A PROPOSED ESTIMATOR FOR A DIRECT TORQUE CONTROL OF INDUCTION MOTOR BY USING RADIAL BASIS FUNCTION NEURAL NETWORK TECHNIQUE

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ABSTRACT:- The purpose of this paper is to use Radial Basis Function Neural Network (RBFNN) as an estimator for stator flux and electromagnetic torque in Direct Torque Control (DTC) systems used as a driver of a 3-phase induction motor, in order to reduce the ripples in the output torque. This paper includes design, construction and training for three different modes of operation of RBFNN, in which the spread constant has a different value for each estimated parameter during the network training. Then, the network, which has independent outputs, gives the best results choused as an estimator in the proposed DTC system. Matlab/neural network toolbox used for training the proposed estimator at different load torques.

   The Simulation results are obtained using program of Matlab/Simulink. The coincidence of the values of the output data obtained from the proposed estimator and that from the conventional one proves the proposed system accuracy.

Keyword: Induction Motor, Radial Basis Function Neural Network, Direct Torque Control.

1- INTRODUCTION

   Direct Torque Control (DTC) system used as a variable speed driver for induction machines has emerged in the middle of 1980's by Isao Takahshi and M. Depenbrock. In this system, the control of the stator flux and the torque occurs directly by selecting the appropriate inverter state. DTC system is the first technology to control the "real" motor control variables of torque and flux [1], [2].

   The main features of DTC system are summarized as follows:
1- It operates with closed torque and flux loops without current controllers.
2- It needs stator flux and torque estimation.
3- It is a speed sensorless control method.
4- It has simple and robust control structure; however, the performance of DTC strongly depends on the quality of the estimation of the flux and torque.

   In order to improve DTC performance there was many control strategies presented since 1990's, one of these methods was the Artificial Intelligent (AI) [Artificial Neural Networks (ANNs), Fuzzy Logic Control (FLC)], This control strategy can be used as an estimator to improve the DTC system fed induction motor [3], [4].

   This paper uses the radial basis function neural networks (RBFNN) to operate as an estimator for stator flux and electromagnetic torque instead of conventional estimator to

improve the estimation process of the above parameters, subsequently improves the performance of the DTC system.

2- THE DIRECT TORQUE CONTROL TECHNIQUE

Figure(1) shows schematically the block diagram of DTC system that requires an efficient flux and torque estimator. In normal operation, two of the motor phase currents (i_a, i_b) and the DC bus voltage ($V_{d.c}$) are simply measured, together with the inverter's switch positions (V_{sa}, V_{sb}, V_{sc}). The measured information from the motor fed to the stator flux and torque estimators (Adaptive Motor Model) [5], [6]. This system depending on the measured values of voltages and currents for the induction motor to estimate the stator flux and electromagnet torque and to use them as a feedback signals for control.

The estimated values are compared with the reference ones; the magnitude of the error between them compared by hysteresis comparators. A switching table (that uses the outputs of the comparators and the position sector detector of the stator flux) is achieved to get the optimal voltage vector needed for the power-switching device of the inverter. The construction of DTC model is performed using Matlab/Simulink program [7].

The equations (1) to (7) refer to the dynamic model of a 3-phase balanced squirrel cage-induction motor in a d-q stationary reference frame, neglecting the saturation effects [9].

$$\frac{d\overline{\lambda_{sd}}}{dt} = \overline{V_{sd}} - r_s.\overline{i_{sd}} \tag{1}$$

$$\frac{d\overline{\lambda_{sq}}}{dt} = \overline{V_{sq}} - r_s.\overline{i_{sq}} \tag{2}$$

$$\frac{d\overline{\lambda_{rd}}}{dt} = -\omega_r \lambda_{rq} - \frac{r_r}{L_r}\overline{\lambda_{rd}} + \frac{r_r L_m}{L_r}\overline{i_{sd}} \tag{3}$$

$$\frac{d\overline{\lambda_{rq}}}{dt} = -\omega_r \lambda_{rd} - \frac{r_r}{L_r}\overline{\lambda_{rq}} + \frac{r_r L_m}{L_r}\overline{i_{sq}} \tag{4}$$

$$\overline{i_{sd}} = \frac{\overline{\lambda_{sd}}}{\sigma L_s} - \frac{L_m}{\sigma L_s L_r}\overline{\lambda_{rd}} \tag{5}$$

$$\overline{i_{sq}} = \frac{\overline{\lambda_{sq}}}{\sigma L_s} - \frac{L_m}{\sigma L_s L_r}\overline{\lambda_{rq}} \tag{6}$$

where

$$\sigma = (L_s L_r - L^2_m)/L_r$$

The voltage selection based on a 6-sector d-q plane, with the stator flux magnitude and the torque angle involved. The following equation relates the electromagnetic torque and the stator flux**:**

$$T_e = C \left|\overline{\lambda_s}\right| * \left|\overline{i_r}\right| \sin\theta \tag{7}$$

where: (C) is a constant; (θ) is the angle existing between the stator flux and the rotor flux, (torque angle).[6]

In each sector, the stator flux and electromagnetic torque change depend on the voltage vector selected. For example, if in the first sector a [V_3 (0 1 0)] voltage vector is selected, the stator flux magnitude decreases; but the electromagnetic torque increases along with the torque angle. For each sector, a specific voltage vector selection, changes stator flux magnitude and torque characteristics in a different way, as it show in Figure(2). [7].

