A Neural Network Based Stator Current MRAS Observer for Speed Sensorless Induction Motor Drives

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***Abstract*- This paper presents a novel Model Reference Adaptive System (MRAS) speed observer for induction motor drives based on stator currents. The measured currents are used as reference model for the MRAS observer to avoid the use of a pure integrator. A two-layer Neural Network (NN) stator current observer is used as the adaptive model which requires the rotor flux information. This can be obtained from the voltage or current model but instability and dc drift can downgrade the overall observer performance. To overcome these problems another off-line trained multilayer feedforward NN is proposed here as a rotor flux observer. Speed estimation performance of the MRAS scheme using the three different rotor flux observers is studied and compared when applied to an indirect vector control induction motor drive. Promising results have been obtained when using the NN flux observer with less sensitivity to parameter variation and stability in the regenerating mode of operation.**

I. INTRODUCTION

Several techniques have been proposed for rotor speed estimation in sensorless induction motor drives based on the machine model. These strategies make use of the instantaneous values of stator voltages and currents to estimate the flux linkage and the motor speed. The block diagram of a model based sensorless indirect vector control scheme is shown in Fig.1. Model Reference Adaptive Systems (MRAS) offer simpler implementation and require less computational effort compared to other methods and are therefore the most popular strategies used for sensorless control [1]. Various MRAS observers have been introduced in the literature based on rotor flux, back EMF and reactive power [2-4]. Rotor flux MRAS, first proposed by Schauder [3], is the most popular MRAS strategy and a lot of effort has been focused on improving the performance of this scheme. This scheme suffers from stator resistance sensitivity and pure integration problems which may cause dc drift and initial condition problems [4]. These problems may limit the performance at low and zero speed region of operation [2]. Low-Pass Filters (LPF) with low cut-off frequency have been proposed to replace the pure integrator [5]. This introduces phase and gain errors and delays the estimated speed relative to the actual, which may affect the dynamic performance of the drive in addition to inaccurate speed estimation below the cut-off frequency [4, 6]. To overcome this problem, Karanayil et al [6] introduces 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. Nonlinear feedback integrators for drift and dc offset compensation have been proposed in [7]. Moreover, Neural Networks (NN) have been proposed to replace the conventional adaptive model used in rotor flux-MRAS [5]. To avoid the problems associated with rotor flux schemes, back EMF and reactive power schemes have been proposed [2]. Back EMF schemes avoid using a pure integration in the reference model but are sensitive to stator resistance variation and may have stability problems at low stator frequency [1]. A reactive power technique has been proposed offering robustness against stator resistance variation while avoiding pure integration [4]. However, this scheme suffers from instability at some operating conditions.

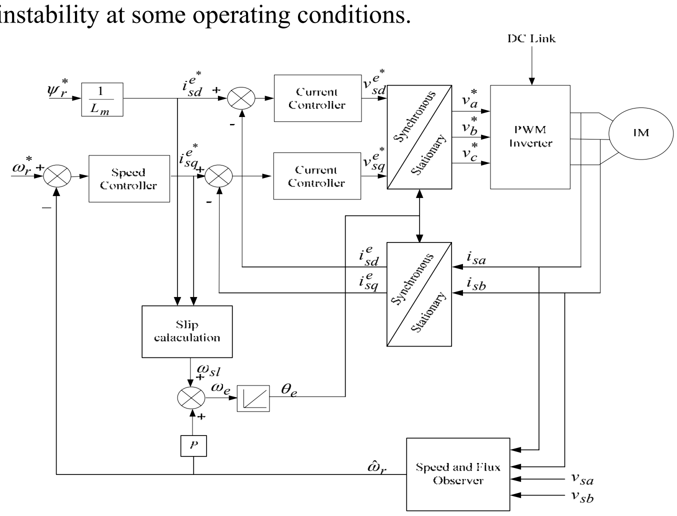


Fig.1 Sensorless indirect vector control scheme

Recently, a stator current MRAS scheme has been introduced for stator resistance identification for induction motor drives [8]. In this scheme the reference model comprises the measured stator current components. This makes the reference model free of pure integration problems and insensitive to motor parameter variations. A two layer linear NN stator current observer is used as an adaptive model where the stator resistance is one of the neural network weights. A backpropagation learning algorithm is used to train the NN online to update the value of the stator resistance. A conventional current model is used for rotor flux estimation.

