Speed Estimation of DTC Induction Motor Using Single Current Sensor Based on Wavenet Theory

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Abstract:

In this paper induction motor and its direct torque control are simulated and a speed estimator scheme based on wavenet (WN) theory has been developed and compared with the actual speed. The wavenet speed estimator inputs are a single line current and the state of the torque comparator output which are trained to follow the relationship between the motor current and the rotor speed. To ensure the validity of this scheme, the estimated speed is compared with a speed estimated from a conventional model reference adaptive system (MRAS). The operation of direct torque control (DTC) drive with the actual speed and the estimated wavenet speed as a feedback signal are simulated and compared. The results show that the wavenet method is effective for rotor speed estimation.

Keywords: Rotor Speed Estimation, Wavenet, DTC, Induction Motor.

استنباط السرعة في منظومة التحكم المباشر لعزم المحرك الحثي باستخدام حساس واحد للتيار اعتمادا على نظرية الشبكات العصبيه المويجية.

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الخلاصة

في هذا البحث تمت محاكاة المحرك الحثي ونظام التحكم المباشر لعزمه وبسطت طريقة استنباط السرعة اعتمادا على نظريه الشبكات العصبية المويجية، كما تم مقارنة هذه السرعة مع السرعة الحقيقية للمحرك. ان ادخالات مستنبط السرعة هي تيار الخط وحالة اخراج مقارن العزم حيث تم تدريبها للحصول على العلاقة بين تيار وسرعة المحرك. ولتأكيد امكانية مستنبط السرعة تمت مقارنة النتائج مع سرعة مستنبطة بواسطة نظام تقليدي (MRAS) . كما وتم في هذا البحث محاكاة النظام المذكور باستخدام السرعة الحقيقية مرة والسرعة المستنبطة مرة اخرى كأشارة راجعة لايجاد العزم المرجع مع مقارنة النتائج. اظهرت النتائج فعالية مستنبط السرعة المعتمد على نظرية الشبكات العصبية المويجية.

1- Introduction:

Speed estimation for senserless induction motor drives forms a huge research topic. Speed signal is required for close loop speed position control in both vector and scalar controlled drives. It is also required in indirect vector controlled in the whole speed range [1]. In direct torque control, speed signal is necessary to generate the reference torque signal. A mechanical speed encoder is undesirable in a drive because it adds cost and reliability problems besides the need for a shaft extension and mounting arrangement.

Several methods have been developed which allow eliminating mechanical speed encoder. The observer-based [2-6] and the MRAS-based [7-9] speed estimators seem the most promising ones. The MARS-based estimators are preferred because of their simplicity ease of implementation and their proven stability [10]. On the other hand it has disadvantage in the low speed area. Moreover it requires to sense all the terminal voltages and all the line currents . of the machine.

The application of neural network has been developed to estimate the rotor speed [11-12]. It is a popular method because it can identify approximate nonlinear function. However the estimated rotor speed could not precisely follow its target reference if the input vector parameter is only stator current [13]. Thus perfectible result could not be obtained. This method has also a few problems such as trapping into local minima and slow convergence.

Recently, wavelet neural network (wavenet) has been researched and applied, which combine the capability of artificial neural network for learning from processes and the capability of wavelet transform [14-17]. Wavelet can approximately realize the time frequency analysis using a mother wavelet. The mother wavelet has a square window in the time frequency space. The size of the window is freely variable by two parameters named dilation and translation. Thus, wavelet can identify the localization of unknown signals at any level. This application has been developed to estimate the rotor speed of a small power induction motor [13] for starting and load condition without containing speed reversal condition. Moreover two line currents are used as the inputs to the estimator. In this paper, two different schemes are investigated to estimate the rotor speed of direct torque controlled high power induction motor based on wavenet and MRAS system. A brief overview of the operation of each scheme is presented followed by results from Mathlap simulink simulation. A single line current and the state of the torque comparer output are applied as the inputs to the wavenet identifier. The simulation results show that the drive performance is perfectible using the wavenet estimated speed as a feedback signal compared with the corresponding drive using the actual speed as a feedback signal.

2- Wavenet Structure and Learning Algorithm:

2.1- Wavelet Transform

Wavelet is a little wave of a least minimum oscillation sieving with special satisfaction condition. The wavelet function is defined as follows:

$$h_{a,b}(t) = \frac{1}{\sqrt{|a|}}\ h\left(\frac{t-b}{a}\right) \qquad (1)$$

The corresponding families of dilated and translated wavelet are defined as follows

$$\left[\ h_{m,n}(x) = a^{\frac{2}{m}}\ h(a^{-m}\ x - nb),\ (m,n) \in z^2\ \right] \qquad (2)$$

where $\{h_{m,n}(x)\}$ is called discrete daughter wavelets, $(m,n) \in z^2$ represent the successes resolution level, a and b are the dilation and translation respectively.

