Sensorless Control of Induction Motor Drives at Very Low and Zero Speed Using Neural Network Flux Observers

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***Abstract*—A new method is described which considerably improves the performance of rotor flux-MRAS based sensorless drives in the critical low and zero speed region of operation. It is applied to a vector controlled induction motor drive and experimentally verified. The new technique uses an Artificial Neural Network as a rotor flux observer to replace the conventional voltage model. This makes the reference model free of pure integration and less sensitive to stator resistance variations. This is a radically different way of applying Neural Networks to MRAS schemes. The data for training the Neural Network is obtained from experimental measurements based on the current model avoiding voltage and flux sensors. This has the advantage of considering all the drive nonlinearities. Both open loop and closed loop sensorless operation for the new scheme are investigated and compared with the conventional MRAS speed observer. The experimental results show the great improvement in the speed estimation performance for open loop and closed loop operation including at zero speed.**

***Index Terms*— Flux estimation, Induction Motor, Model Reference Adaptive Systems (MRAS), Neural Networks (NN), Sensorless Control.**

I. INTRODUCTION

THERE has been much recent development of sensorless vector controlled induction motor drives for high performance industrial application [1]. Such control reduces the drive cost, size and maintenance requirements while increasing the system reliability and robustness. However, parameter sensitivity, high computational effort and stability at low and zero speed can be the main shortcomings of sensorless control. Much recent research effort is focused on extending the operating region of sensorless drives near zero stator frequency [2, 3].

Several solutions for sensorless control of induction motor drives have been proposed based on the machine fundamental excitation model and high frequency signal injection methods, as summarized recently [1]. Fundamental model based strategies use the instantaneous values of stator voltages and currents to estimate the flux linkage and the motor speed. Various techniques have been suggested such as: Model Reference Adaptive Systems (MRAS), Luenberger and Kalman-filter observers, sliding-mode observers and Artificial Intelligence (AI) techniques. MRAS schemes offer simpler implementation and require less computational effort compared to other methods and are therefore the most popular strategies used for sensorless control [3, 4].

Various MRAS observers have been introduced in the literature based on rotor flux, back EMF and reactive power [5-8]. However, rotor flux MRAS, first introduced by Schauder [6], is the most popular MRAS strategy and significant attempts have been made to improve its performance [1]. This scheme suffers from parameter sensitivity and pure integration problems [7] which may limit the performance at low and zero speed region of operation [5].

Online adaptation of the stator resistance can improve the performance of the MRAS sensorless drive at low speed [9]. In [4], a simultaneous estimation of rotor speed and stator resistance is presented based on a parallel MRAS observer where both the reference and adaptive models switch roles based on two adaptive mechanisms. Moreover, pure integration for flux represents a crucial difficulty which may cause dc drift and initial condition problems [2, 7, 10]. Low-Pass Filters (LPF) with low cut-off frequency have been proposed to replace the pure integrator [11]. This introduces phase and gain errors and delays the estimated speed relative to the actual, which may affect the dynamic performance of the drive [12, 13] in addition to inaccurate speed estimation below the cut-off frequency [7]. To overcome this problem, Karanayil et al [12] introduce a programmable cascaded low pass filter (PCLPF) to replace the pure integration by small time constant cascaded filters to attenuate the dc offset decay time. In [14] another technique is used where the rotor flux is estimated by defining a modified integrator having the same frequency response as the pure integrator at steady state. A nonlinear feedback integrator for drift and dc offset compensation has been proposed in [15]. Further research has tried to entirely replace the voltage model (VM) with a state observer with current error feedback or with full order stator and rotor flux observers which reduces the scheme's simplicity [10, 16].

Neural Networks (NN) have been introduced as universal function approximators to represent functions with weighted

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sums of nonlinear terms [17]. Multilayer feedforward NN have shown a great capability to model complex nonlinear dynamic systems [18]. Various attempts to model machine flux from measured quantities such as stator voltages, currents and motor speed have been discussed [17-20]. A comprehensive review of applications of NN in the field of power electronics and motor drives is covered in [21].

NN have been used before with MRAS schemes. In [22] an Artificial NN (ANN) detects the thermal variations in the stator resistance at different operating conditions. Better low speed operation was shown when this ANN open loop model is combined with the MRAS observer. NN were also combined with MRAS for online stator and rotor resistance estimation based on stator current and rotor flux [23]. In [11] a two layer linear neural network is proposed to represent the conventional adaptive current model (CM) using a simple forward Euler integration method. The estimated speed represents one of the neural network weights updated online using a back propagation algorithm. An evolution to this scheme is presented in [24, 25] where an Adaptive linear NN (ADALINE) is employed in the adaptive model using modified Euler integration to represent the CM. The Ordinary Least Square (OLS) algorithm is used to train the NN online to obtain the rotor speed information. A NN has also been presented as an adaptive filter used for signal integration to eliminate the offset in the flux integration for the VM flux observer [25, 26].

This paper describes a completely novel application of the NN for MRAS. This new MRAS scheme employs a NN rotor flux observer to entirely replace the conventional VM (and not the CM as described in [11, 24]) to improve the sensorless drive performance at low and zero speed. A multilayer feedforward NN estimates the rotor flux from present and past samples of the terminal voltages and currents. Compared to a VM flux observer, the NN does not employ pure integration and is less sensitive to motor parameter variations. Compared to other conventional schemes that make use of a LPF for flux estimation, the NN observer does not employ any filtering. This avoids delaying the estimated speed and prevents estimation errors below the filter cut-off frequency. The training data for the NN is obtained from experimental measurements giving a more accurate model that includes all the drive nonlinearities. This avoids using search coils which are not a suitable way to obtain flux measurements in most applications [17]. In this paper outputs from the CM are used as target values for the NN to provide harmonic-free signals and an accurate output at low speed. An experimental implementation of the new NN MRAS observer is described. The training was done at 0-25% load, reflecting the expected application, but additional tests at 100% load are also included. The new NN scheme is compared with the conventional, which employs a VM for flux estimation, in both open loop and closed loop sensorless modes for an indirect vector control induction motor drive. The drive performance is tested when running at very low and zero speed at various load levels. Experimental results confirm the great improvement in the performance of the MRAS observer.