In this paper, the NN based MRAS observer proposed in [8] is used for online motor speed identification instead of stator resistance estimation. The NN weight corresponding to motor speed is updated online using the backpropagation learning algorithm in such a way as to minimize the error between the measured and estimated currents. Rotor flux is needed for the stator current estimation in the adaptive model and conventionally a current model flux observer has been employed. However as will be shown, the use of such a model gives instability in the regenerating mode of operation. Therefore the paper suggests an off-line trained multi-layer feedforward NN which estimates the rotor flux from present and past samples of terminal voltages and currents. By using this NN the flux estimation is independent of the rotor speed and does not require the use of pure integration. Superior results have been obtained from the NN flux observer scheme in terms of stator resistance sensitivity and stability over the whole speed control range.

II. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks are based on the basic model of the human brain with the capability of generalization and learning. They can be used as universal function approximators to represent functions with weighted sums of nonlinear terms [9]. This is useful when representing some systems which do not have an accurate mathematical model. The unit of structure of ANN is the neuron which consists of a summer and an activation function as shown in Fig. 2. The commonest type of ANN is the multilayer feedforward neural network which consists of layers; each layer consists of neurons [5, 9].

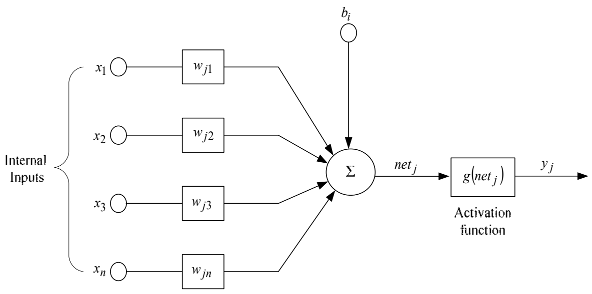


Fig.2 Structure of the artificial neuron

Multilayer feedforward neural networks have shown a great capability to model complex nonlinear dynamic systems [10]. Various attempts to model machine flux from measured quantities such as stator voltages, currents and motor speed have been discussed [9, 10].

A training process is performed to enable the NN to understand the model to be represented. A set of input/ target data is used to train the neural network. The neural network output is compared with the target value and a weight correction via a learning algorithm is performed in such a way to minimize the error between the two values. This is an optimization problem in which the learning algorithm searches for the optimal weights that can represent the solution to the approximation problem [10]. Neural Networks can be trained online or off-line. For online training, the NN weights are continuously updated during operation rather than being constant as for off-line training.

III. NN STATOR CURRENT MRAS SCHEME

The basic concept of MRAS used in this paper is the presence of a reference model which determines the desired states and an adaptive model which generates the estimated values of these states. The error between reference and estimated states is fed to an adaptation mechanism to generate the estimated value of the rotor speed which is used to adjust the adaptive model. This process continues till the error between two outputs tends to zero [4]. Block diagram of a MRAS scheme is shown in Fig.3. For the stator current MRAS observer, the reference model will consist of the actual stator currents [8], and hence the induction motor itself will work as a reference model. This has the advantages of avoiding pure integration and the estimator is less sensitive to parameters. A stator current observer can be represented by a linear two layer NN where the motor speed is expressed as one of its weights. A backpropagation learning algorithm is used in order to minimize the error in current estimation and hence generating the estimated speed.