3- RADIAL BASIS FUNCTION NEURAL NETWORK(RBFNN) MODEL

The name "*Radial Basis Function*" stems from the radial symmetry with respect to the center. The RBFNN constructed from input, hidden layers of normalized Gaussian activation

functions and output. The RBFNN based on the concept of the locally tuned and overlapping receptive field structure. RBFNN is widely used as a universal approximator in the area of nonlinear mapping due to its performance despite a simple structure [10].

Figure (3) shows a radial basis function neural network with i^{th} inputs. Notice that the expression for the net input of a (*radbas*) neuron is different from that of neurons in conventional NN. Here the net input to the (*radbas*) transfer function is the vector distance between its weight vector (W) and the input vector (*x*) multiplied by the bias (*b*). The (||dist||) box in this figure accepts the input vector (*x*) and the single row input weight matrix, and produces the dot product of the two. Figure (4) shows a plot of the (*radbas*) transfer function. The transfer function for a radial basis neuron (*radbas*) is:

$$radbas \; (n) = e^{-n^2} \qquad\qquad (8)$$

The radial basis function has a maximum of (1) when its input is (0). As the distance (||dist||) between (W) and (*x*) decreases, the output increases. Thus, a radial basis neuron acts as a detector that produces (1) whenever the input (*x*) is identical to its weight vector (W). The bias (b) allows the adjustment of the sensitivity of the (*radbas*) neuron.

For example, if a neuron had a bias of (0.1) its output is (0.5) for any input vector (*x*) at vector distance of (8.33) [0.833/b] from its weight vector (W) (see Figure (4)) [11][12].

4- DTC BASED ON RBFNN AS AN ESTIMATOR

Figure (5) shows the use of RBFNN for DTC system as an estimator instead of classical estimator. From this figure, the input data used in the trained RBF networks are two motor phase currents (i_{sa} , i_{sb}), the DC bus voltage (V_{dc}), and the inverter's switch positions (V_{sabc}), while the output data are the electromagnetic torque (T_e), stator flux (λ_s), and sector (S_k)[flux angle (θ_s)].

In order to achieve a satisfactory DTC system, the design, construction and training of a three different cases of the RBFNNs operates as flux and torque estimators of DTC system by using neural network toolbox in Matlab program as follow:

A- Case No.1:

RBFNN has six inputs include (i_{sa}, i_{sb}, V_{dc}, V_{sa}, V_{sb}, V_{sc}) and one output appose (T_e, λ_s, S_k) together, as it show in Figure (6).

B- Case No.2:

RBFNN has six inputs include (i_{sa}, i_{sb}, V_{dc}, V_{sa}, V_{sb}, V_{sc}), two outputs appose (λ_s, S_k) together and (T_e), as it show in Figure (7).

C- Case No.3:

RBFNN Network has six inputs include (i_{sa}, i_{sb}, V_{dc}, V_{sa}, V_{sb}, V_{sc}), three separated outputs; (T_e), (λ_s) and (S_k) as it show in Figure (8).

5- SIMULATION RESULTS

The simulation and training for RBFNN of the three different cases as estimators for stator flux and electromagnetic torque in the DTC driver of induction motor by using NN-tool box and Simulink in Mat lab program, gives the ability to compare their results at (no-load, half-load, full-load) with these of the classical one. The errors values of the three parameters for both estimators, the electromagnetic torques (T_e), stator fluxes (λ_s) and sectors (S_k) for the three case and the three different loading conditions are shown in Figures (9, 10, 11).
where (ET_e-Net, $E\lambda_s$-Net, ES_k-Net): Values of the difference between Estimated values from conventional DTC and that of the proposed one for electromagnetic torque (T_e), stator fluxes (λ_s) and sectors (S_k) respectively for the three Nets (Net1, Net2, Net3).

Table (1) shows the average values of errors of (T_e, λ_s, S_k) for the above three cases, and then the best case of the RBFNN has been chosen to be simulated.

where errors of (T_e, λ_s, S_k): are calculated taking into consideration that the spread constant is not the same for the different parameters, it has the following values for the three variable (T_e, λ_s, S_k) as (1, 0.5, 0.3) respectively.

Table (1) leads to a conclusion that Net-3 is the best choice because of its reduced error as compared with that of Net-1 and Net-2. This is because in this net, the training occurs separately and the output of each parameter is independent on the others, so this feature will leads to easiness in network operation and gives fastest response and accurate results.

A simulation was carried out to verify the RBFN estimator where the squirrel cage induction motor used in this case study is a 2.2Kw, 400V, 4pole, 50Hz, (T_{ref}= 14.6Nm).[see appendix-A].

Figures (12), (13) and (14) show performance accuracy of training RBFNN.

Also, value of spread constant is equal to (1) when RBFNN trained on data with different values for electromagnetic torque while value of spread constant of stator flux is equal to (0.5) and the sectors is equal to (0.3), at different values of load torque , this means, the network which has three independent outputs gives right results and exact.

6-CONCLUSION

The paper presents a proposed estimator suitable to work with the DTC system used as a speed controller for three-phase induction motor in order to reduce the torque ripples. The proposed RBFNN shows a good substitute to the conventional one due to its easiness in network operation and gives fastest response and accurate results. These features will help to reduce the torque ripples of the output torque.