Any function $h(x) \in L^2(R)$ (the set of all square integrable or a finite energy function) that satisfy the admissibility condition;

$$\int_R \frac{|h(\omega)|^2}{|\omega|}\, d\omega < \infty \qquad (3)$$

is defined as a wavelet function, where $h(w)$ is the Fourier transform of $h(x)$. The wavelet transform is defined as follows [18].

$$\langle h_{m,n}, f \rangle = \int h_{m,n}(t)\ f(t)\ dt \qquad (4)$$

and by using a linear combination of discrete wavelet basis function, equation (4) yields to:

$$f(t) = \sum \langle h_{m,n}, f \rangle\ h_{m,n}(t) \qquad (5)$$

The wavelet transform is widely applied to the analysis of time and frequency space. Therefore it is useful for the analysis of non-stationary signals and the learning of the nonlinear functions.

2.2 Wavenet Structure

Wavenet is a multi-layer feedforward network based on wavelet transform. The structure of wavenet is similar to that of the feedforward network except that the sigmoid function were replaced by wavelet basis function [19] as illustrated in Fig.(1).

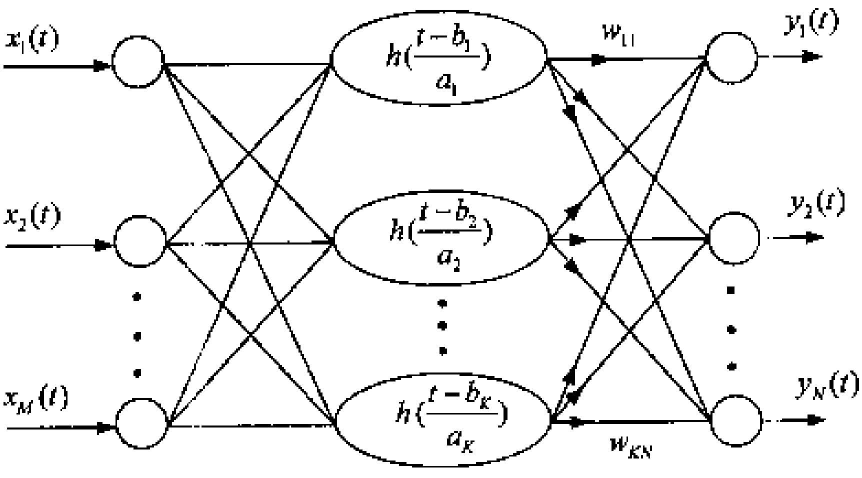

Fig.(1) The structure of wavenet.

The wavenet structure can be expressed by the following formula:

$$y_i = g\left[\sum_{k=1}^{K} w_{ki} \sum_{m=1}^{M} X_m(t)\, h_m((t-b_k)/a_k)\right] \quad (6)$$

where $X_m\,(m=1,2,\ldots,M)$ is the input for the m-th training vector $X(t)$, $y_i(i=1,2,\ldots,N)$ is the output for the i-th training vector $Y(t)$, M is the number of nodes of the input layers, K is the number of nodes of hidden layers, w_{ki} is the weight between the k-th node of the hidden layer and the i-th node of the output layer, $h(t)$ is the mother wavelet and g is the nonlinear function.

2.3 Learning Algorithm

In order to determine the adjustable weighs $w_{ki}(k=1,2,\ldots,K, n=1,2,\ldots,N)$ and the adjustable parameters a_k and b_k, a least mean square (LMS) energy minimizing function can be applied [19]:

$$E = \frac{1}{2}\sum_{l=1}^{q}\sum_{i=1}^{N}[e_i^{\,l}(t)]^2 \quad (7)$$

where $e_i^{\,l}(t)=F_i^{\,l}(t)-y_i^{\,l}(t)$, q and $F_i^{\,l}(t)$ are the number of training samples and the desired value of $y_i^{\,l}(t)$. To minimize the energy error E, a method of steepest descent which requires the gradients $\frac{\partial E}{\partial w_{ki}}, \frac{\partial E}{\partial a_k}$ *and* $\frac{\partial E}{\partial b_k}$ is used for updating the incremental changes to each parameter w_{ki}, a_k, *and* b_k. The gradients of E are.

$$\frac{\partial E}{\partial w_{ki}} = -\sum_{l=1}^{q}\sum_{i=1}^{N}\sum_{m=1}^{M} e^l(t)\, X^l(m)\, h(\tau) \quad (8)$$

$$\frac{\partial E}{\partial b_k} = -\sum_{l=1}^{q}\sum_{i=1}^{N}\sum_{m=1}^{M} e^l(t)\, X^l(m)\, w_{ki}\, \frac{\partial h(\tau)}{\partial b_k} \quad (9)$$

$$\frac{\partial E}{\partial a_k} = -\sum_{l=1}^{q}\sum_{i=1}^{N}\sum_{m=1}^{M} e^l(t)\, X^l(m)\, w_{ki}\,\tau \frac{\partial h(\tau)}{\partial b_k} = \tau\frac{\partial E}{\partial b_k} \quad (10)$$

where $\tau = \frac{t-b_k}{a_k}$. The updated weighs w_{ki} and the parameters a_k and b_k are:

$$w_{ki}(n+1)=w_{ki}(n)-b_w\frac{\partial E}{\partial w_{ki}}+a_w\Delta w_{ki}(n) \quad (11)$$

$$a_k(n+1)=a_k(n)-b_a\frac{\partial E}{\partial a_k}+a_a\Delta a_k(n) \quad (12)$$

$$b_k(n+1)=b_k(n)-b_b\frac{\partial E}{\partial b_k}+a_b\Delta b_k(n) \quad (13)$$

where b_w, b_a, and b_b are steps size, a_w, a_a, and a_b are the forgetting factors which are variable factors and can greatly reduce the number of iterations for convergence.