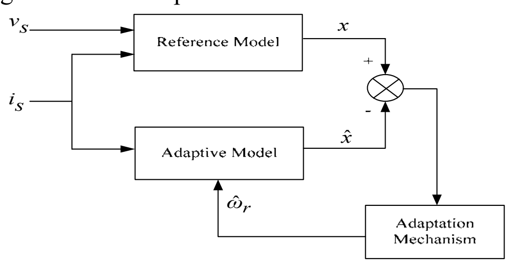


Fig.3 Block diagram of a MRAS scheme

The stator current equations of the induction motor can be written as [8]:

$$\hat{i}_{sd}(k)=w_1\hat{i}_{sd}(k-1)+w_2\hat{\psi}_{rd}(k-1)+w_3\hat{\psi}_{rq}(k-1)+w_4 v_{sd}(k-1) \quad (1)$$

$$\hat{i}_{sq}(k)=w_1\hat{i}_{sq}(k-1)+w_2\hat{\psi}_{rq}(k-1)-w_3\hat{\psi}_{rd}(k-1)+w_4 v_{sq}(k-1) \quad (2)$$

where:

$$w_1 = 1-\frac{TR_s}{\sigma L_s}-\frac{TL_m^2}{\sigma L_s L_r T_r} \quad (3)$$

$$w_2 = \frac{TL_m}{\sigma L_s L_r T_r} \quad (4)$$

$$w_3 = \frac{TL_m}{\sigma L_s L_r}\omega_r \quad (5)$$

$$w_4 = \frac{T}{\sigma L_s} \tag{6}$$

where T is the sampling time for the stator current observer and σ is the leakage coefficient given by:

$$\sigma = 1 - \frac{L_m^2}{L_s L_r} \tag{7}$$

Equations (1) and (2) can be represented by a two layer linear NN with weights as defined in equations (3)-(6) [8]. This NN will represent the adaptive model for the MRAS scheme where w_3 is adjusted online in such a way as to minimize the error between actual and estimated currents.

To derive the weight adjustment law of the NN stator current observer, define the energy function E to be minimized:

$$E = \frac{1}{2}\boldsymbol{\varepsilon}^2(k) \tag{8}$$

where:

$$\begin{aligned}\boldsymbol{\varepsilon}(k) &= \mathbf{i_s}(k) - \hat{\mathbf{i}}_\mathbf{s}(k) \\ &= \left[i_{sd}(k) - \hat{i}_{sd}(k) \;\; i_{sq}(k) - \hat{i}_{sq}(k)\right]^T = \left[\varepsilon_d(k) \;\; \varepsilon_q(k)\right]^T\end{aligned} \tag{9}$$

To obtain a minimum squared error between actual and estimated stator current the weight adjustment has to be proportional to the negative of the error gradient with respect to the weight as:

$$\Delta w_3 \propto -\frac{\partial E}{\partial w_3} \tag{10}$$

The weight adjustment law can be written as:

$$\begin{aligned}\Delta w_3(k) &= -\eta \frac{\partial E}{\partial w_3} \\ &= \eta\left\{\varepsilon_d(k)\hat{\psi}_{rq}(k-1) - \varepsilon_q(k)\hat{\psi}_{rd}(k-1)\right\}\end{aligned} \tag{11}$$

where η is a positive constant called the learning rate. Large values of η may accelerate the NN learning and consequently fast convergence but may cause oscillations in the network output whereas low values will cause slow convergence. Therefore, the value of η has to be chosen carefully to avoid instability.

The new weight can be written as:

$$w_3(k) = w_3(k-1) + \Delta w_3(k) \tag{12}$$

To ensure accelerated convergence, the last weight change is added to the weight update as [5]:

$$w_3(k) = w_3(k-1) + \Delta w_3(k) + \alpha \Delta w_3(k) \tag{13}$$

where α is a positive constant called the momentum constant. The motor speed can be estimated from the weight w_3 as:

$$\omega_r(k) = \frac{\sigma L_s L_r}{T L_m} w_3(k) \tag{14}$$

IV. ROTOR FLUX ESTIMATION BASED ON THE CURRENT MODEL

Since rotor flux estimation is required for the stator current MRAS scheme, voltage model and current model flux observers can be used.