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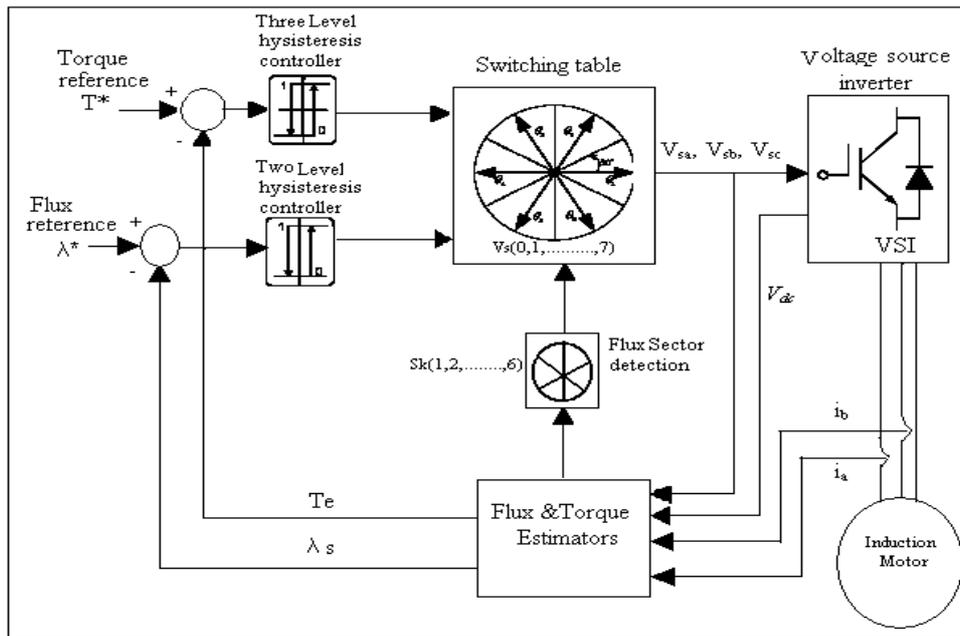12- H. Demuth, M.Beale, "Neural Network Toolbox for Use with Matlab" User's Guide, Version 4, 2000.
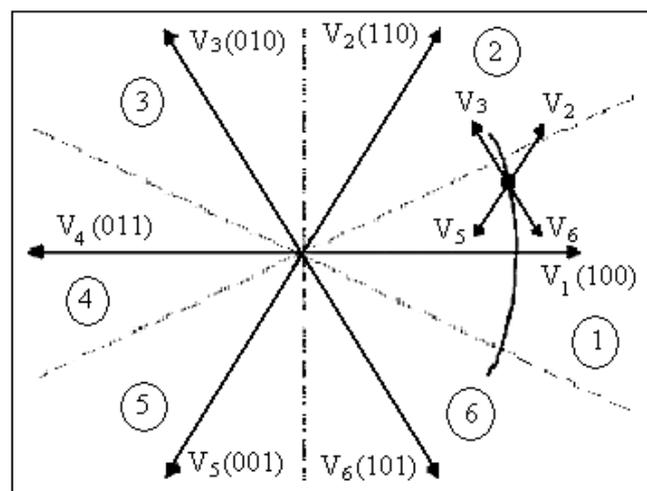
Fig.(1): Basic diagram of the DTC system [8].