3. Direct Torque Controlled Induction Motor and MRAS Drive

3.1 Induction Motor Model

Based on the theory of induction motor in the stationary reference frame d-q axis,
The voltage (v) and the flux linkage ($\bar{\lambda}$) state equations are [1]:

$$\begin{bmatrix} v_{ds} \\ v_{qs} \\ v_{dr} \\ v_{qr} \end{bmatrix} = \begin{bmatrix} R_s+L_sP & 0 & L_mP & 0 \\ 0 & R_s+L_sP & 0 & L_mP \\ L_mP & 0 & R_r+L_rP & 0 \\ 0 & L_mP & 0 & R_r+L_rP \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \end{bmatrix} \quad (13)$$

$$\begin{bmatrix} \lambda_{ds} \\ \lambda_{qs} \\ \lambda_{dr} \\ \lambda_{qr} \end{bmatrix} = \begin{bmatrix} L_{1s}+L_m & 0 & L_m & 0 \\ 0 & L_{1s}+L_m & 0 & L_m \\ L_m & 0 & L_{1r}+L_m & 0 \\ 0 & L_m & 0 & L_{1r}+L_m \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \end{bmatrix} \quad (14)$$

where v_{ds}, v_{qs}, i_{ds}, i_{qs}, R_s, L_s, and L_m, are the dq-axis stator voltages, stator currents, stator resistance, stator self inductance and mutual inductance between the stator and the rotor winding, respectively. v_{dr}, v_{qr}, i_{dr}, i_{qr}, R_r, L_r, and P are the dq-axis rotor voltages, rotor currents, rotor resistance, rotor self inductance and derivative operator, respectively. L_{1s} and L_{1r} are the stator and rotor leakage inductances respectively.

The electromagnetic torque (T_e) equation for the induction motor can be expressed as follows:

$$T_e=\frac{3\,p\,L_m}{2\sigma\,L_s\,L_r}\,\bar{\lambda}_s\;j\;\bar{\lambda}_r \quad (15)$$

where p, σ, j are the number of pair poles, leakage factor and the j operator respectively. The electromagnetic dynamic equation describing the mechanical model of the induction motor is:

$$T_e - T_L = J\;P\omega_m + \beta\omega_m \quad (16)$$

where T_L, J, β and ω_m are the load torque, moment of inertia, friction coefficient and the mechanical speed.

Equations (13)-(16) represent the dynamic mathematical model for induction motor in two phase stationary coordinates

3.2 DTC Scheme for Induction Motor

Direct torque control is one of the advanced control schemes for ac drives. It is characterized by simple control algorithm, easy digital implementation and robust operation [20]. Figure (2) shows a typical block diagram of a DTC based induction motor drive.

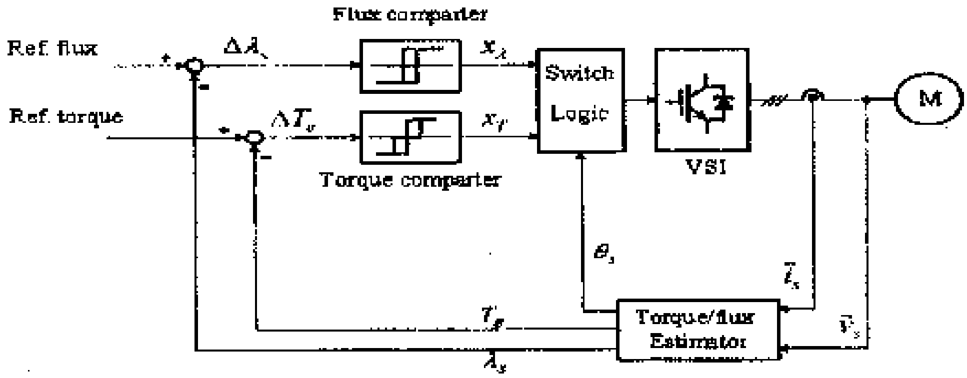

Fig. (2) Block diagram of DTC scheme.

The stator flux reference is compared with the estimated flux and the difference is sent to flux comparator of two outputs 0 and 1. The torque reference is compared with the estimated one and the difference is sent to torque comparator of three outputs -1, 0 and 1. The output of the later is 0 or 1 for a certain speed direction. For the opposite direction the output of this comparator is 0 or -1. The output of the flux and torque comparators are sent to a switching logic unit for proper selection of the voltage vector of a two level voltage source inverter (VSI).

3.3 Model Reference Adaptive System (MRAS)

The rotor speed of the induction motor can be estimated by the model referencing adaptive system. Figure (3) shows the way of speed estimation by MRAS.

