sampling time equal 0.1ms is assumed. First tests present correct work of the modeled drive system. Transients of state variables in the structure, shown in Fig. 3, are realized for step trajectory of the reference speed, assumed equal 40% of the nominal speed. The learning rates equal 0.03 in both NNC controllers trained on-line were assumed. Short settling time of the driving motor speed on reference level is observed (Fig. 3a). At time *t* = 0.6s the load torque is applied. Output signal of the both NNCs is limited on the value equal 3 [p.u.]. Effective decoupling of the electromagnetic torque and rotor flux control circuits is observed (Fig. 3c). Increase of the i_{sy} current is related to the load torque change (Fig. 3d).

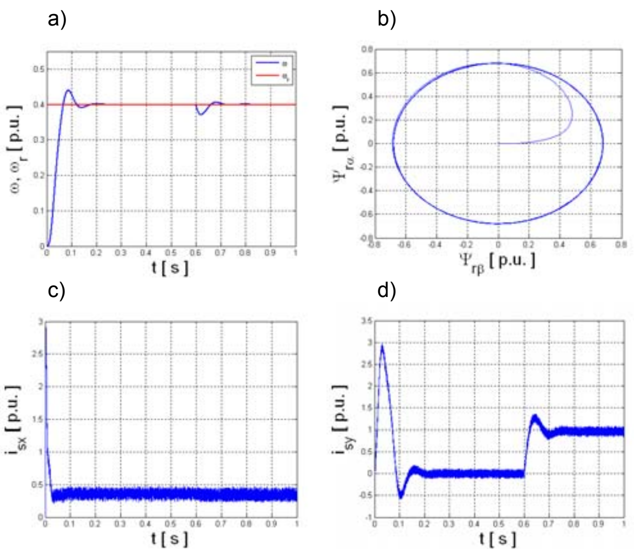


Fig. 3. Transients of state variables in analyzed drive: the actual and reference speed (a), hodograph of the rotor flux (b), components of the stator current vector (c, d)

Next tests are realized for a wide range of changes of the reference speed and step changes of the load torque. Results are presented in Fig. 4. It should be noticed that even in case if rotor is stopped, the electromagnetic torque required by the load condition is generated. Very high dynamics of the system is obtained.

In all presented tests initial values of NNs' weights are chosen randomly. Adaptation of weights is realized on-line very quickly, so the design process of those two main controllers is simplified. Trajectory of the drive speed is almost the same as the reference speed, even in the reverse operation of the motor.

In Fig. 4c transient of the i_{sy} component of the stator current is presented. During transient states (changes of the reference speed or the load torque) fluctuation of this state variable can be observed. During significant changes of the reference speed (in time *t*=1.5s, *t*=5s, *t*=5.5s) relatively big overshoots of this current component are appearing. On contrary, overshoots of i_{sy} current during load torque changes are relatively small. However it should be noticed that presented results are from simulation; in the real drive limitation of the dynamics of the control signal should be correctly introduced. So it can be concluded that application of the proposed NN controller leads to forcing of high dynamics of the control structure.

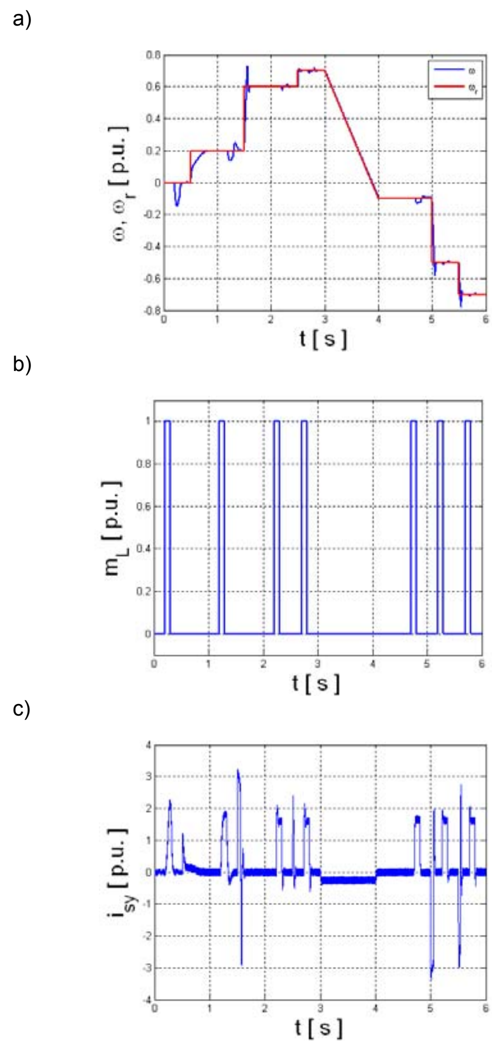
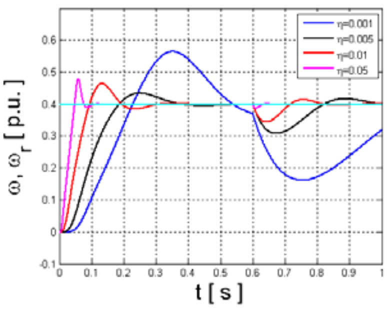


