Research Journal of Applied Sciences, Engineering and Technology 7(8): 1582-1586, 2014
DOI:10.19026/rjaset.7.435
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: May 17, 2013 Accepted: June 14, 2013 Published: February 27, 2014

Research Article

New Optimized Soft Computing Speed Controller for PMSM Drive

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Abstract: This study proposes a soft computing speed controller where recurrent neural network speed controller is trained by genetic extended kalman filter, based on a predetermined genetic Proportional Integral (PI) controller. A genetic PI gives to this proposed speed controller exact values without mathematical equations, unlike the classical PI who is need for it necessary. With this proposed method the results of simulation obtained is as they are of real state of the Permanent Magnet Synchronous Motor (PMSM). The harmonic ripples of speed response are also minimized with Genetic Extended Kalman Filter (GEKF) and Neural Network Space Vector Modulation (NNSVM). This fusion between the Artificial Intelligence (AI) and optimized method of the extended kalman filter gives more superiority to the method proposed, like shows the simulations results compared to classical Neural Network Controller (NNC).

Keywords: Direct torque control, extended kalman filter, genetic algorithm, permanent magnet synchronous motor, recurrent neural network, space vector modulation

INTRODUCTION

Before the appearance of artificial intelligence the automation of dynamical systems was always based on the mathematical models and since modeling never reaches the real systems because of the negligence of some physical phenomena, the classical automation did not see a remarkable growth during this time, in spite of the mathematics contribution to the development of physics. But the last decade saw great advances in intelligent control theory. McCulloch and Pitts (1943) formulated the neuron like human brain. After a long time the first industrial application left to the automatic domain and in Zadeh (1965) introduced the human logic to the industry by concept called fuzzy logic. Genetic Algorithm, swarm optimization, bee colony and ant colony intelligent soft computing methods are also developed the industrial automation (Lin and Chiu, 1998; Wai, 2001; Jan *et al*., 2008; Ren and Chen, 2006). Recently a lot of studies present a fusion of several artificial theory (Elmas *et al*., 2008; Wang and Huang, 2009, 2011). The results of experimental and soft simulation demonstrate de performance of soft computing in this domain.

This study presents a novel speed control scheme of PMSM drive with a newly developed soft controller based on the optimized emergence between soft and optimal techniques for drive. A complete simulation model of Direct Torque Control (DTC) of PMSM incorporating the proposed method is programmed with C language and plotted with MATLAB. The performance of the proposed controller based PMSM drive is investigated at different operating conditions in simulation. In order the performances of this study are also compared to those obtained by a conventional NNC to prove it superiority. The soft controller based PMSM drive is found to be more robust as compared to the conventional NNC based drive and hence found suitable for high performance industrial applications.

MATERIALS AND METHODS

Mathematical model of PMSM: By developing the coupled three-phase mathematical model of PMSM, the (dq) axis of current, voltage and flux will be obtained from two transformations. The first part transfers the three phases (abc) to two phases (αβ). The second part is the quantities at stationary to rotational frame (dq). Electromechanical behavior of the PMSM in the (dq) frame is as follows (El Janati El Idrissi and Zahid, 2011; El Janati El Idrissi *et al*., 2012; Bimal, 2002):

$$V_d = Ri_d - \omega_r \lambda_q + \frac{d\lambda_d}{dt} \tag{1}$$

$$V_q = Ri_q + \omega_r \lambda_d + \frac{d\lambda_q}{dt} \tag{2}$$

$$\lambda_d = L_d i_d + \lambda_m \tag{3}$$

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Table 1: Parameters of PMSM

Features	Values	Units
Stator resistance	1.40000	Ω
d-axis inductance	6.60000	mH
q-axis inductance	5.80000	mH
Magnetic flux constant	0.15460	Wb
Friction coefficient	0.00038	N.m/rad/s
Motor inertia	0.00176	$Kg{:}m^2$

$$\lambda_q = L_q i_q \tag{4}$$

$$T_e = \frac{3}{2} p\left(\lambda_m i_q + \left(L_d - L_q\right) i_d i_q\right) \tag{5}$$