Fig.(2): Voltage space vector and sector representation.
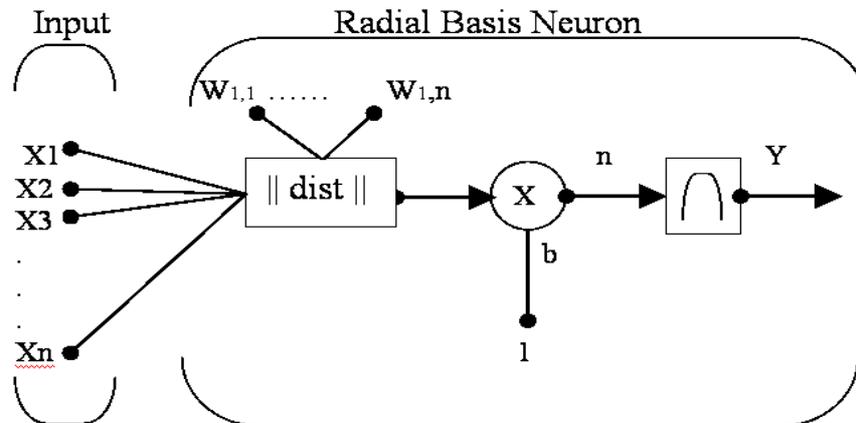
Fig.(3): Radial Basis Function Neural Network Model.
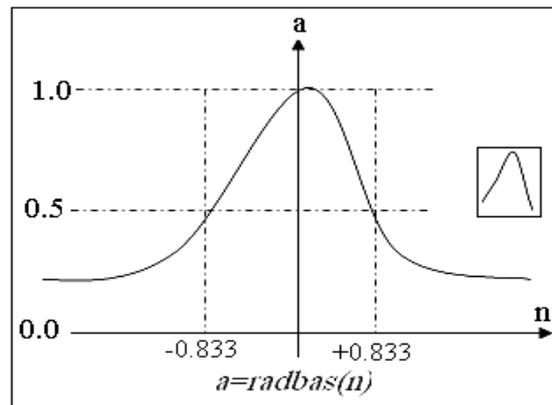
Fig.(4): Radial basis function.
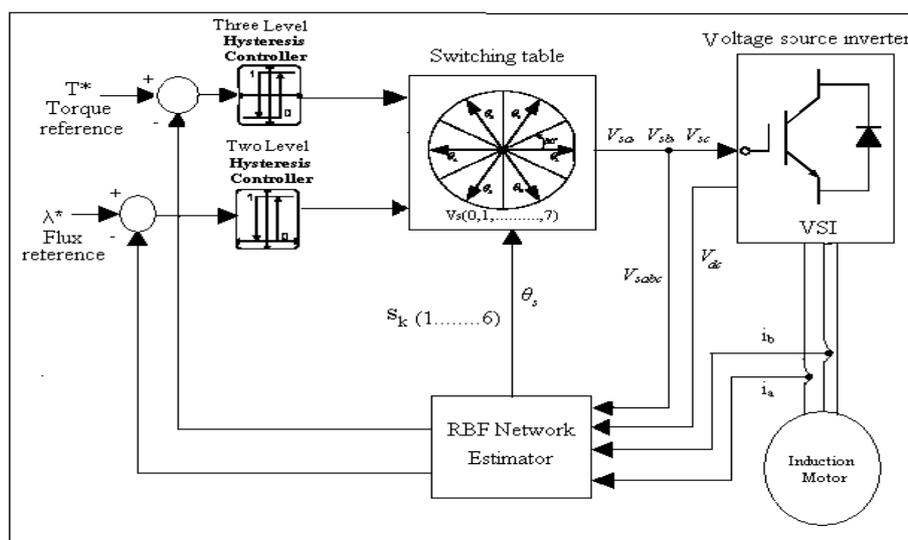
Fig.(5): Scheme of DTC based on RBFNN.
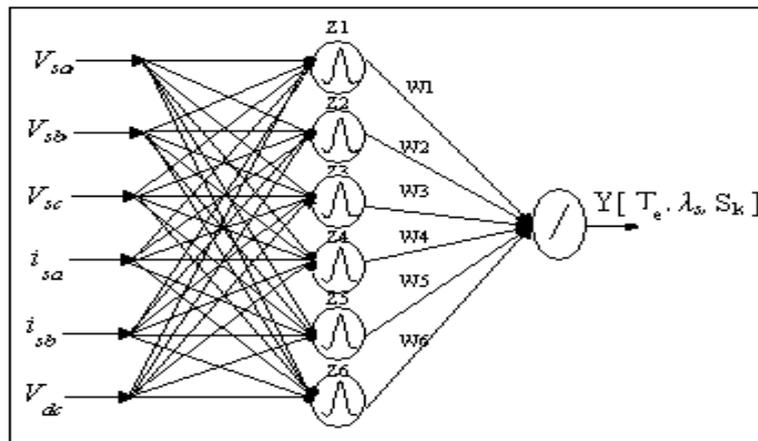
Fig.(6): RBFNN estimator for (Case No.1).
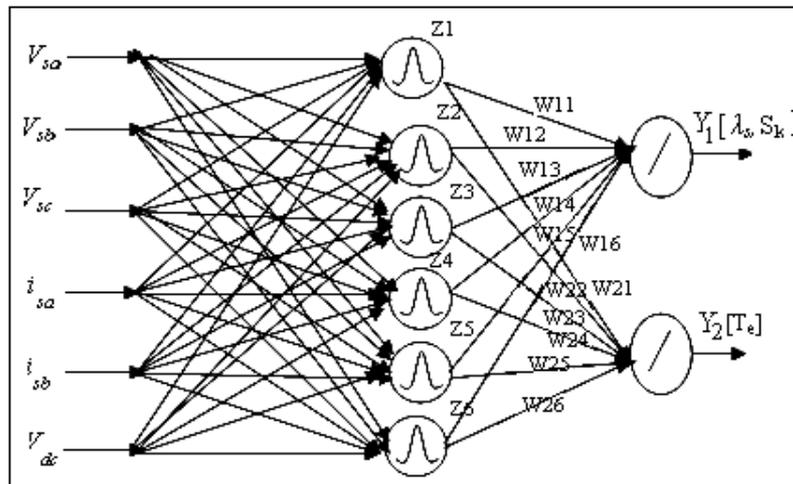
Fig.(7): RBFNN estimator for (Case No.2).
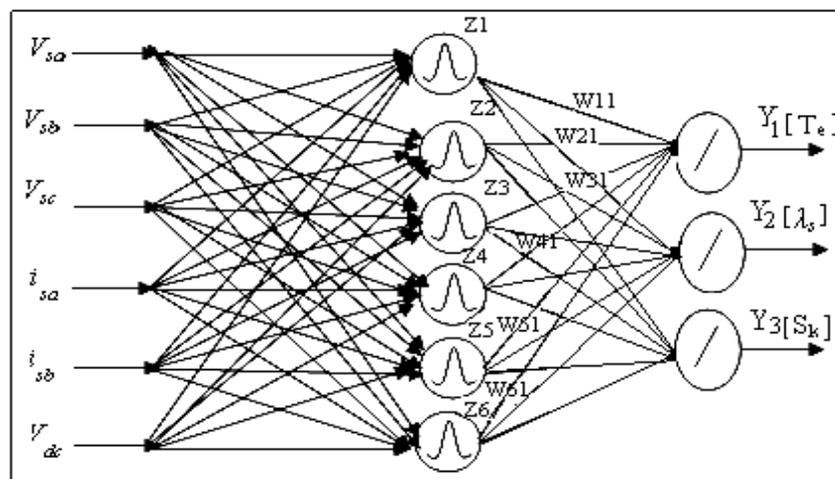
Fig.(8): RBFNN estimator for (Case No.3).
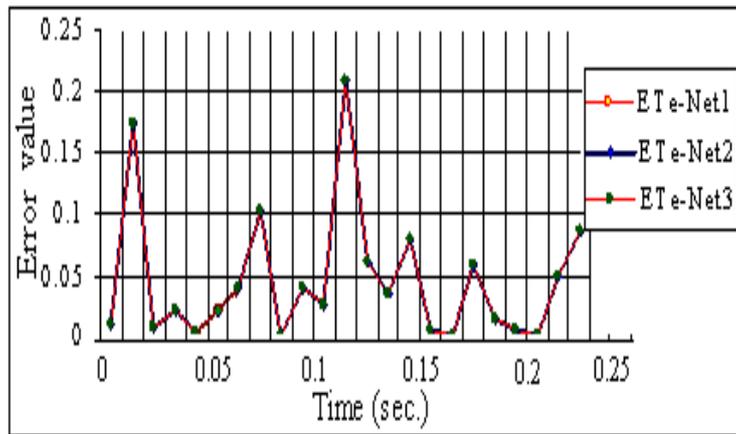
(a) Torque error values (ET$_e$) for Net1, Net2, Net3.
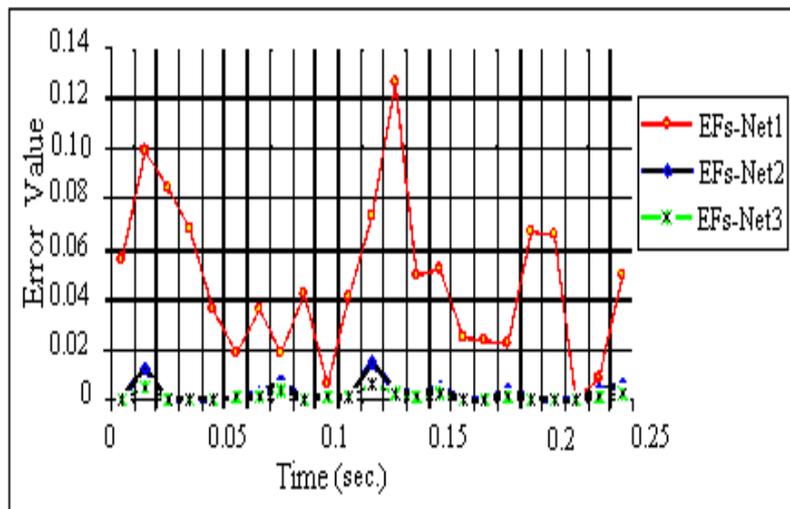
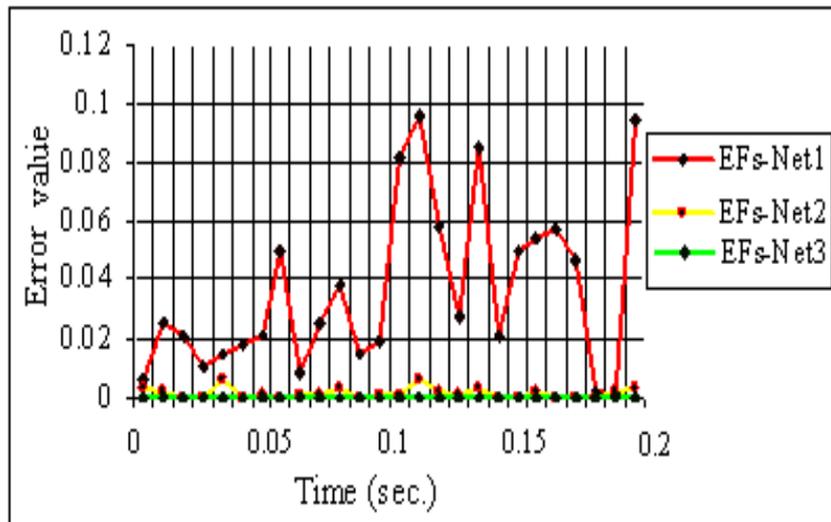