Fig. 4. Transients of the drive and reference speed (a), load torque changes (b) and i_{sy} component of the stator current (c)

In Fig. 5 the influence of the learning rate factor η of the speed controller to the operation of the drive system is demonstrated. For better transparency of η changes influence on the drive system operation, only NN adaptive speed controller is implemented in control structure (the rotor flux controller is assumed as classical PI controller in this test). The value of the η coefficient determines the time of adaptation of NN weights and ultimately influences the dynamics of the speed transients. Increase of the learning rate gives higher dynamics of the controlled signal as well as the bigger values of the output signal of the speed controller. In result for higher values of the η parameter, response of the system is faster and speed of the drive is fixed on reference value in shorter time (Fig. 5a).

It is important that during on-line training of the NN, the problem of the controller structure selection is almost eliminated. It is essential problem during application of neural models trained off-line, where NN topology significantly influences its generalization properties [11].

a)



b)

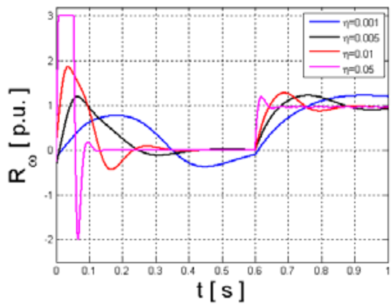


Fig. 5. Influence of the η coefficient of the speed controller to the speed transient (a) and the output signal of the speed controller (b).

Conclusion

This paper presents the Direct Field Oriented Control structure of the induction motor drive with the adaptive neural network controllers. Obtained results present the effective speed control of induction motor with very high dynamics in tuning of the reference speed signal. Important advantages of the presented rotor speed and flux controllers are also the simplicity of the structure and design process. It should be highlighted that just one parameter of the controller - its learning is selected, independently on the parameters of the induction machine. In presented case both controllers have the same value of the learning rate, neural network structure and input vector. Learning rate of the neural network significantly influences the system dynamics. Described NNCs can be applied also in the other control structures. The future works of authors will be concentrated on FPGA realization of the described control structure.

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REFERENCES

[1] Yongxian Song, Juanli Ma, Hanxia Zhang, Naibao He, Digital implementation of neural network inverse control for induction motor based on DSP, *2nd International Conference on Future Computer and Communication ICFCC*, (2010), 174–178

[2] Bose B.K., Neural Network Applications in Power Electronics and Motor Drives, *IEEE Trans. Industrial Electronics*, 54 (2007), n. 1, 14 – 33

[3] Abd El-Halim A.F., Yousef H.A., El-Genaidy M.M., Neural network control schemes for induction motor drive systems, *Proc. IEEE 46th Midwest Symp. on Circuits and Systems*, Cairo, Egypt, (2003), 1055 – 1058

[4] Tien-Chi Chen, Tsong-Terng Sheu, Model reference neural network controller for induction motor speed control, *IEEE Trans. Energy Conversion*, 17, (2002), n. 2, 157 - 163

[5] Grzesiak L.M., Megnack V., Sobolweski J., Ufnalski B., Genetic Algorithm for Parameters Optimization of ANN-based Speed Controller, *Proc. of the Int. Conf. Computer as a Tool*, Warsaw, Poland, (2007), 1700 - 1705

[6] Toufouti R., Meziane S., Benalla H., Direct torque control for induction motor using intelligent techniques, *Journal of Theoretical and Applied Information Technology*, 3 (2007), n. 3, 35 - 44

[7] Toliyat H.A., Wlas M., Krzeminski Z., Neural-Network-Based Parameter Estimations of Induction Motors, *IEEE Trans. Industrial Electronics*, 55 (2008), n.4, 1783 - 1794

[8] Aguiar V.P.B., Thepontes R.S., Braga A.P.S., De Aguiar S., A strategy for induction motor stator flux estimation using neural networks, *Proc. of Int. Conf. Electrical Machines and Systems ICEMS* (2007), 1923 - 1927

[9] Godoy Simoes M., Bose B.K., Neural network based estimation of feedback signals for a vector controlled induction motor drive, *IEEE Trans. Industry Applications*, 31 (1995), n. 3, 620 - 629

[10] Bishop M.C., *Neural Networks for Pattern Recognition*, Oxford University Press (1996)

[11] Orlowska-Kowalska T., Kaminski M., Application of the OBD method for optimization of neural state variable estimators of the two-mass drive system, *Neurocomputing*, 72 (2009), n. 13-15, 3034-3045

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