$$\frac{d\omega_r}{dt} = \frac{p}{J}\left(T_e - B\omega_r - T_m\right) \tag{6}$$

$$\omega_r = p\omega_m \tag{7}$$

where,

- R = Resistance
- θ = The rotor position
- V_d, V_q = Stator voltage at rotational reference frame
- i_d, i_q = Direct and quadrature stator currents
- ω_r, ω_m = Electrical and mechanical rotor speed
- λ_d, λ_q = Stator flux at rotational reference frame
- λ_m = Stator flux linkages due to the permanent magnet
- T_e = Electrical torque
- p = The number of pole pairs
- J = Rotor inertia
- B = Friction
- T_m = Mechanical load torque
- L_d, L_q = Stator inductance

Table 1 presents parameters of PMSM

Training RNN by the proposed genetic EKF: The EKF solution to the training problem is given by the following recursion (Isabelle and Lon, 1998; Haykin, 2001; Rubioa and Yu, 2007). In the first, the proposed genetic algorithm determinate the parameters, that take times to handling or not with manual method. Then, we calculate the ξ (k) error by comparing the output h (k) with the desired output d (k). The partial derivatives of F (k) with weights of neural network are formed by the matrix H (k):

$$H(k) = \begin{bmatrix} \frac{\partial F(Q_1)}{\partial W_{11}} & \cdot & \cdot & \frac{\partial F(Q_1)}{\partial W_{11}} \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \frac{\partial F(Q_1)}{\partial W_{11}} & \cdot & \cdot & \frac{\partial F(Q_1)}{\partial W_{11}} \end{bmatrix} \tag{8}$$

Then:

$$A(k) = \left[\eta(k) S(k)^{-1} + H(k)^T P(k) H(k)\right]^{-1} \tag{9}$$

Extended kalman filter gain matrix is defined by:

$$K(k) = P(k) H(k) A(k) \tag{10}$$

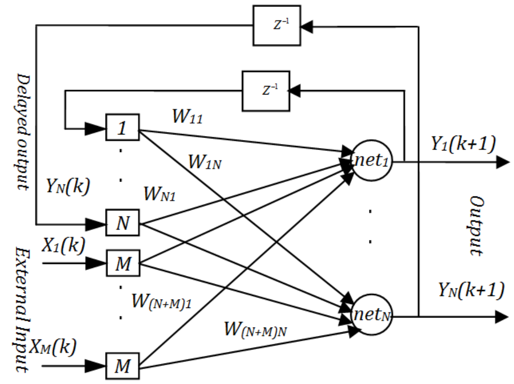

Fig. 1: General RNN architecture

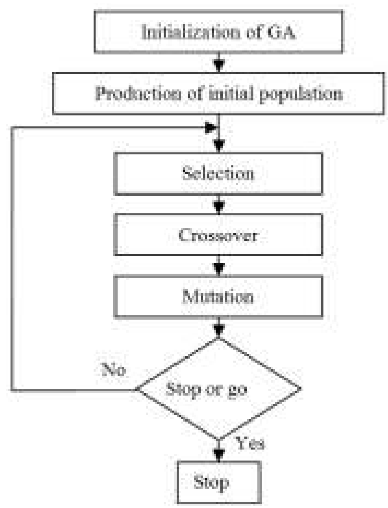

Fig. 2: Genetic algorithm flowchart

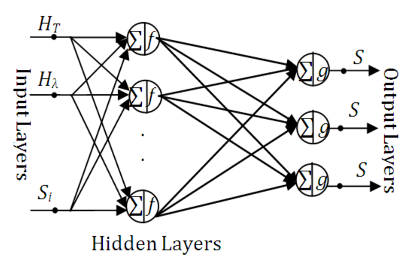

Fig. 3: Architecture of NNSVM

The network weights are calculated by the following recursive relation:

$$\hat{W}(k+1) = \hat{W}(k) + K(k)\xi(k) \tag{11}$$

Finally the error covariance matrix is predicted by a relation:

$$P(k+1) = P(k) - K(k) H(k)^T P(k) + Q(k) \tag{12}$$

where,

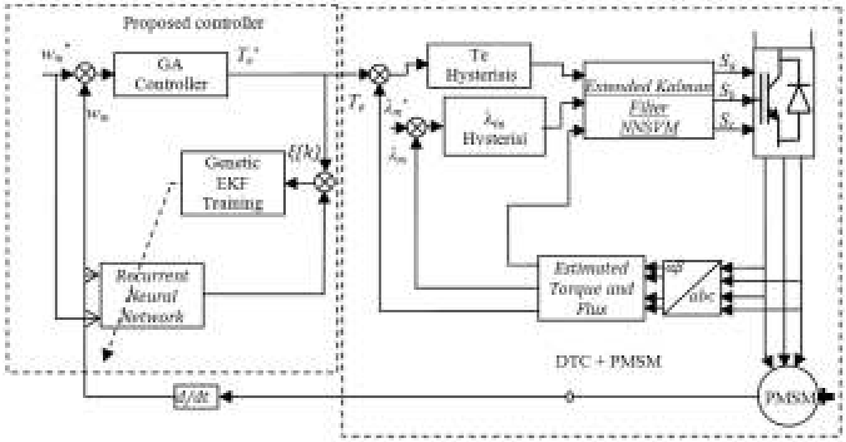

Fig. 4: Structure of proposed method based on new optimized soft computing controller

A = Denotes state prediction
K = Kalman gain
W = Neural network weights
S = User specified non negative definite weighting matrix
ξ = Scalar learning parameter
P = Error covariance matrix
Q = Diagonal covariance attenuating error matrix

RNN architecture: In many applications a neural network is required to be dynamic, that is should be able to emulate a dynamic system with temporal behavior such us PMSM. Figure 1 shows a general structure of RNN for dynamic systems.

This figure has N outputs and (N+M) inputs; M is the external inputs. The error between the output Y = h (k) and the target d (k) is calculated in each discrete time with the Eq. (13):

$$\xi(k) = d(k) - Y(k) \tag{13}$$

Genetic algorithm: Currently genetic science becomes able to transmit a good character of an animal or plant to other, by the transmission of allele corresponding, of the one with the other. Often we transmit the goods and qualifying alleles which enable us to obtain powerful individual. Lately a whole of the researchers applied this development to the level of the automatic and they obtained powerful results which gave a remarkable quantum leap to the automatic (Oh *et al*., 1999; Linkens and Nyongesa, 2002). The general flowchart of GA is shown in Fig. 2.

The fitness of each individual is calculated with the expression in Eq. (14) (Vakkas and Metin Demirtas, 2009):

$$fitness = \frac{1}{MO + 2 \cdot ST + 1} \tag{14}$$

MO : The overshot
ST : The settling time

Table 2: GA parameters

Parameter	Value
Crossover probability	0.850
Mutation probability	0.001
Generation number population	100
Population	80
Chromosome length	24 bit

In this study we are using the genetic optimization with the parameters presented in the Table 2.

Neural network space vector modulation: Neural-network-based implementation of Space-Vector Modulation (SVM) of a two-level voltage-fed inverter is proposed in this study. A neural network has the advantage of very fast implementation of an SVM algorithm. Using a general flowchart for neural network with genetic EKF training algorithm and after several tests the architecture 3-17-3 with tansig hidden layer and purelin output layer is established to illustrate the neural network voltage selector (Fig. 3).

The proposed neuro speed controller based genetic EKF for PMSM: The block diagram of proposed neuro speed controller based on genetic extended kalman filter training is presented with the following schema (Fig. 4).

In the first, the GA controller find the exact optimal values of K_I and K_P, then the proposed controller compares the output with the desired target and trains the recurrent neural network with genetic EKF to find the optimum response of speed by minimizing the speed error. To reduce more the ripples of speed the neural space vector modulation is also proposed (Fig. 3).