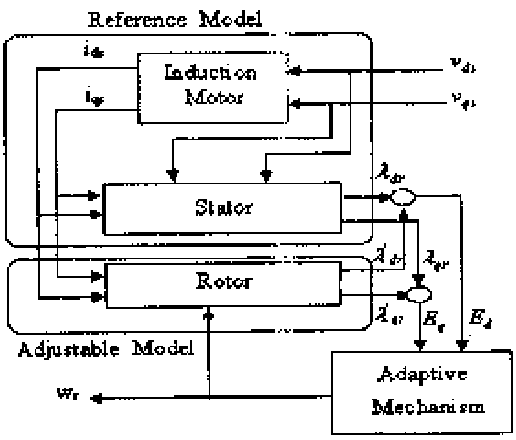

Fig.(3) The structure of MRAS speed estimator

Two independent observers are used, one based on equation (17), which does not involve the rotor speed (w_r) and the other on equation (18) as follows [1]:

$$\begin{bmatrix} \frac{d}{dt}\lambda_{dr} \\ \frac{d}{dt}\lambda_{qr} \end{bmatrix} = \frac{L_r}{L_m}\left\{ \begin{bmatrix} v_{ds} \\ v_{qs} \end{bmatrix} - \begin{bmatrix} R_s+\sigma L_s S & 0 \\ 0 & R_s+\sigma L_s S \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} \right\} \tag{17}$$

$$\begin{bmatrix} \frac{d}{dt}\lambda_{dr} \\ \frac{d}{dt}\lambda_{qr} \end{bmatrix} = \begin{bmatrix} -\frac{R_r}{L_r} & -w_r \\ w_r & -\frac{R_r}{L_r} \end{bmatrix} \begin{bmatrix} \lambda_{dr} \\ \lambda_{qr} \end{bmatrix} + L_m \frac{R_r}{L_r} \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} \tag{18}$$

The error between the states of the two models is used to drive an adaptation algorithm in order to estimate the rotor speed. The state error equations are nonlinear for which hayperstability is assumed when Popov criterion is satisfied for the nonlinear feedback. The estimated rotor speed has the following structure:

$$w_r = \Phi_2 + \int_0^t \Phi_1\, dt = k_1 E + \int_0^t k_2 E\, dt \tag{19}$$

where Popov's inequality is satisfied for the following functions:

$$\Phi_1 = k_2(E_q \hat{\lambda}_{dr} - E_d \hat{\lambda}_{qr}) = k_2(\lambda_{qr}\hat{\lambda}_{dr} - \lambda_{dr}\hat{\lambda}_{qr}) = k_2 E \tag{20}$$

$$\Phi_2 = k_1(E_q \hat{\lambda}_{dr} - E_d \hat{\lambda}_{qr}) = k_1(\lambda_{qr}\hat{\lambda}_{dr} - \lambda_{dr}\hat{\lambda}_{qr}) = k_1 E \tag{21}$$

4. Speed Estimation Algorithms

As the observation of the speed is necessary for any drive, it is also necessary to generate the torque reference signal in DTC drive. In this work the speed is observed from different sources. The actual measured speed is taken as a reference speed and used to compare with the estimated speed from the following estimators:

4.1 Wavenet (WN) Speed Estimator

The wavenet speed estimator has been trained off-line as estimation model into the direct torque control system. Input learning sample is a single line current and the output is the rotor speed. A three neurons are used in the hidden layer and the Mexican hat function is selected as a mother wavelet function as follows:

$$h(\tau)=\frac{2}{\sqrt{3}}\,\pi^{\frac{1}{4}}\,(1-\tau^{2})\,e^{-\frac{\tau^{2}}{2}} \qquad (22)$$

It must be noted that the input samples are normalized using the following equation:

$$X_{nor.} = (X - X_{min.}) / (X_{max.} - X_{min.}) \qquad (23)$$

and the output is demoralized using the following equation:

$$Y = Y_{nor.} * (Y_{max.} - Y_{min.}) + Y_{min.} \qquad (24)$$

The model of the wavelet estimator which has been used for training is shown in Fig. (4).

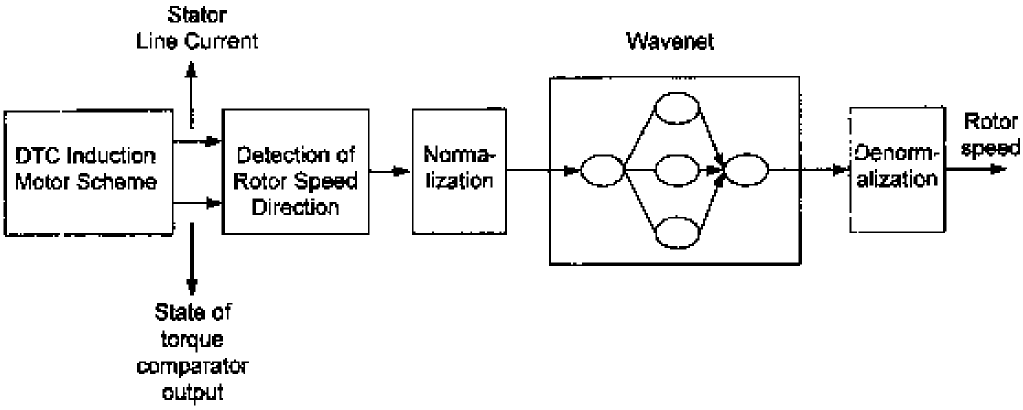

Fig.(4) Wavenet model for speed estimation.