II. ROTOR FLUX MRAS SPEED OBSERVER

The classical rotor flux MRAS speed observer structure shown in Fig.1 consists of a reference model, an adaptive model, and an adaptation scheme which generates the estimated speed. The reference model, usually expressed as a VM, represents the stator equation. It generates the reference value of the rotor flux components in the stationary reference frame from the stator voltage (estimated to avoid a direct measurement as discussed later) and monitored current components. The reference rotor flux components obtained from the reference model are given by [6, 7]:

$$p\psi_{rd} = \frac{L_r}{L_m}\{ v_{sD} - R_s i_{sD} - \sigma L_s p i_{sD} \} \tag{1}$$

$$p\psi_{rq} = \frac{L_r}{L_m}\{ v_{sQ} - R_s i_{sQ} - \sigma L_s p i_{sQ} \} \tag{2}$$

The adaptive model, usually represented by the CM, describes the rotor equation where the rotor flux components are expressed in terms of stator current components and the rotor speed. The rotor flux components obtained from the adaptive model are given by [6, 7]:

$$p\hat{\psi}_{rd} = \frac{L_m}{T_r} i_{sD} - \frac{1}{T_r}\hat{\psi}_{rd} - \hat{\omega}_r \hat{\psi}_{rq} \tag{3}$$

$$p\hat{\psi}_{rq} = \frac{L_m}{T_r} i_{sQ} - \frac{1}{T_r}\hat{\psi}_{rq} + \hat{\omega}_r \hat{\psi}_{rd} \tag{4}$$

Based on Popov's hyperstability theory, the adaptation mechanism can be designed to generate the value of the estimated speed used so as to minimize the error between the reference and estimated fluxes [7, 8]. In the classical rotor flux MRAS scheme, this is done by defining a speed tuning signal, ε_ω, minimized by a PI controller which generates the estimated speed which is fed back to the adaptive model. The expressions for the speed tuning signal and the estimated speed can be given as [7]:

$$\varepsilon_\omega = \psi_{rq}\hat{\psi}_{rd} - \psi_{rd}\hat{\psi}_{rq} \tag{5}$$

$$\hat{\omega}_r = \left(k_p + \frac{k_i}{p}\right)\varepsilon_\omega \tag{6}$$

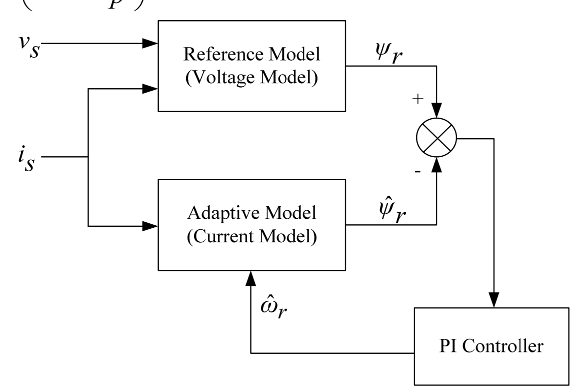


Fig.1 Classical rotor flux MRAS speed observer

The main problems associated with the low speed operation of model based sensorless drives are related to machine parameter sensitivity, stator voltage and current acquisition, inverter nonlinearity and pure integration for flux. Since all model based estimation techniques rely on rotor induced voltage, which is very small and even vanishes at zero stator frequency, these techniques fail at or around zero speed [2].

A. Parameter sensitivity

Since the speed estimation is based on the machine model, it is highly sensitive to machine parameter variations. Stator resistance variation with machine temperature is a most serious problem at low speed. Since the fundamental component of the stator voltage becomes very low, the stator resistance drop becomes comparable to the applied voltage. Hence continuous adaptation of the stator resistance is required to maintain stable operation at low speed.

B. Stator voltage acquisition and inverter nonlinearity

The most accurate stator voltage acquisition is that measured across the machine terminals. This cannot be used easily since it requires a very high sampling rate [2]. Low pass filtering the PWM voltage waveform may solve the problem at medium and high speed but not at low speed, where the effect of filter gain and phase error causes performance to deteriorate. A synchronous integrator technique can aid a solution. However, not using voltage sensors is preferred in industrial applications. Using the reference voltages, available in the control unit, is possible since they are harmonic free. However, at low speed these reference voltages deviate substantially from the actual machine voltages due to inverter dead time effects and inverter nonlinearities due to the characteristics of the power switches including threshold voltages and voltage drops.

C. Stator current acquisition and pure integration problems

Errors in the measured currents can be due to unbalanced gains of the measurement channels, DC offset and drift. This may cause oscillation in the measured speed [27].

Rotor flux estimation based on VM needs open loop integration for flux calculation. This pure integration is difficult to implement because of DC drift and initial condition problems. Replacement of pure integration by a low pass filter may help [7, 14, 26]. However, the flux estimation deteriorates below the filter cut-off frequency.

III. NEURAL NETWORK MRAS OBSERVER

To overcome these problems of the conventional RF-MRAS scheme a NN was used to completely replace the VM. The training of this network was based on the CM and hence the MRAS scheme effectively uses two versions of the CM - one based on (3) & (4) and one based on the trained NN. This greatly improves the performance of the speed estimator as will be experimentally proved later. This section briefly describes various network topologies and training methods; a 0-25% load range was used. A range reflecting the application is required for best performance, e.g. 0-100% if high loads at very low speeds are expected.

The unit of structure of ANN is the neuron which consists of a summer and an activation function. The commonest type of ANN is the multilayer feedforward neural network which consists of layers; each layer consists of neurons [11, 17].

Consider a neuron *j* in a layer *m* with *n* inputs in the (*m-1*) layer and a threshold (*b*). The net input to the neuron is given by:

$$net_j = \sum_{k=1}^{n} w_{jk} x_k + b_j = w_{j1}x_1 + w_{j2}x_2 + \dots\dots + w_{jn}x_n + b_j \tag{7}$$

And the neuron output is given by:

$$y_j = g\left(net_j\right) = g\left(\sum_{k=1}^{n} w_{jk} x_k + b_j\right) \tag{8}$$

where (*g*) is the activation function or the neuron transfer function.

Here an 8-25-2 multilayer feedforward NN is used to estimate the rotor flux components in the stationary reference frame. To obtain good estimation accuracy, the inputs to the network are the present and past values of the d-q components of the stator voltage and current in the stationary reference frame. Compensated versions of the reference voltages are used, as discussed later. One of the major drawbacks of NN is the lack of design techniques. Hence the number of neurons in the hidden layer is chosen by a trial and error technique to compromise between computational complexity, if a larger number is selected, and approximation accuracy, if a smaller number is selected [18]. This degree of trial and error may increase the training process time. The output layer consists of two neurons representing the rotor flux components in the stationary reference frame. Since the case is approximating a nonlinear function with bipolar input/output pattern, hyperbolic tan (*tansigmoid*) activation functions will be used in both hidden and output layers [21].