(b) Flux error values (EF$_s$) for Net1, Net2, Net3.
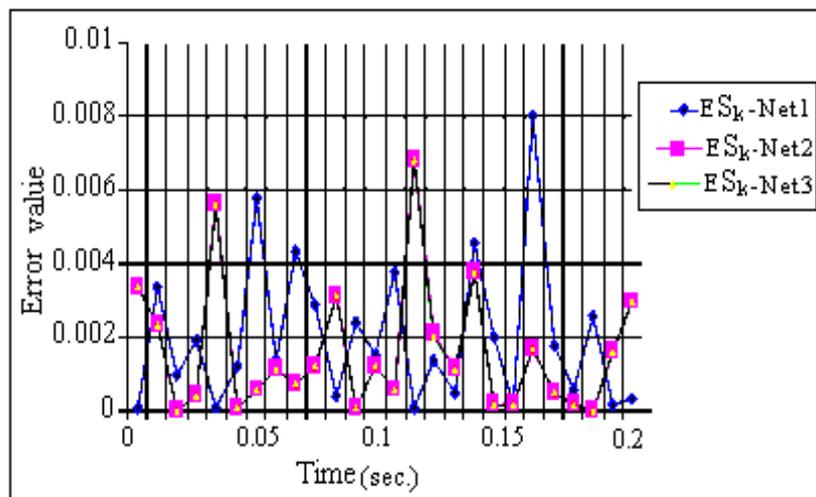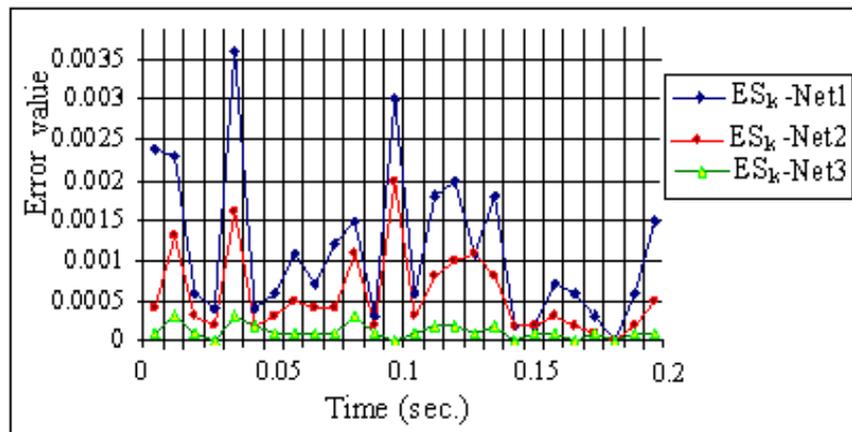