The purpose of learning is to update the weighs w_{ki} and the parameters a_k and b_k. The training algorithm is listed below:

1- Initiate all the network parameters w_k, a_k and b_k with smaller numbers at random and calculate the value of the output from equation (6).
2- Set the output positive if the state of the torque comparator is 0 or 1 and set it negative if the torque comparator output is 0 or -1.
3- Set initial step and calculate the new iteration point then calculate the energy error from equation (7).
4- If the energy error turns big, update the parameters w_{ki}, a_k and b_k using equations (11-13) and do the forgetting factors equal its original value times ζ where ζ is a constant between 0 and 1.
5- Else, update the parameters w_{ki}, a_k and b_k using equations (11-13) and do the forgetting factors equal its original value times η where η is a constant bigger than 1.

6- Calculate the next iteration point and repeat until the system energy error is reduced to a satisfied value.

4.2 MRAS Speed Estimator

The MRAS estimation principle is illustrated in the previous section. Inputs to the estimator are three terminal voltages and three input currents to the motor while the output is the rotor speed. A Park transformation is used to produce the two-axis d-q voltages and currents. Mathlap simulink deals with integration more than derivation [21]. Therefore integrating the two sides of equation (17) is useful to eliminate the derivate inside this equation.

After the integration, equation (17) yields to:

$$\lambda_{dr}=\frac{L_r}{L_m}\left[\ \int v_{ds}\,dt-R_s\int i_{ds}\,dt-\sigma L_s i_{ds}\ \right] \qquad (23)$$

$$\lambda_{qr}=\frac{L_r}{L_m}\left[\ \int v_{qs}\,dt-R_s\int i_{qs}\,dt-\sigma L_s i_{qs}\ \right] \qquad (24)$$

Equations (18),(19),(22) and (23) represent the MRAS speed estimator system.

5. Simulation Results

Figure (5) shows the Matlab/Simulink simulation for DTC induction drive. The torque reference is generated by a speed controller that compares the reference rotor speed with the detected or estimated rotor speed.

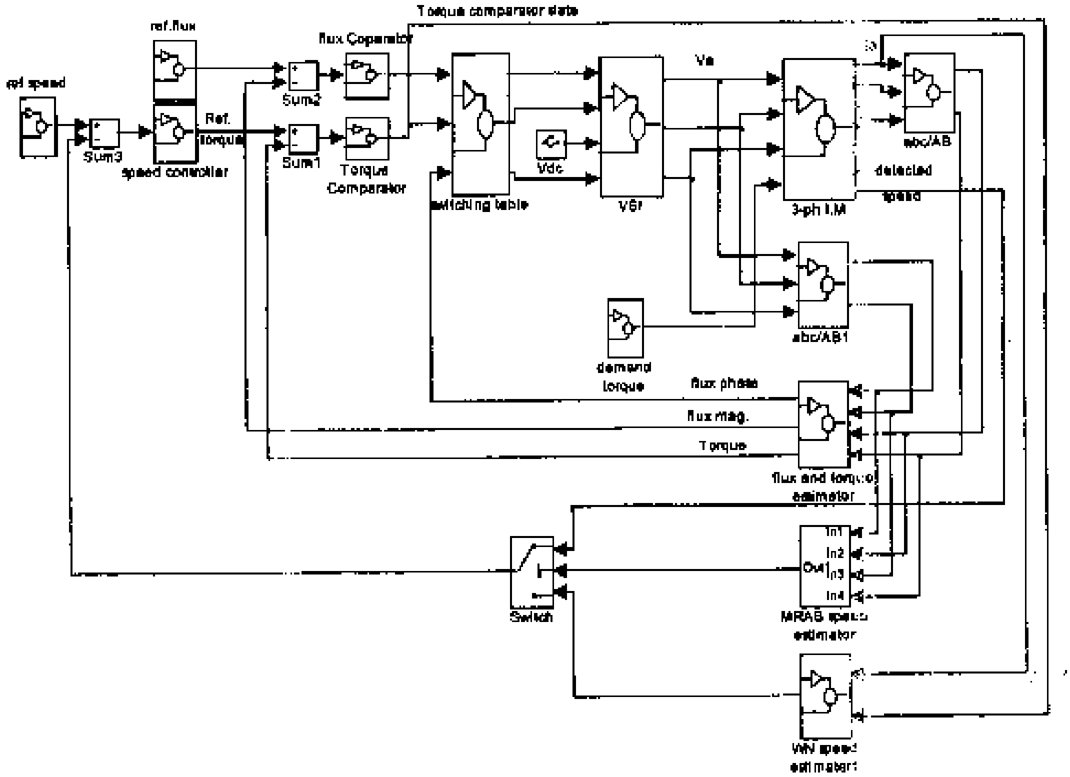

Fig. (5) Mathlap simulink block diagram for DTC induction motor drive.

The motor parameters used in the simulation are listed in the Appendix. In order to compare as fairly as possible the estimation techniques considered in this paper, the following conditions have been provided:

1- Same speed change conditions and;

2- Same load change conditions.