The voltage model (VM) flux estimator is based on the stator equations which estimates the rotor flux from the monitored stator voltages and currents [3, 4]:

$$\dot{\boldsymbol{\psi}}_\mathbf{r} = \frac{L_r}{L_m}\left\{\mathbf{v_s} - R_s\mathbf{i_s} - \sigma L_s \dot{\mathbf{i}}_\mathbf{s}\right\} \tag{15}$$

The main drawback associated with voltage model (VM) implementation is the use of a pure integration which can cause dc drift, sensitivity to machine parameter variation, accurate stator voltage and current acquisition.

The current model (CM) can also be used to avoid these problems but as it will be proved it shows poor stability margins. This model is based on the rotor equations 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 [3, 4]:

$$\dot{\hat{\boldsymbol{\psi}}}_\mathbf{r} = \left(-\frac{1}{T_r} + j\hat{\omega}_r\right)\hat{\boldsymbol{\psi}}_\mathbf{r} + \frac{L_m}{T_r}\mathbf{i_s} \tag{16}$$

The block diagram of the NN-based stator current MRAS scheme using CM rotor flux observer is shown in Fig. 4.

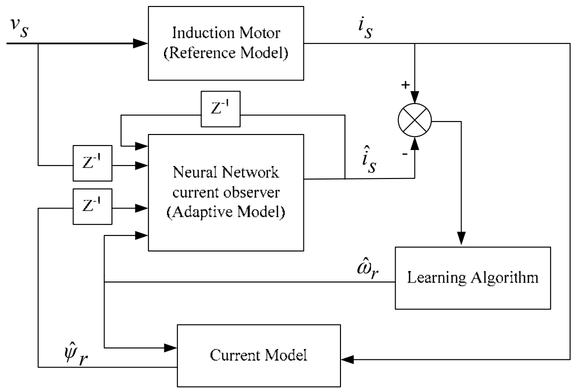


Fig.4 Neural Network based stator current MRAS speed observer using current model flux observer

V. NN ROTOR FLUX ESTIMATION

As will be shown in the next section the use of a current model to estimate the rotor flux causes instability at the regenerating region. To overcome this problem another way to estimate rotor flux needed for the stator current MRAS scheme is proposed here which uses an offline trained NN. To estimate the rotor flux components in the stationary reference frame an 8-25-2 multilayer feedforward NN is proposed. 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. The number of neurons in the hidden layer is chosen by a trial error technique as a compromise between computational complexity, if a larger number is selected, and approximation accuracy, if a smaller number is selected [10]. The output layer consists of two neurons representing the rotor flux components in the stationary reference frame. Since a nonlinear function is being approximated, tansigmoid activation functions will be used in both hidden and output layers.

To obtain the training data, the vector control drive is run with different operating conditions in the low speed region (100 rpm to -100 rpm) at various load levels. The present and past samples of the d-q components of the reference stator voltages and output stator currents are obtained: $v_{sd}(k)$, $v_{sd}(k-1)$, $v_{sq}(k)$, $v_{sq}(k-1)$, $i_{sd}(k)$, $i_{sd}(k-1)$, $i_{sq}(k)$, $i_{sq}(k-1)$ which will be used as inputs to the NN. Outputs from the rotor flux current model $\psi_{rd}(k)$, $\psi_{rq}(k)$ are obtained from stator currents components and actual speed and are used as target values for the neural network. 5000 input/output patterns are used to train the NN. The training is performed off-line using the Levenberg-Marquardt algorithm which is faster than gradient descent back propagation [10]. After the training the Mean Squared Error (MSE) between targets and neural network outputs decays to 0.000317 after 2200 epochs. Once trained, the NN will be suitable for generalization with a fast execution speed due to their parallel processing [10]. The offline trained NN is proposed for rotor flux estimation in the stator current MRAS observer shown in Fig. 5.