The ripples reduced by this SVM aid more the proposed controller to minimize the error between feedback and desired speeds.

RESULTS AND DISCUSSION

This study presents the modeling and simulation method of PMSM with optimized AI control system,

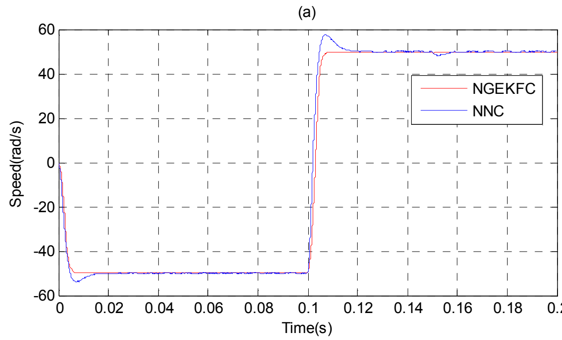

Fig. 5: Simulated speed, responses of the PMSM drive with normal NNC and NGEKFC controller for a -50, +50 speed reference with fixed load 4 N.m

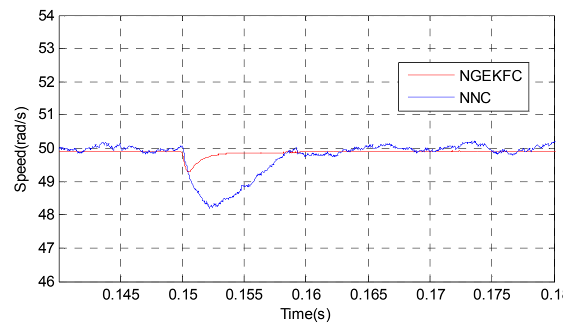

Fig. 6: Zoom of speed during applied fixed load 4 N.m

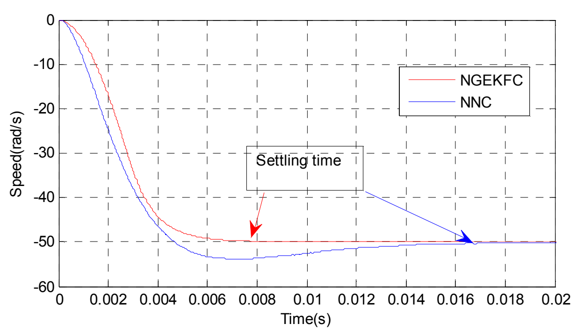

Fig. 7: Zoom of the speed during transitory mode

the speed controller of PMSM system is a new optimized soft computing controller According to the design method, the function model is built in Borland C++ 5.0 and plotted with MATLAB environment. In order to demonstrate the high performance of the proposed controller, numerous simulation tests were performed under different operating conditions. Sample significant simulation results are presented below. Figure 5 to 7 shows the response of the speed in case of load 4N applied at (0.15s) using classical SVM a normal NN Controller (NNC) and proposed neural network controller based genetic EKF with Neural Network Space Vector Modulation (NNSVM). The speed reference is applied as order, respectively with -50, +50 rad/sec. It is clear that the system follows these references with proposed controller faster than the results shown with classical NNC. The speed undulations due to the harmonic of SVM are reduced in comparison with conventional NNC (Fig. 6). It is found that the proposed neuro controller based genetic EKF for PMSM drive reached the speed quickly and tightly without overshoot/undershoot with t = 0.007 sec for both positive and negative speed without any overshoot/undershoot.

In contrast to classical NN controller that has important overshoot/undershoot with the settling time (0.017 sec). A comparison between the normal NN controller and the proposed controller in Fig. 5 proves the superiority of the proposed soft controller (Neuro Genetic Extended Kalman Filter Controller (NGEKFC).

CONCLUSION

The simulation results shown with Borland C++ and MATLAB in this proposed study prove the superiority of soft computing to control PMSM systems. Our future research work is to develop and improve other intelligent techniques such as the fusion of neural network with fuzzy logic by using the evolutionary algorithms to reduce more the speed ripples of the PMSM. We will work also about other algorithm to train the neural network.

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