In this case, the neuron transfer function can be written as:

$$y_j = \tanh\left(net_j\right) = \frac{1-\exp(-net_j)}{1+\exp(-net_j)} \tag{9}$$

In this type of learning a set of input/ target data is used to train the NN [21]. At each sample the NN output is compared with the target value and a weight correction via a learning algorithm is performed to minimize the error between the two values [18, 22].

Once trained, the NN gives a fast execution speed due to its parallel processing [18, 21]. The offline trained NN is used as a reference model for the MRAS observer to form the new NN-MRAS scheme as shown in Fig.2.

IV. THE EXPERIMENTAL SYSTEM

The experimental platform consists of a 7.5 kW, 415 V, delta connected three phase induction machine loaded by a 9 kW, 240 V, 37.5 A separately excited DC load machine allows separate control of load torque and speed. A 15 kW four quadrant DC drive from the Control Techniques “Mentor” range is used to control the DC machine to provide different levels of loading on the induction machine up to full load. The parameters of the induction machine are shown in Appendix.

The AC drive power electronics consists of a 50 A 3 Phase Diode Bridge and 1200 V, 50 A half bridge IGBT power modules. To control the induction motor a dSPACE system is used which contains a PowerPC 604e running at 400 MHz, and a Slave TMS320F240 DSP.

Hall effect current sensors were used to measure the motor line currents. The actual motor speed is measured by a 5000 pulses/revolution speed encoder. The inverter switching frequency is 15 kHz and the vector control is executed with the same sampling frequency. The observer and the speed control loop have a sampling frequency of 5 kHz and the speed measurement is executed with a sampling frequency of 250 Hz.

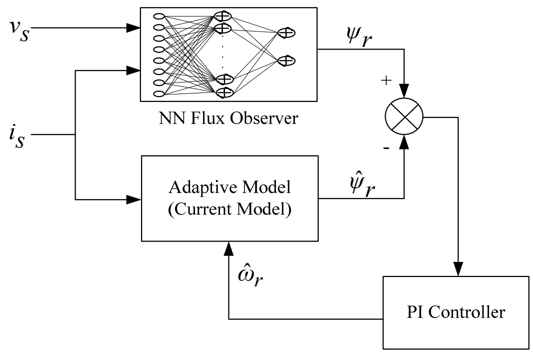


Fig.2 Proposed NN MRAS speed observer

During practical implementation of the conventional MRAS scheme it was necessary to cascade a low cut-off frequency HPF with the outputs of the VM (VM) to remove integrator drift and initial condition problems. The cut-off frequency should be selected as low as possible since the purpose is just to remove the DC component and therefore a value of 1 Hz was chosen. Moreover, the rotor flux CM (3) - (4) did not show stable operation due to the mutual coupling between the d-q axis fluxes. Therefore, an implementation in the rotor reference frame was used instead, which eliminates the cross coupling [15, 28]. In the rotor reference frame, the rotor flux based on the CM can be written as:

$$\psi_r{}^r = \frac{L_m}{1+T_r s} i_s{}^r \tag{10}$$

A simple dead time compensator similar to [29, 30] is implemented and reference voltages which are available in the control unit are used as the real stator voltages and will be used for both VM and NN flux observers. Hence, no stator voltage sensors are to be used.

V. EXPERIMENTAL RESULTS

In this section NN training based on experimental data will be demonstrated to overcome the problems that are mentioned in section II. The NN is trained to match the performance of the CM which is free from stator resistance dependency and dc-drift problems. Once the NN is trained it is shown that it accurately matches the CM. Hence it is possible to replace the VM with the proposed ANN. Since the performance of the conventional MRAS scheme improves at higher speeds. NN is suggested to replace the VM only in the low speed region. This will dramatically reduce the number of training samples and consequently the training time in addition to reducing the NN size. At high speed conventional MRAS employing VM can be used. To further experimentally validate the proposed scheme open and closed loop sensorless operation will be compared for the new and conventional schemes.

A. Neural Network training and testing

To generate the training data the encodered vector control drive is run with different operating conditions in the low speed region (100 rpm to -100 rpm) including the zero speed at various load levels ranging from 0 to 25% of rated load. Small and large references speed changes were applied to the drive during the training phase. The reference voltages and measured stator currents are transformed from 3-phase (*a*, *b*, *c*) to 2 phase (*d*, *q*) for the NN training data. A LPF with 40 rad/s cut-off frequency was used to remove drift and noise from the reference stator voltage signals. The present and past samples of filtered stator voltages and stator currents components are obtained which will be used as inputs to the NN model .Even using direct flux sensing via search coils [18], noise and rotor slot harmonic effects on the measurements require that a LPF be used.

The outputs from the rotor flux CM, which are obtained from stator currents components and encoder speed, are used as target values for the NN. This is an effective way to obtain the correct values of the rotor flux since the obtained signals are relatively noise and harmonic-free including all the drive nonlinearities. Moreover, the CM flux observer produces accurate flux estimation even at low speed [16]. A block diagram of the training data acquisition is shown in Fig. 3.

The training is performed off-line with Matlab-Simulink using the Levenberg-Marquardt training algorithm which is faster than the gradient descent back propagation algorithm but needs a large memory [18, 21]. A 5000 input/output pattern was used to train the NN. After the training the Mean Squared Error (MSE) between targets and neural network outputs decays to a satisfactory level (4.5×10^{-4}) after about 2200 epochs. The training lasts for less than one hour on a Pentium ® IV PC running at 3 GHz with 512 MB of RAM.