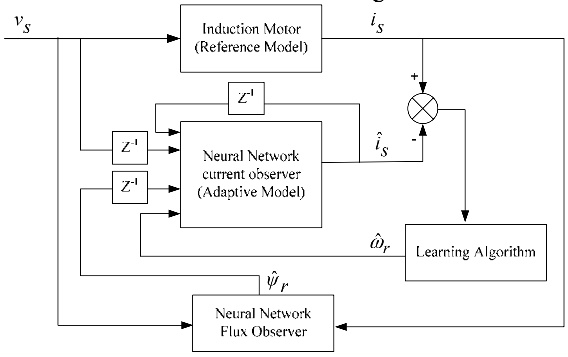


Fig.5 Neural Network based stator current MRAS speed observer with Neural Network flux observer

VI. RESULTS AND DISCUSSION

To test the NN-based stator current MRAS observer performance, a 7.5 kW, 415V induction machine with parameters given in Table1 is simulated using Matlab-Simulink. The drive is running under indirect vector control with different reference speed and various loading levels. The stator current MRAS scheme using three rotor flux observers, VM, CM and NN, is tested for sensitivity to stator resistance variation for reference speed changes and load torque application. Furthermore, speed estimation performance is investigated at different operating conditions in the low speed region of operation including the regenerating mode. In this mode of operation, the machine is subjected to positive load torque when running at negative speed. The sampling time for the NN stator current observer is 1/5000 sec with η=0.0005 and α=0.001. Selected simulation results for the tests are shown in the following section.

A. Sensitivity to stator resistance variation

The purpose of this test is to compare the speed estimation performance of the MRAS observer for motor parameter variation. The vector control drive is run with a 25% increase in the motor stator resistance and subjected to a reference speed change from 5 rad/s to 7 rad/s at no load at t=5s followed by a 25% load torque application at t=8s. The speed estimation performance using the three different rotor flux observers is shown in Fig. 6.

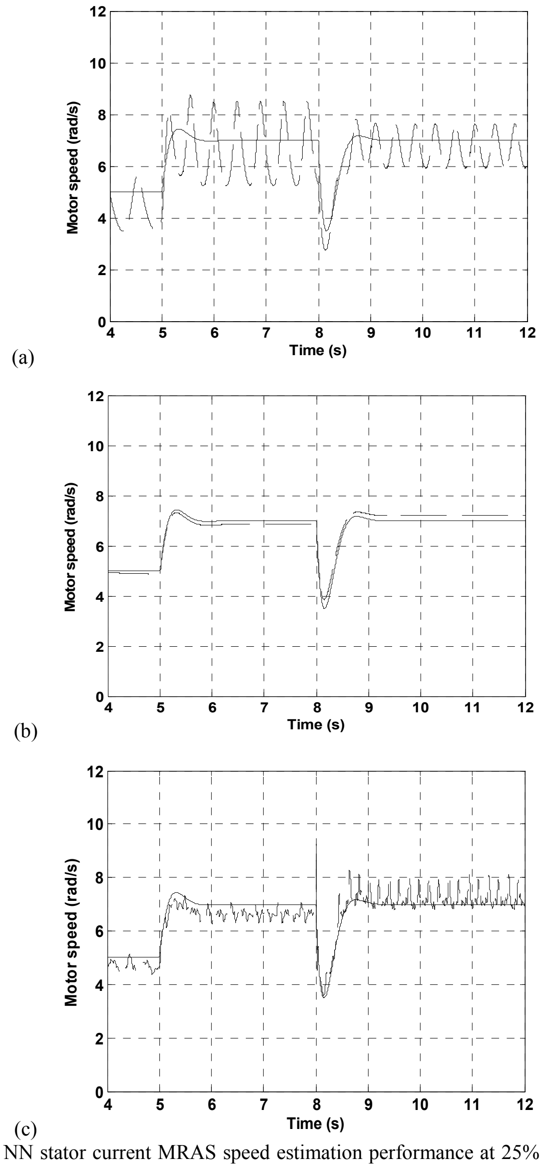


Fig.6 NN stator current MRAS speed estimation performance at 25% increase in R_s Actual speed solid, estimated speed dashed (a) Voltage model flux observer (b) Current model flux observer (c) Neural Network flux observer

Due to the presence of R_s in the stator current observer equations, speed estimation for all schemes is affected by the variation in R_s. The effect of R_s variation on the VM is more serious and causes oscillations in the estimated speed due to the presence of R_s in the flux estimation equation as well. Although R_s is not present in the CM observer equation, the flux estimation is still affected since the model makes use of the estimated speed which deviates from the actual. The NN flux observer shows less sensitivity to R_s variation compared to VM without being dependent on the estimated speed and therefore shows good speed estimation performance close to that obtained when using CM.