(c) Sector error values (ES$_k$) for Net1, Net2, Net3.

Fig.(9): No-load error values for the three cases (a, b, c).
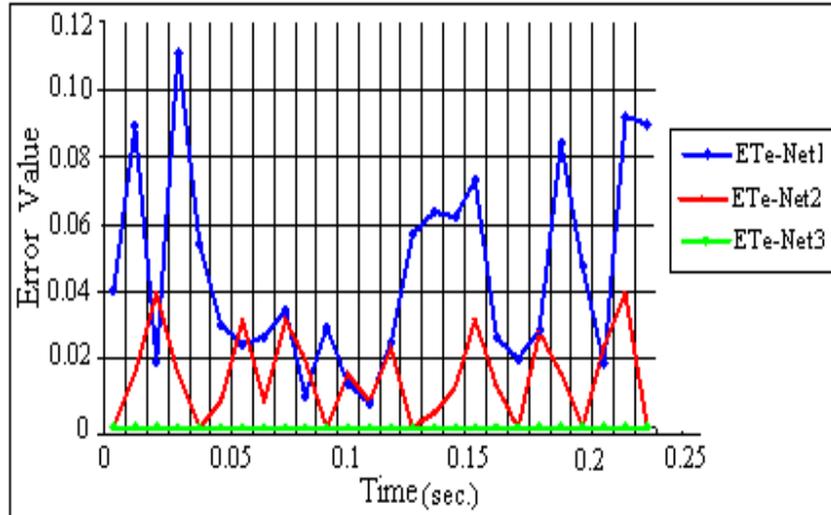
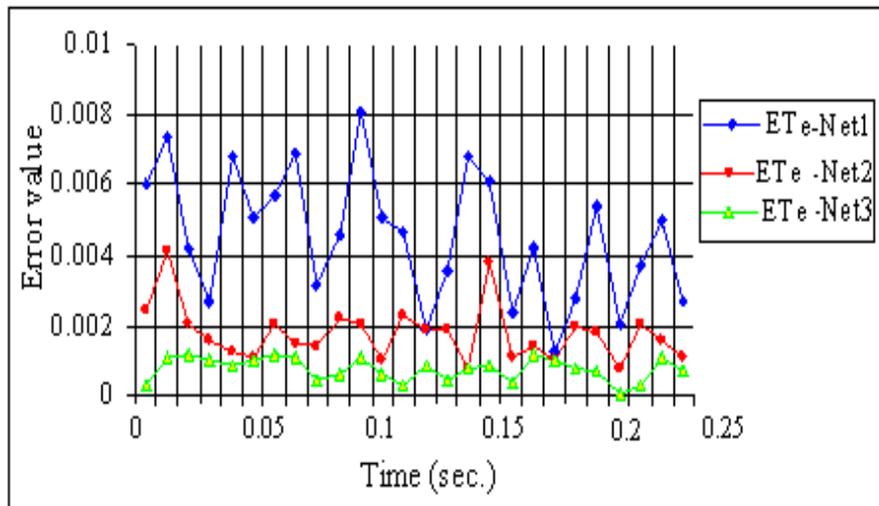(a)Torque error values (ET$_e$) for Net1, Net2, Net3.

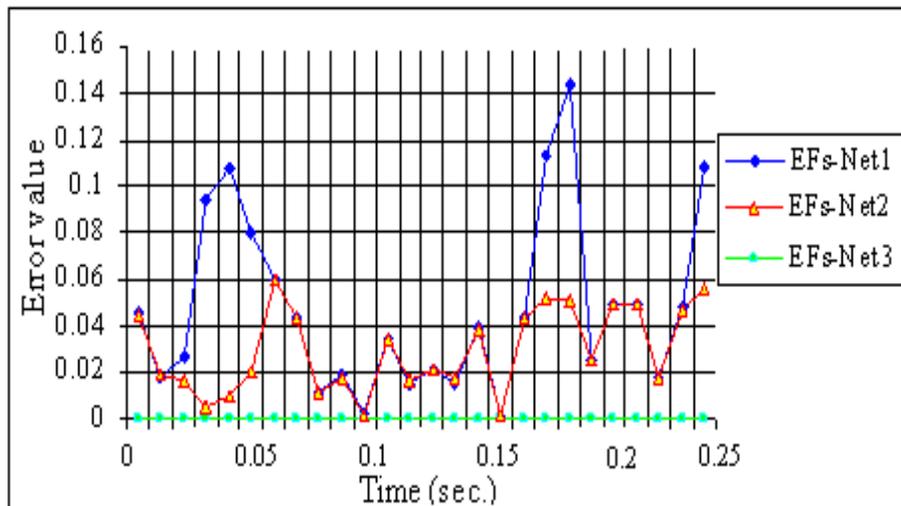

(b)Flux error values (EF$_s$) for Net1, Net2, Net3.