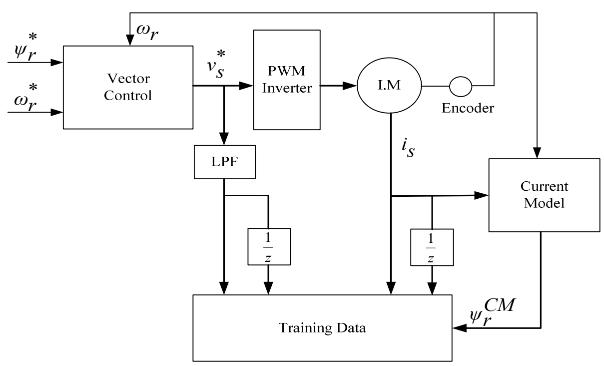


Fig.3 NN Training data acquisition

Extensive experimental tests were carried out to test the performance of the NN observer in various operating conditions not seen during training to ensure the generalization capability of the NN model. Compared to the VM, the NN matches the CM extremely well in both transient and steady state conditions even when the drive is operating at low speed. To further validate the NN observer, three tests are conducted. The performance of both observers is compared to the CM when the encodered drive is working at 20 rpm and

5Nm. Attenuation and phase delay take place in the VM due to the filter effect where as NN output closely track the CM output at this very low speed as shown in Fig. 4(a). To test the NN observer sensitivity to parameter variation, simulations have been conducted with variations in R_s and R_r. Experimental verification of R_s sensitivity can only be done with a NN by switching an external resistor, since there is no explicit value for R_s in the observer. Although desirable this was not attempted, so instead simulation was used for verification. Performance of VM and NN flux observers for 25% increase in R_s is shown in Fig. 4(b). NN shows less sensitivity to R_s variation than the VM. NN observer also shows good performance with 50% R_r variation as shown in Fig. 4(c).

These results show that the NN can fairly handle the parameter variation problem with a good level of robustness. Consequently, for integrated drive applications, where the inverter and machine are sold as one unit, the NN observer can be trained on the actual inverter-machine combination. The NN should be able to cope with changes from these nominal parameters for other drives in the production line which is due to the manufacturer's tolerance.

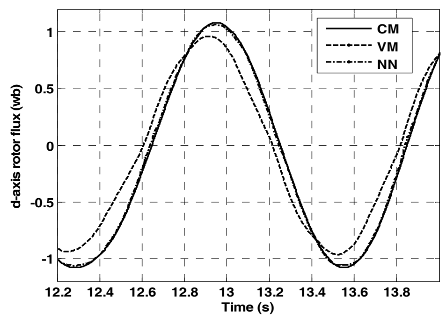
However, in a mass-production environment, where the inverter can be used with several sizes of motors, the application of this technique is more difficult. In this case, a standard NN scheme becomes unsuitable unless the training is performed during commissioning for each inverter-machine combination. This may present a drawback of the proposed method. However, this could be overcome by using a range of previously trained networks where an appropriate one can be selected according to the machine nameplate rating.

B. *Open loop operation*

The new scheme was tested in open loop with the drive operated as an encodered vector control, i.e. the encoder speed is used for speed control and rotor flux angle estimation. The open loop performance of the conventional and the new NN-MRAS speed observers is compared. PI controller gains of each scheme are tuned separately for optimal performance to allow a comparison between the best performance of each scheme. Figs. 5-6 show the open loop performance of both schemes for a ±30 rpm speed reversal at 10% load and disturbance rejection for a 20% step of load torque at 25 rpm. The NN MRAS observer demonstrates better transient and steady state performance and less sensitivity to machine parameters than the conventional scheme.

Operation up to rated load can be achieved by extending the training range of the NN observer by applying various loads ranging from 0 to 100% rated load over the same speed region using the same training procedure described in section V.*A*. Results for a ±25 rpm speed reversal at 100% rated load are shown in Fig.7. NN MRAS scheme performance is clearly superior to that of the classical scheme at rated load.

At low speed a steady state error in the estimated speed is observed for the conventional MRAS observer. This is mainly due to the stator resistance mismatch between the motor and the observer. Moreover, dead time effects cannot be completely removed even by complicated compensation schemes [2]. So the reference voltages used for the VM do not match the actual stator voltages across the machine terminals representing another source for the steady state error in the estimated speed. Using the new NN-MRAS scheme completely removes the steady state error in the estimated speed and improves the load torque disturbance rejection performance of the speed observer at low speed. This improvement in the performance can be explained based on the fact that the NN estimates a flux, similar to the CM flux, which is not directly dependent on use of the actual stator voltage, unlike the situation with use of the VM in the conventional scheme. Moreover, no filters are needed in the flux observer with no pure integrator present in the NN model. Less sensitivity to parameter variation is given, with the new NN-MRAS scheme showing much better performance compared to the conventional MRAS observer at low and zero speed.



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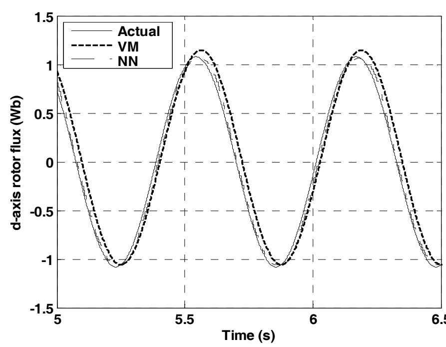

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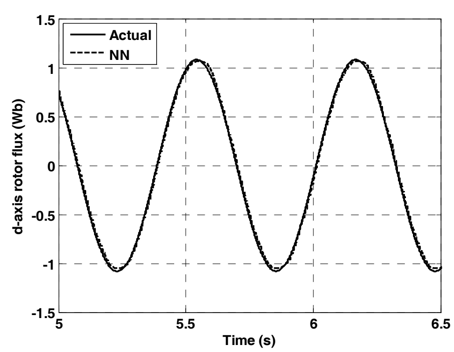


(c)

Fig.4 NN observer testing (a) LPF effect (experimental) (b) R_s 25% variation (simulation) (c) R_r 50% variation (simulation)