Figure (6) shows actual, MRAS estimated and WN estimated rotor speed during starting while Fig. (7) shows the same results for no-load speed reversal. The rotor speed identified by wavenet speed estimator can adaptively follow the true rotor speed. It shows higher dynamical following performance rather than MRAS speed estimator. At low speed, the rotor flux synthesis based on reference model in MRAS system is difficult to implement because of the pure integration of the voltage signals. Moreover, the estimation accuracy can be good if machine parameters are considered as constant.

A simulation was carried out to verify the function of the WN speed estimation. When the DTC drive starts for 4 sec, the load torque changes directly from zero to full load (7490 N.m) and decrease to 1000 N.m at 6 sec. Figure (8) and (9) show the load torque and the load current for the drive when the feedback speed signal is taken from the detected and the WN estimated speed. Figure (10) shows the torque and current error between the two states. It can be shown that the wavenet is valuable for rotor speed estimation and can replace the speed sensor of the DTC drive and realize the control of the drive without speed sensor.

6. Conclusions

A direct torque controlled induction motor was designed and simulated using Matlab/Simulink. A rotor speed estimator based on wavenet theory has been evaluated and compared with classical MRAS speed estimator. The data for training the WN estimator is extracted from a single line current with the detected speed as a feedback signal to achieve the operation for all changes in the drive operations.

The WN speed estimator performs well under DTC drive for starting, speed reversal and load conditions. Therefore it can lead to an improvement in the performance of speed sensorless drives. The WN speed estimator was presented in a way that will contribute to a better understanding of the wavenet theory applications to motion control.

7. Appendix

The nameplate and the parameters of the three phase induction motor used for simulation purpose are given in Table (1).

Table (1): Motor nameplate and parameters

Motor Ratings		Motor Parameters	
Rated Power	1250hp	Stator Resistance	0.21 Ω
Rated Voltage	4160V	Rotor Resistance	0.146 Ω
Rated Torque	7490N.m	Stator Leakage inductance	5.2 mH
Rated Stator Flux	9Wb	Rotor Leakage inductance	5.2 mH
Rated Current	150A	Magnetizing Inductance	0.155 H

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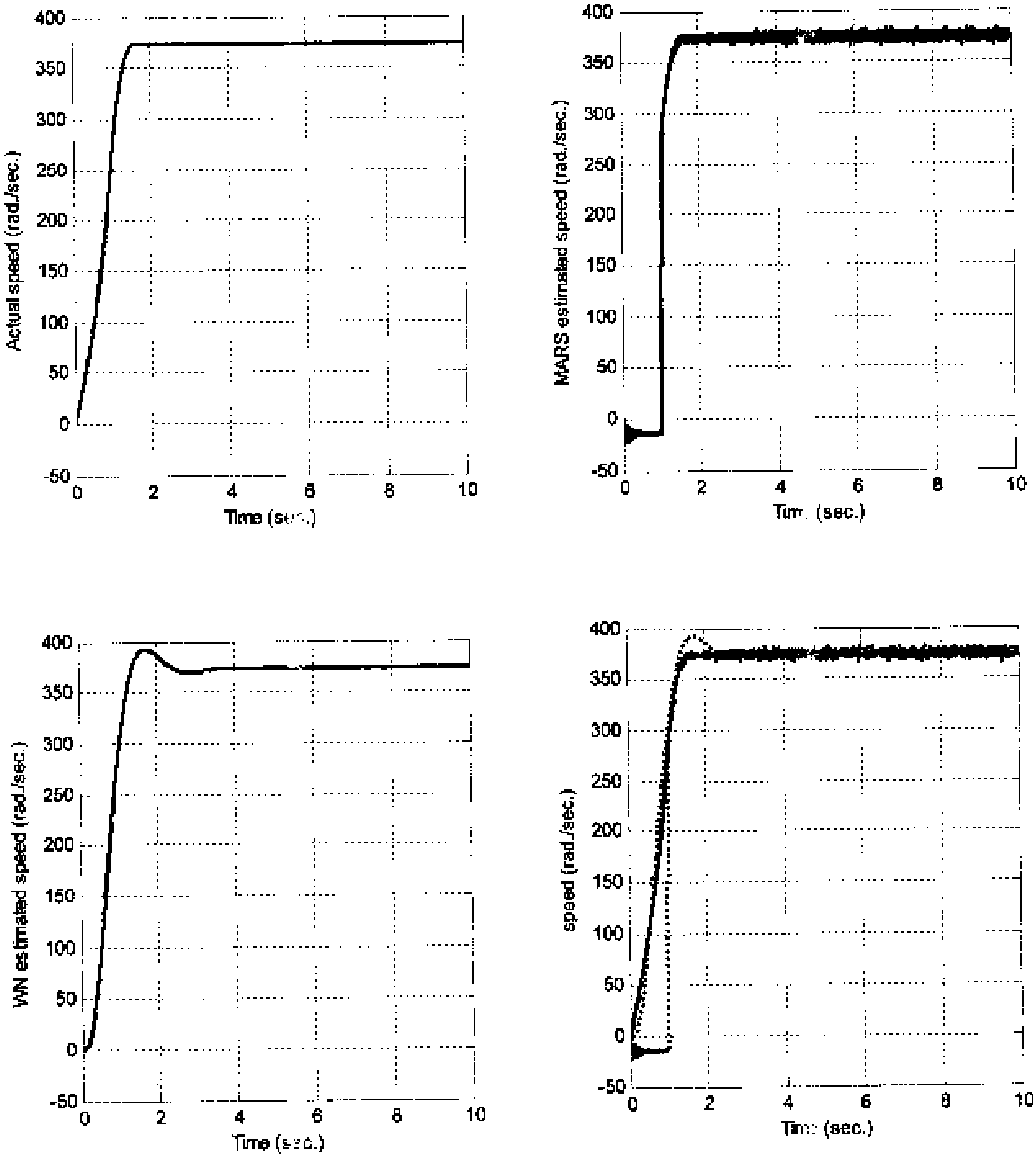