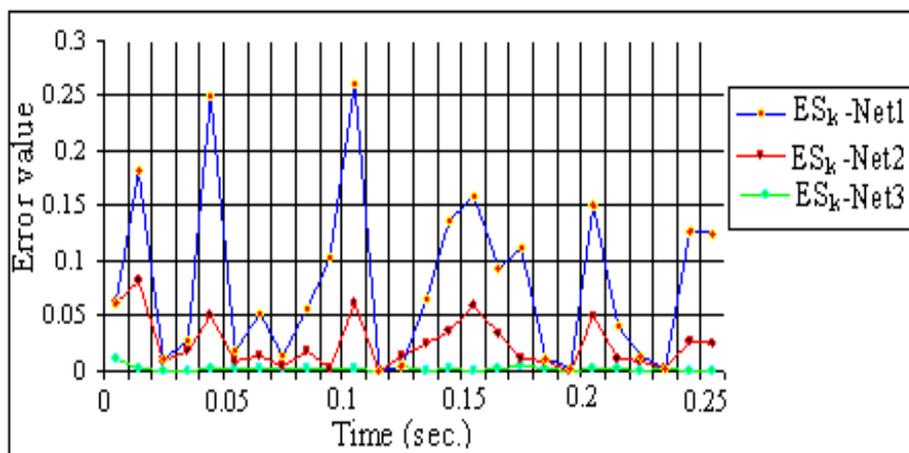
(c) Sector error values (ES$_k$) for Net1, Net2, Net3.

Fig.(10): Half-load error values for the three cases (a, b, c).

(a) Torque error values (ETₑ) for Net1, Net2, Net3.


(b) Flux error values (EFₛ) for Net1, Net2, Net3.


(c) Sector error values (ESₖ) for Net1, Net2, Net3.

Fig.(11): Full-load error values for the three cases (a, b, c).

Table (1)

| Average Error	No load	Half load	Full load
T_e -case1	0.0471	0.1327	0.0045
T_e - case 2	0.0471	0.0373	0.0018
T_e - case 3	0.04711	0.00034	0.00078
λ_s case -1	0.0462	0.0365	0.0474
λ_s case -2	0.0327	0.0016	0.0296
λ_s case -3	0.00143	0.00004	0.00010
S_k case -1	0.0020	0.0011	0.0877
S_k case -2	0.0016	0.0006	0.0246
S_k case -3	0.00596	0.00022	0.00225
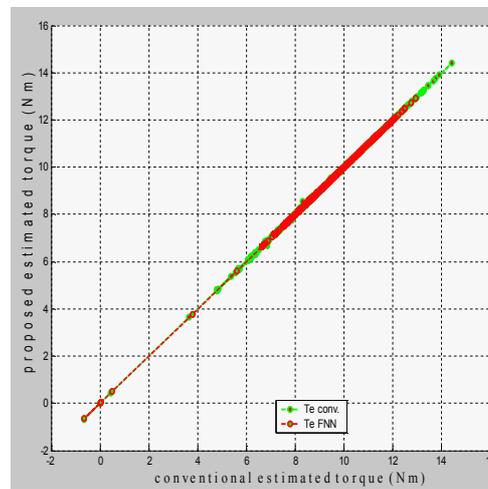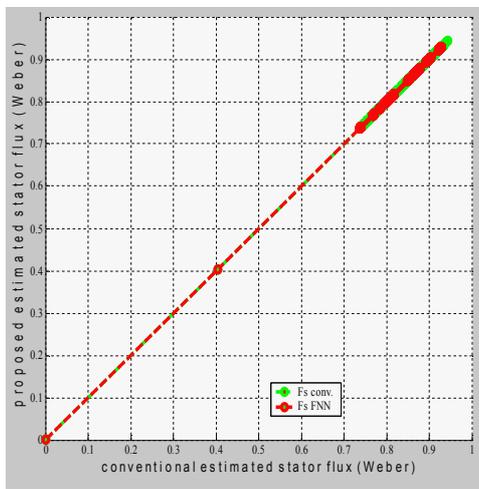
(a) Estimated stator flux.   (b) Estimated electromagnetic torque.
Fig.(12): Performance accuracy of training RBFNN at (T_L=14 Nm).
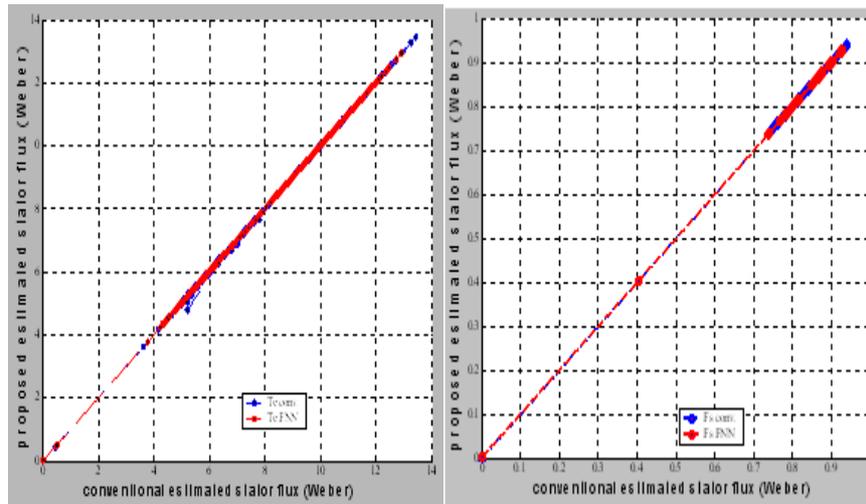
   (a) Estimated stator flux   (b) Estimated electromagnetic torque