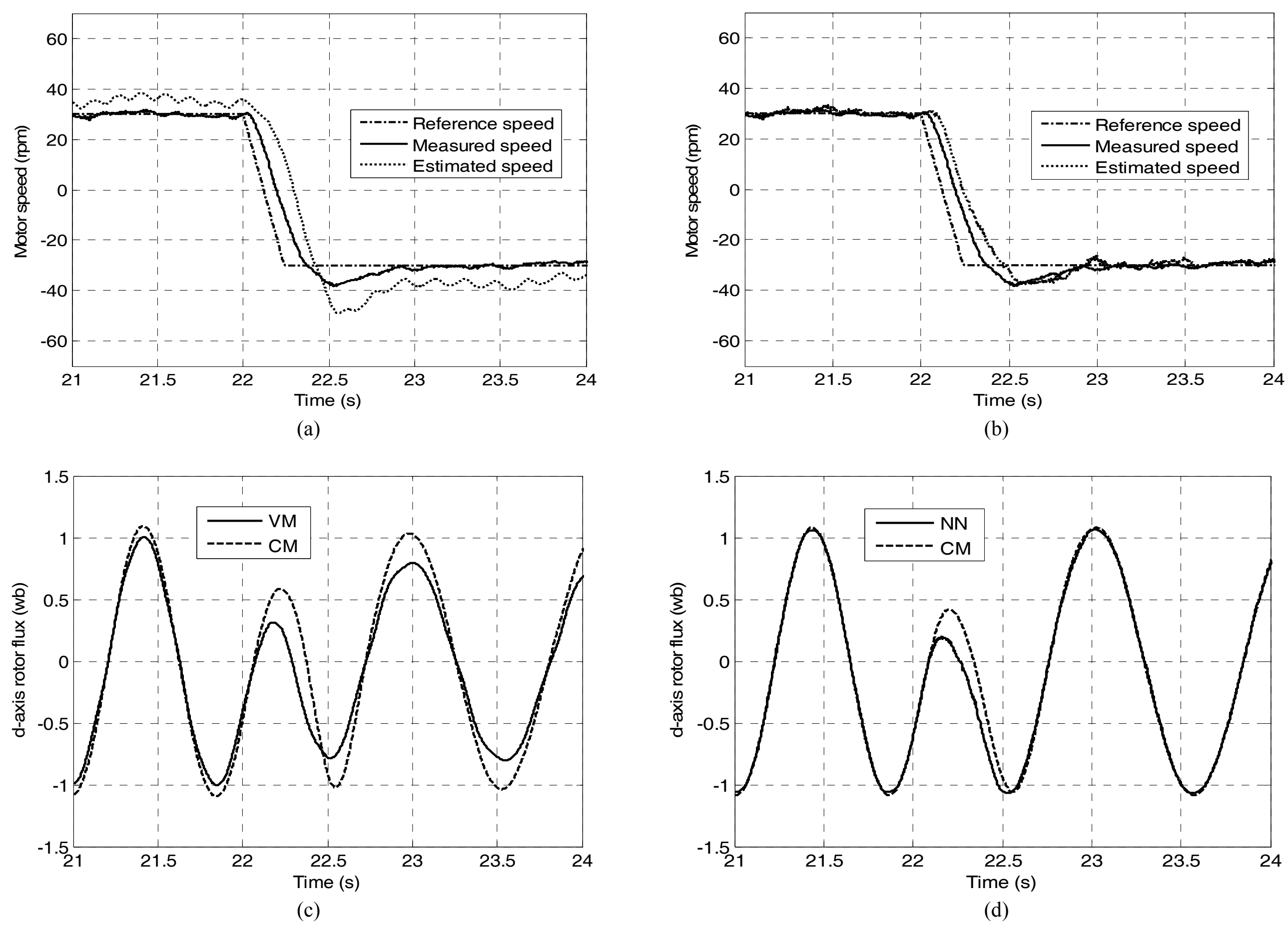


Fig.5 Open loop speed reversal 30 rpm to -30 rpm, 10% load. Speed: (a) Conventional MRAS (b) NN MRAS. Model outputs: (c) Conventional MRAS (d) NN MRAS

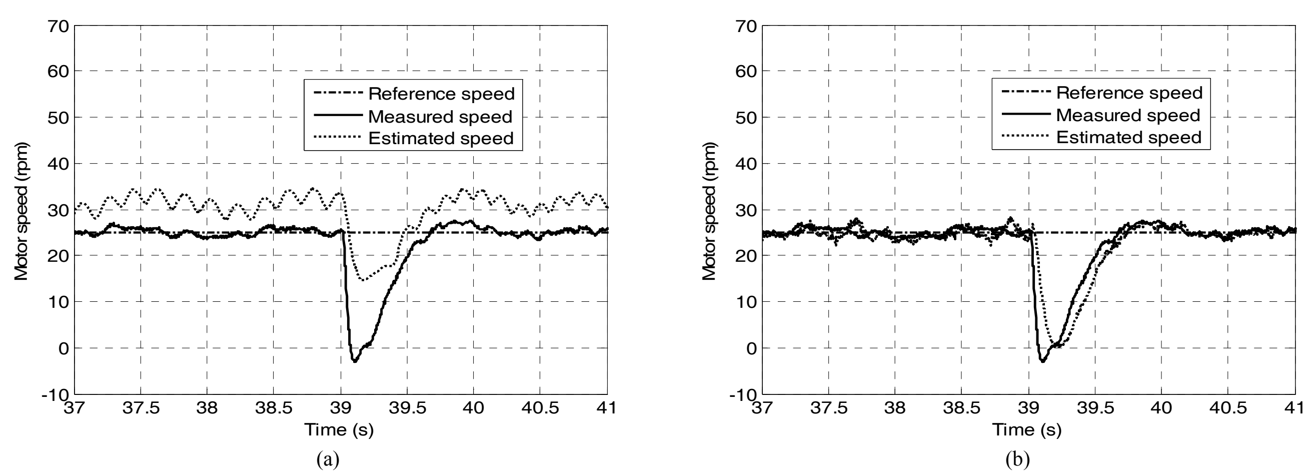
C. Sensorless closed loop operation

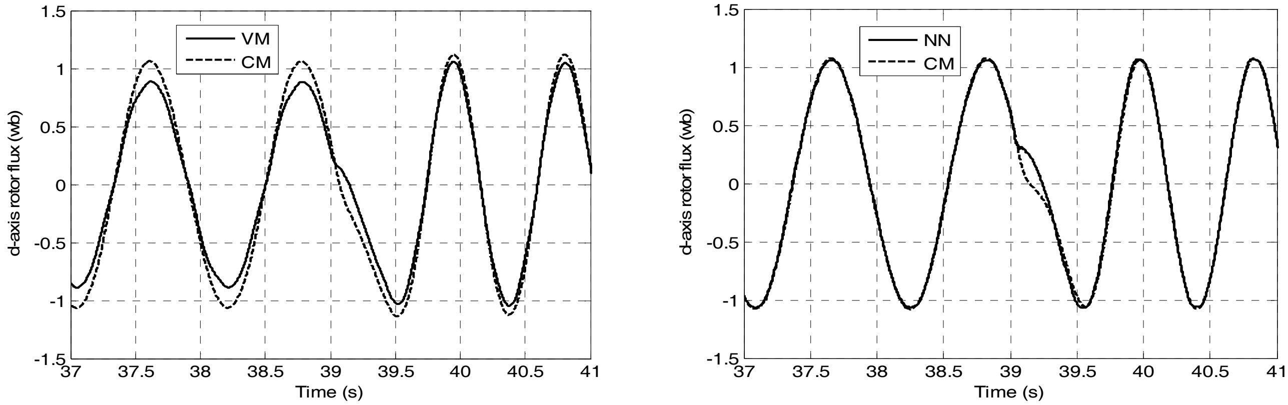
In the following tests, the estimated speed is used for speed control and field orientation where the drive is working as sensorless indirect rotor flux oriented. The encoder speed is used for comparison purposes only.