Fig. (6) Speed during starting, (a) actual speed, (b) MARS estimated speed, (c) WN estimated speed, (d) the three-speed together.

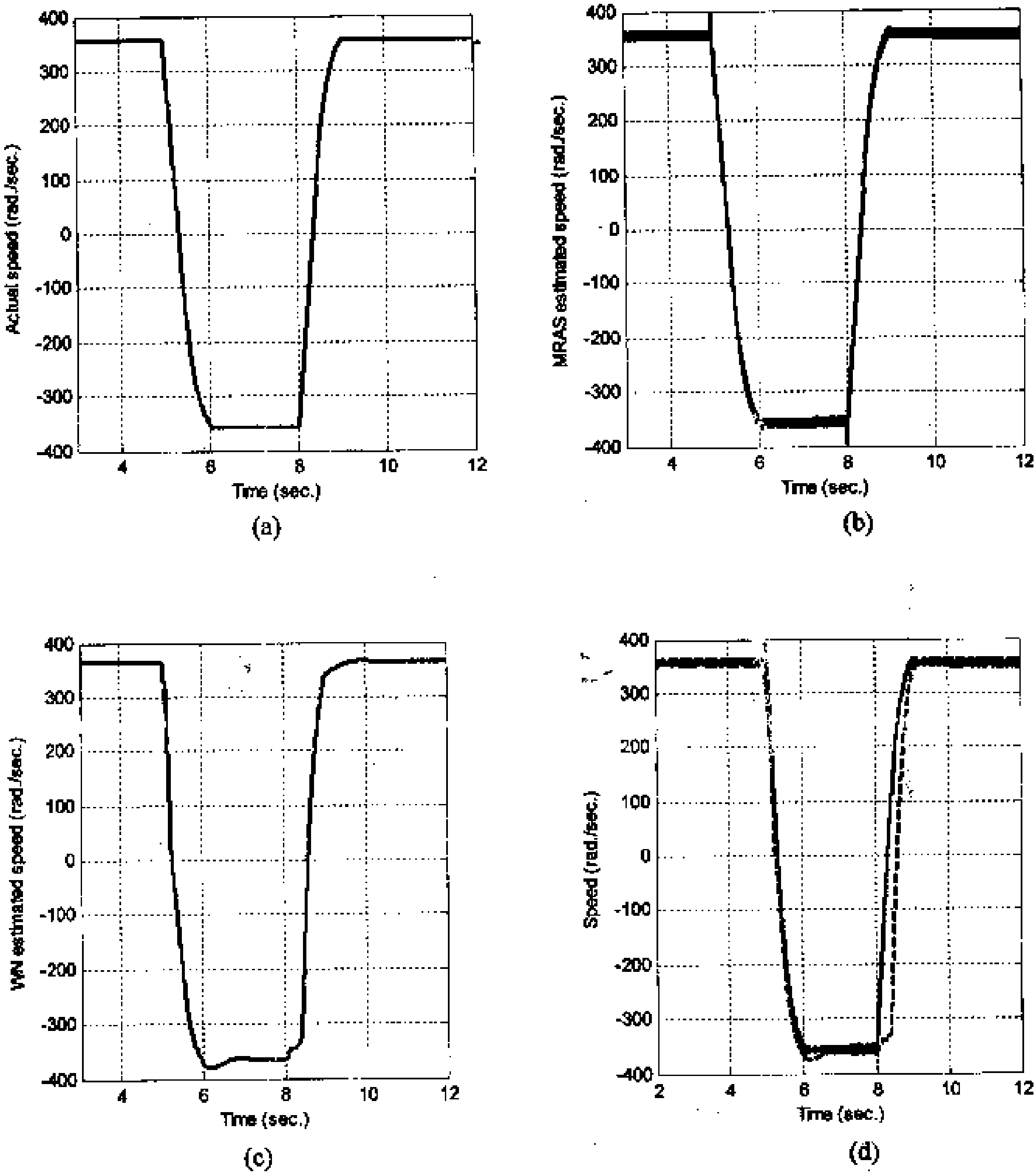
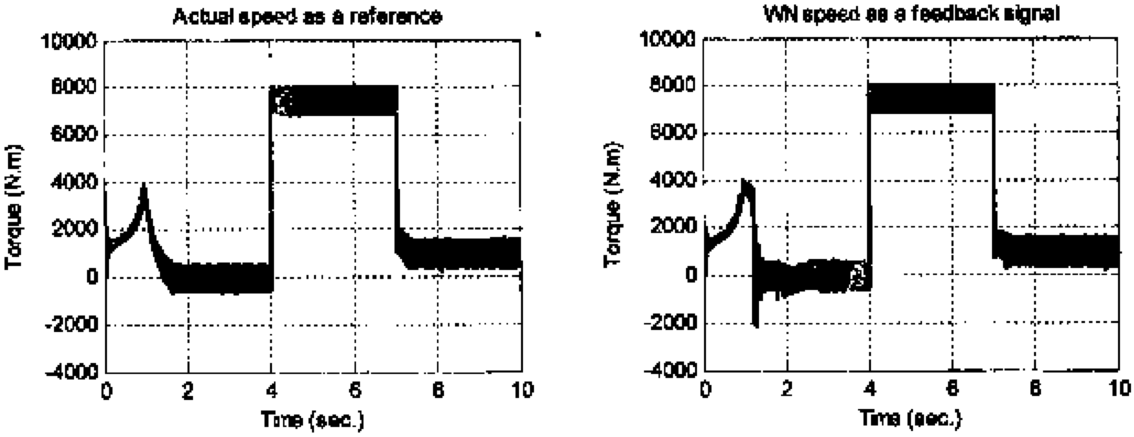
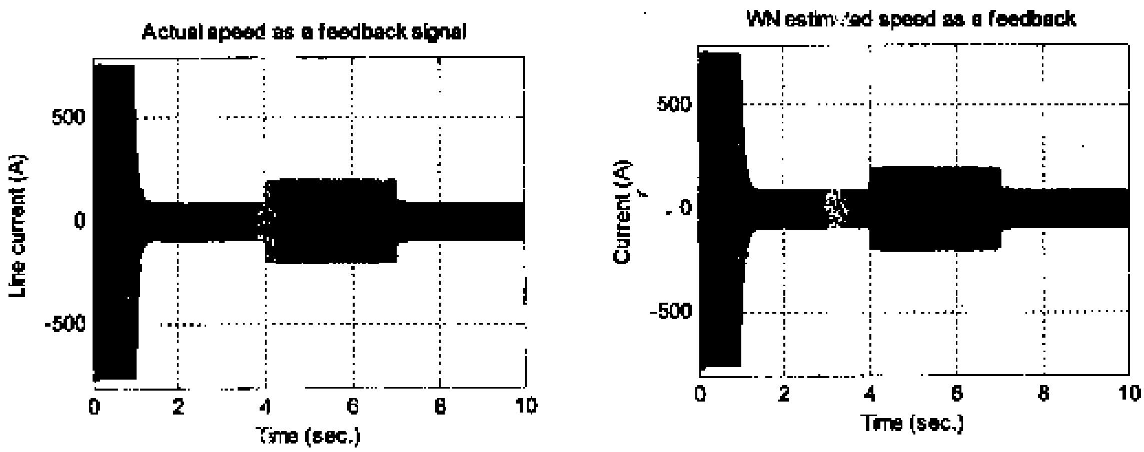