Fig.(13): Performance accuracy of training RBFNN at (T_L=10 Nm).
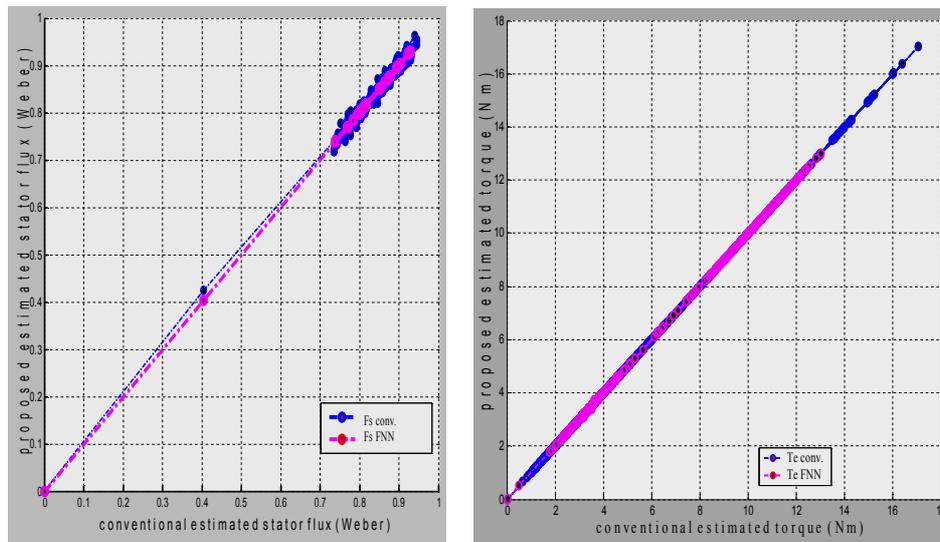
   (a) Estimated stator flux.   (b) Estimated electromagnetic torque.

Fig.(14): Performance accuracy of training RBFNN at (T_L=6 Nm).

APPENDIX-A

The 3-phase Squirrel–cage induction motor parameters are, 400 volt, 50 Hz, 2.2k watt shown in the table (A-1).

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Table (A-1): the motor parameters.

Parameters	Symbol	Value
Stator Resistance	r_s	367 Ω
Rotor Resistance	r_r	2.10 Ω
Stator Leakage Inductance	L_{ls}	0.0209 H
Rotor Leakage Inductance	L_{lr}	0.0209 H
Magnetizing Inductance	L_m	0.224 H
Number of Pole	p	4
Moment of Inertia	J	0.0155 kg.m^2
Viscous Friction Coefficient	β	0.0025 N.m.s
Rated Speed	ω_r	1430 r/min.
Rated Torque	T_{ref}	14.6 N.m
Rated Current per Phase	I_{rat}	5.0Amp.
Rated Power Factor	cosΦ	0.81

مخمن مقترح للسيطرة المباشرة على العزم لمحرك حثي باستخدام تقنية شبكة دالة الأساس الشعاعي العصبية

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الخلاصة

الغرض من هذا البحث هو استخدام مقترح لشبكة دالة الاساس الاشعاعي العصبية (RBFNN) كمخمن لقيم العزم الكهرومغناطيسي والفيض في نظام السيطرة المباشرة على العزم (DTC) الذي يستخدم كمسوق لمحرك حثي ثلاثي الطور و ذلك لتقليل التموجات الحاصلة في العزم المتولد. يتضمن هذا البحث ، تصميم وبناء و تُـدريّبُ ثـلاث حالاتٍ مختلفة لشبكة دالة الاساس الاشعاعي العصبية، حيث أن ثابت الانتشارالمعتمد عند تدريب الشبكة كان بقيم مختلفة لكل من العزم وفيض الساكن وموضع زاوية الفيض. تم اختيار الشبكة ذات المخارج المستقلة لانها تعطي افضل النتائج واستعملت في النظام المقترح للسيطرةِ المباشرةِ على العزم، أن الشبكة المختارة تدربت لقيم مختلفة مـن عـزم الحمـل باسـتخدام برنـامج إلــ(Matlab/NN-toolbox). تـم الحـصول علـى نتـائج المحاكـاة باسـتخدام برنـامج الــ(Matlab/Simulink). دقة اداء النظام المقترح استنتجت من التطابق في قيم خرج الشبكة المقترحة كمخمّن مع قيم خرج المخمّن التقليدي.