Tests are conducted in the low speed and at or around the zero speed region based on some recommended benchmark tests [15, 31, 32]. Selected experimental results for the tests are shown in the following section.

1) Test 1: Stair case speed transients from 100rpm to 0rpm to -100 rpm at no load:

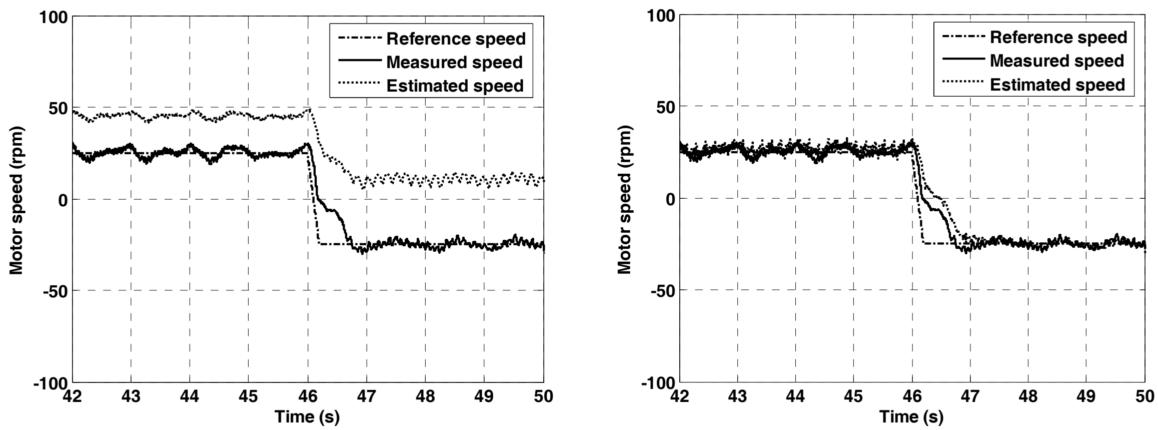
In this test the sensorless vector control drive is subjected to a stair case speed demand from 100 rpm to zero speed in a series of five 20 rpm steps continuing to -100 rpm, at no load. The performance of both schemes is shown in Fig. 8. Stable operation is obtained for the NN MRAS scheme especially around zero speed.





(c) (d)

Fig.6 Open loop 20% load torque disturbance rejection, 25 rpm. Estimated speed: (a) Conventional MRAS (b) NN MRAS. Model outputs: (c) Conventional MRAS (d) NN MRAS



(a) (b)

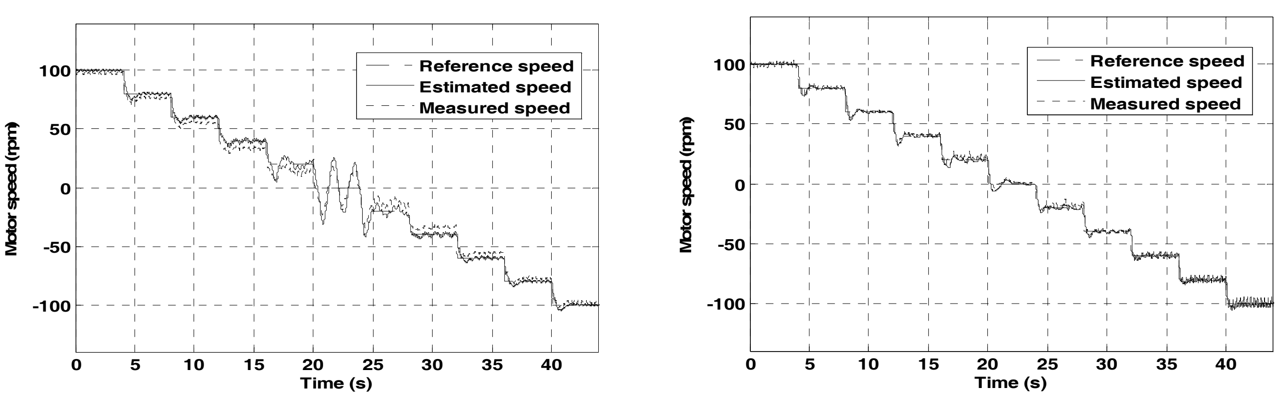
Fig.7 Open loop speed reversal 25 rpm to -25 rpm, rated load (100% load torque). Speed: (a) Conventional MRAS (b) NN MRAS

2) Test 2 Take off from zero speed to 100 rpm after 30 sec at zero at no load:

This tests the drive capability to maintain field orientation at zero stator frequency followed by an application of a finite reference speed. The results of this benchmark test are shown in Fig. 9. Unstable operation at zero speed was observed for the conventional MRAS with oscillation around zero speed. The NN MRAS proves its ability to hold the zero speed at no load without any oscillations. Both schemes succeed in taking off to 100 rpm after 30 s at zero speed.

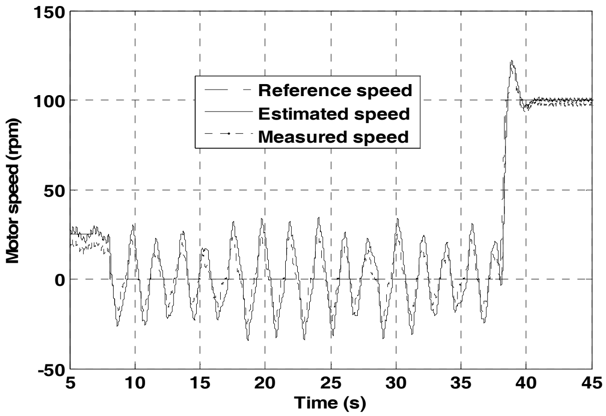
3) Test 3 Speed step down from 20 rpm to 0 rpm in three steps each of 10 rpm at 10% load

This tests the performance of the sensorless drive at very low and zero speed with load. The results are shown in Fig. 10. At a reference speed of 20 rpm, the NN MRAS scheme was stable, showing less steady state error compared to the conventional. At such speeds and below, the conventional MRAS fails to provide stable operation giving large oscillations.