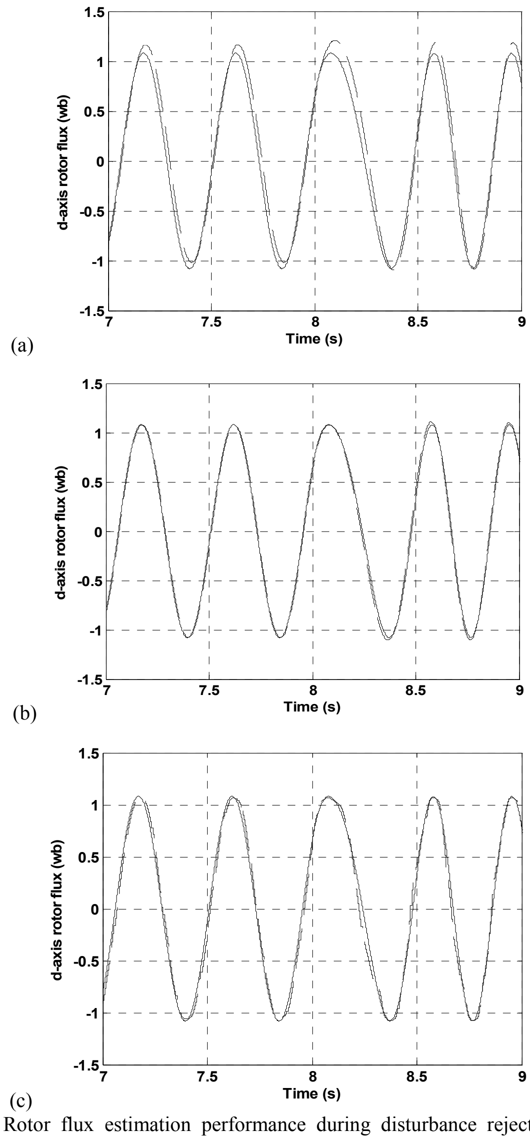


Fig.7 Rotor flux estimation performance during disturbance rejection at 25% increase in R_s Actual flux solid, estimated flux dashed (a) Voltage model flux observer (b) Current model flux observer (c) Neural Network flux observer

The rotor flux estimation performance of the three observers during load torque disturbance rejection is shown in Fig. 7. As can be seen the VM is the most affected by R_s variation compared to the CM and NN observers.

B. Stability in the regenerating mode

In this test the stability of the scheme is tested in the regenerating mode of operation. In this region of operation the motor is running in the negative speed region with a positive load torque applied. Therefore the drive is subjected to a speed reversal command from 5 rad/s to -5 rad/s at 25% load torque with nominal machine parameters. The speed estimation performance of the MRAS observer using CM and NN rotor flux observers is shown in Fig. 8.