Fig.(7) Speed for reverse direction, (a) actual speed, (b) MARS estimated speed, (c) WN estimated speed, and (d) the three-speed together.



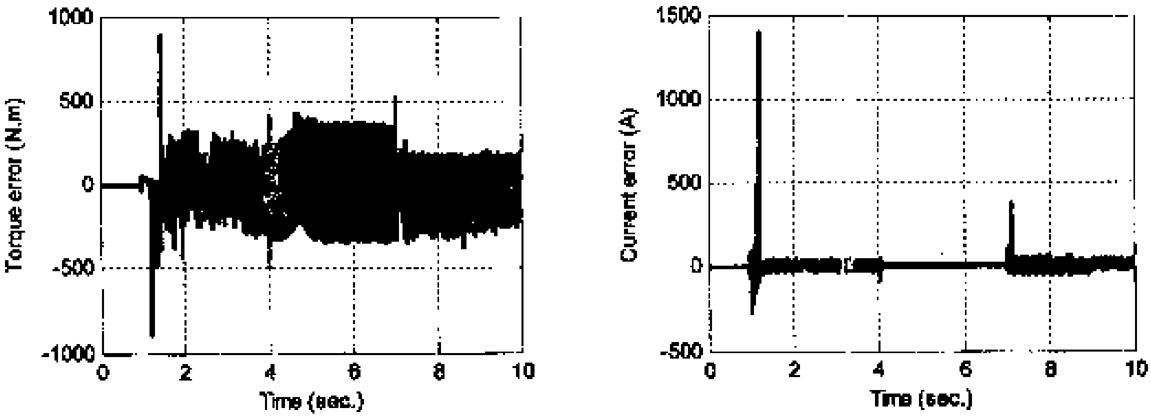
(a) (b)

Fig. (8) Torque response. (a) actual speed as a feedback signal, (b) WN estimated speed as feedback signal



(a) (b)

Fig. (9) Line current. (a) actual speed as a feed back signal, (b) WN estimated speed as a feedback signal.



(a) (b)

Fig. (10). Error between the two drives. (a) Torque error, (b) current error.