(a) (b)

Fig.8 Sensorless performance for benchmark test 1, no load. Speed: (a) conventional MRAS (b) NN MRAS



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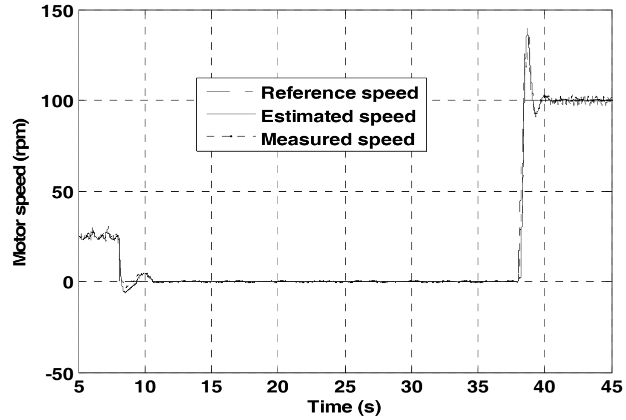

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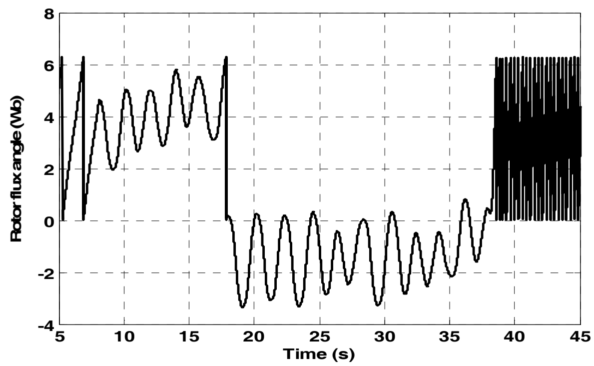

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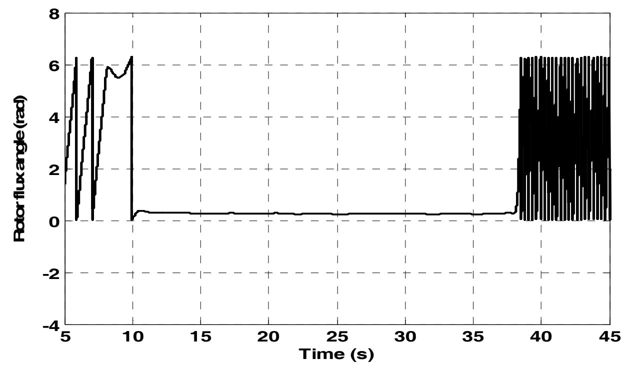
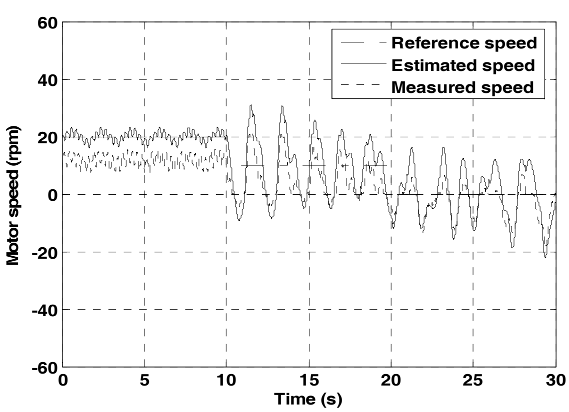


(d)

Fig.9 Sensorless result benchmark test 2, no load. Speed: (a) conventional MRAS (b) NN MRAS. Rotor flux position: (c) conventional MRAS (d) NN MRAS



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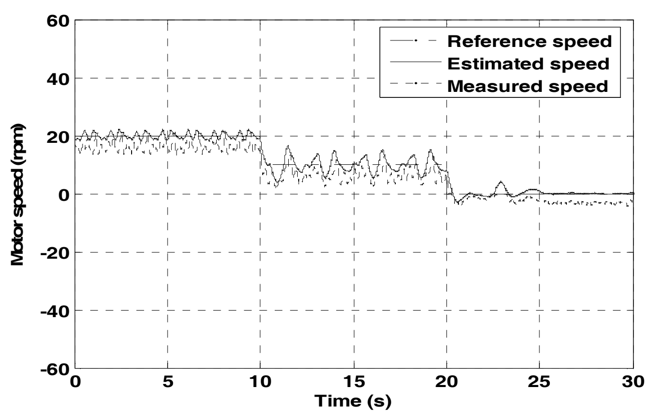

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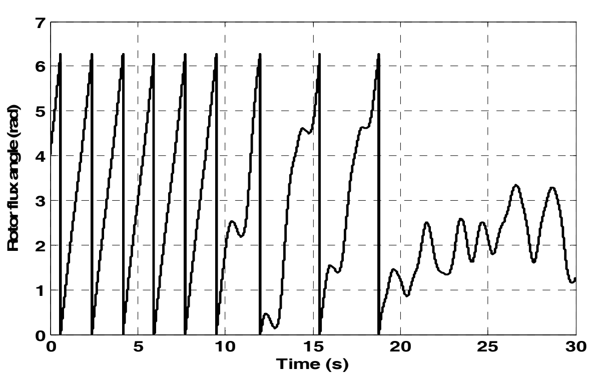
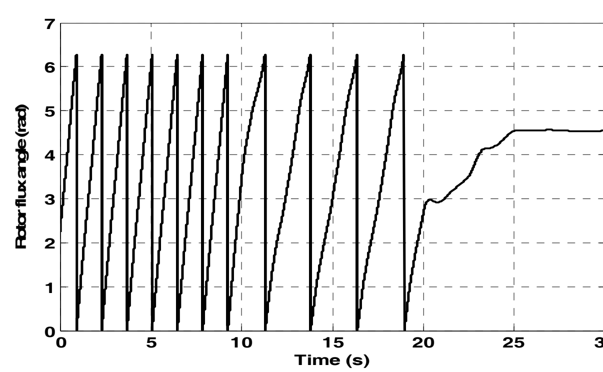
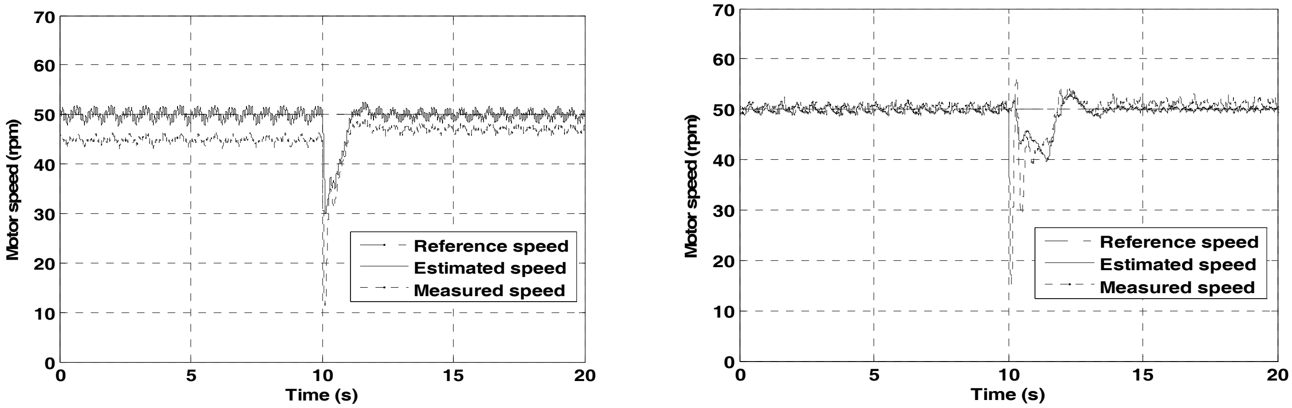