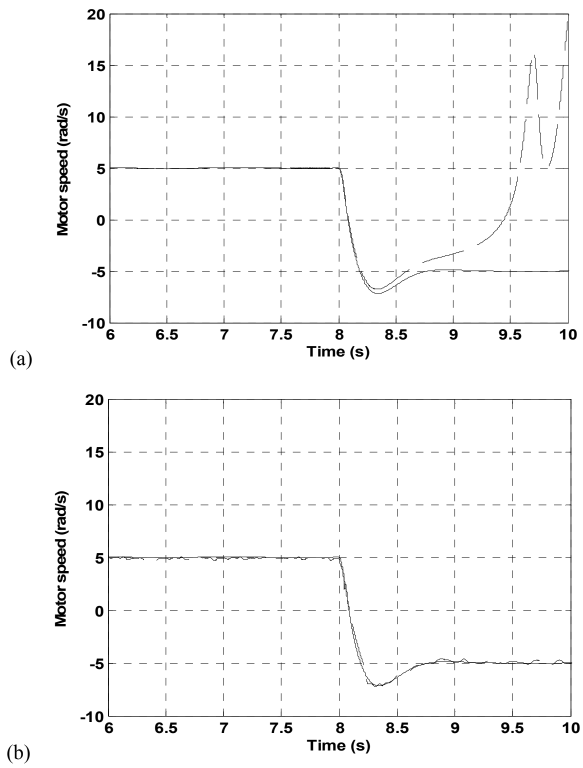
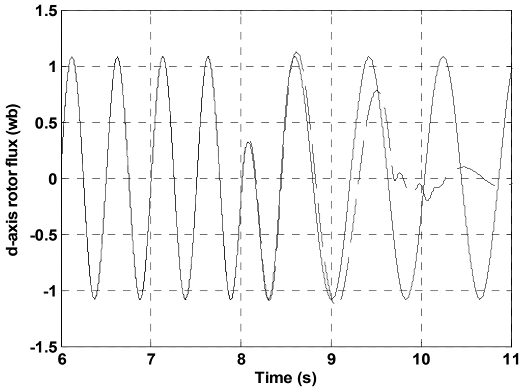
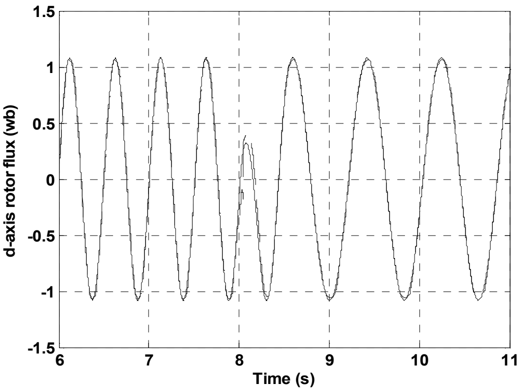


Fig.8 NN stator current MRAS speed estimation performance in the regenerating region of operation actual speed solid, estimated speed (a) Current model flux observer (b) Neural Network flux observer

Since rotor flux estimation using CM depends on the estimated speed, any deterioration in the speed estimation is fed back to the flux observer causing instability in the regenerating mode of operation. Using NN for rotor flux estimation show stable speed estimation performance in the regenerating mode since flux estimation is independent of the estimated speed. Rotor flux estimation performance using the two observers, CM and NN, is shown in Fig. 9.



(a)



(b)

Fig.9 Rotor flux estimation performance in the regenerating region of operation Actual flux solid, estimated flux dashed (a) Current model flux observer (b) Neural Network flux observer

VII. CONCLUSION

In this paper a NN based stator current MRAS is used for speed estimation in sensorless induction motor drives. Rotor flux estimation is required for the speed observer. Using a voltage model for rotor flux estimation causes problems at low speed due to stator resistance sensitivity and the pure integration for flux which may cause DC drift and initial condition problems. A current model can be used instead to estimate the rotor flux from the measured stator currents and the estimated speed, which shows less sensitivity to stator resistance variation. However, the MRAS scheme using the current model flux observer shows instability in the regenerating mode of operation. A multilayer feedforward NN is proposed to overcome this problem for rotor flux estimation from present and past samples of the stator voltage and current. Using the NN flux observer gives less sensitivity to stator resistance variation compared to the voltage model and since the flux estimation is independent of the rotor speed, stable operation has been obtained for regeneration.

TABLE I
Induction motor parameters

Machine parameter	Value	Machine parameter	Value
Rated Power	7.5 [kW]	R_r	0.703 [Ω]
Rated Voltage	415 / 239 [V]	L_s	107.73 [mH]
Rated frequency	50 [Hz]	L_m	103.22 [mH]
R_s	0.7767 [Ω]	L_r	107.73 [mH]
Pole number	4	J	0.22 [Kg/m^2]

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