(c)



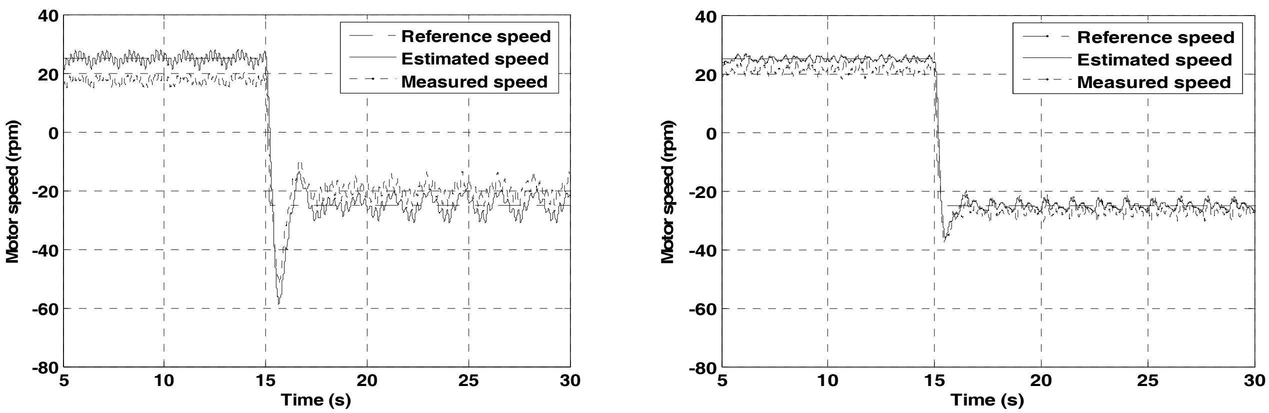
(d)

Fig.10 Sensorless result benchmark test 3, 10% load. Speed: (a) conventional MRAS (b) NN MRAS. Rotor flux position: (a) conventional MRAS (b) NN MRAS



(a) (b)

Fig.11 Sensorless performance for benchmark test 4, 20% load torque rejection, 50 rpm. Speed (a) conventional MRAS (b) NN MRAS



(a) (b)

Fig.12 Sensorless performance benchmark test 5, ±25 rpm speed reversal, 10% load. Speed: (a) conventional MRAS (b) NN MRAS

4) Test 4 20% load torque rejection at 50 rpm

This test examines the load torque disturbance rejection capability of the sensorless drive. Both schemes have been tested when a 20% step change in load torque is applied at 50 rpm. The NN MRAS shows better dynamic and steady state performance with negligible steady state error between the actual and estimated speed as shown in Fig. 11.

5) Test 5 ±25 rpm speed reversal at 10% load

This last test shows the drive performance for a very low speed reversal under load torque. A ±25 rpm speed reversal demand was applied to the drive when working at 10% load. Better performance with negligible steady state error was obtained from NN MRAS observer compared to the conventional MRAS scheme as shown in Fig. 12. A summary of test results from zero to full load using the conventional and new schemes is given in Table I showing the superior behavior of the new scheme under various load conditions.

VI. Conclusion

This paper has presented an entirely new application of a NN to give an improved MRAS speed observer scheme suitable for speed sensorless induction motor drives. A multilayer feedforward NN estimates the rotor flux components from present and past samples of reference stator voltages and measured currents. The new scheme makes use of the off-line trained NN observer as a reference model in MRAS scheme. Training data is obtained from experiments without the need for search coils. Using the new NN scheme for flux estimation eliminates the need for pure integration with less sensitivity to stator resistance variations.

Results obtained from a systematic set of benchmark experimental tests using an 7.5 kW induction motor drive system prove the great improvement of the sensorless drive performance around and at zero speed. Open loop tests show that the steady state error in the estimated speed has been totally removed compared to the conventional observer using a VM. Closed loop sensorless operation is greatly improved at very low and zero speed without using voltage sensors.

Appendix

Motor Parameters

7.5 kW, 3-phase, 415V, delta connected, 50 Hz, 4 pole, Star equivalent parameters: R_s = 0.7767 Ω, R_r = 0.703 Ω, L_s = 0.10773 H, L_r = 0.10773 H, L_m = 0.10322 H, J = 0.22 kgm^2

TABLE I
SUMMARY OF TEST RESULTS

	25 rpm 100% rated load Open loop	-25 rpm 100% rated load Open loop	Zero speed No load Sensorless	Zero speed 10% load Sensorless	Zero speed 20% load Sensorless	20 rpm 10% load Sensorless	10 rpm 10% load Sensorless	50 rpm 20% load Sensorless	-25 rpm 10% load Sensorless	-25 rpm 25% load Sensorless
Conv. MRAS	20 rpm steady state error	35 rpm steady state error	Unstable	Unstable	Unstable	10 rpm steady state error	Unstable	3 rpm steady state error	5 rpm steady state error	Unstable
NN MRAS	Negligible steady state error	Negligible steady state error	Zero steady state error	3 rpm steady state error	7 rpm steady state error	4 rpm steady state error	3 rpm steady state error	1 rpm steady state error	Negligible steady state error	7 rpm steady state error

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