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ANN and MRAS based Speed Observer for Sensorless Control of Induction Motor Drive

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Abstract. The Model Reference Adaptive System (MRAS) is indeed the most widely used strategy for speed estimation in sensorless induction motor drives, thanks to its simplicity and satisfactory performance across a wide speed range. However, this technique has limitations: it is not optimal in medium- and high-speed regions and remains highly sensitive to variations in motor parameters. Therefore, the artificial Neural Network (ANN)-based MRAS scheme is proposed in this paper it replaces the conventional adjustable model in the MRAS structure, using a two-layer Neural Network (NN) rotor flux observer trained online via a backpropagation (BP) algorithm. The error between the reference model and the NN-based adaptive model adjusts the network weights dynamically for robust speed estimation.Speed estimation performance of two different rotor speed observers is studied and compared when applied to a sensorless direct vector control induction motor drive. The ANN-MRAS observer delivers superior response during steady-state operation and at very low speeds, effectively minimizing speed pulsations.
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Key words. MRAS, Induction Motor, Neural Network, Sensorless control

1. NOMENCLATURE

$\overline{V}_s$: Space vector of stator voltage

$\overline{I}_s$: Space vector of stator current

$\overline{\Phi}_S$: Space vector of the stator flux linkage

$\overline{\Phi}_r$: Space vector of the rotor flux linkage

I_{sd} : Direct component of stator current

I_{sq} : Quadrature component of stator current

R_s : Stator resistance

R_r : Rotor resistance

ℓ_r : Rotor inductance

ℓ_s : Stator inductance

M : Mutual inductance

τ_r : Rotor time constant

τ'_σ : Transient stator time constant

σ : Total leakage factor

R_σ : Equivalent resistance

k_r : Coupling factor of rotor

j : Matrix

$\otimes$: Vector product

ω : Speed rotor

$*$: denotes a reference variable

$\wedge$: denotes an estimated value

2. Introduction

Controlled induction motor drives without speed sensor have emerged as a mature technology in the past decade [1], [2]. The advantages of sensorless control are reduced hardware complexity and lower cost, reduced size of the drive machine, elimination of the sensor cable, better noise immunity, increased reliability, and less maintenance requirements. A motor without speed sensor is indicated for operation in hostile environments. Several solutions for sensorless control of induction motor drives have been proposed based on the machine fundamental excitation model, as summarized recently [3]. These algorithms use 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 direct vector control scheme is shown in Fig.1.

Various techniques have been suggested such as: Model Reference Adaptive Systems (MRAS), Luemberger 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 [4]. In fact, the MRAS speed estimators are the most attractive approaches, due to their design simplicity. Depending on the choice of output quantities that form the error vector which provide the advantage of producing rotor flux angle estimated for the field orientation scheme [5].

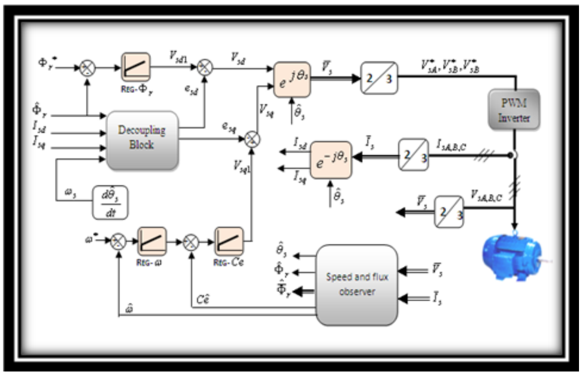


Fig. 1 Sensorless Direct Vector Control Scheme

However the MRAS schemes suffers from parameter sensitivity and pure integration problems which may limit the performance at low and zero speed regions of operation, and the parameters of the PI controller are often tuned by trial and error. To tackle these problems already quoted, the elaboration of an advanced command for the IM has been the subject of multiple efforts [6].

Recently, the re-emerging artificial neural networks (ANN) techniques have been widely applied in the field of system identification and control. In addition, they have been used in some power electronic applications, such as inverter current regulation, dc motor control, flux estimation, and observer based control of IM. Evidently, neural network techniques are showing promise as a competitive method of signal processing for power electronics applications when they have the advantages of extremely fast parallel computation, immunity from input harmonic ripple, and fault tolerance characteristics due to distributed network intelligence.

Neural network is well known for its learning ability and approximation to any arbitrarily continuous function. Nowadays, it has been proposed in the literature that neural networks can be applied to parameter identification and induction motor (IM) state estimation control systems.

In fact, the interest generated by ANN is justified by some of the fascinating properties that they have, such as adaptiveness, generalization, etc., which give a powerful tool to solve problems related to the control of nonlinear complex processes and to overcome the limitations of commonly used techniques [7]. Many different types of ANN have been proposed, however the two-layer linear NN can be used to estimate a rotor speed of induction motor drive.

This paper contains a comparative study between two different schemes structure of rotor speed estimator. The first structure is based on rotor flux classical MRAS, the second is based on neural network MRAS flux observer. The performance and validity of these structures are verified via MATLAB simulink.

3. Rotor Flux MRAS Speed Observer

The model reference approach (MRAS) makes use of the redundancy of two machine models of different structures that estimate the same state variable on the basis of different sets of input variables [2]. The rotor flux MRAS speed observer structure consists of a reference model, an adaptive model, and an adaptation scheme which generates the estimated speed Fig. 2.

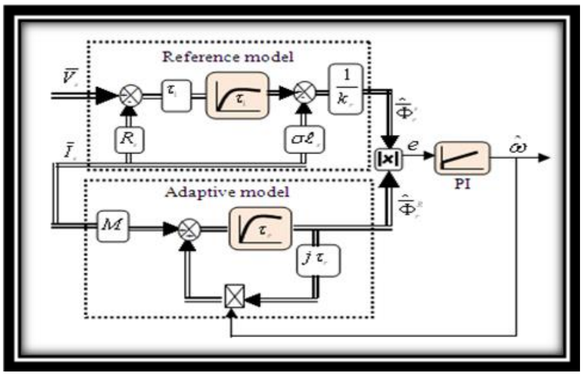


Fig. 2 Rotor flux MRAS Speed Observer

The reference model is used to estimate the stator flux linkage vector or the rotor flux linkage vector without requiring a speed signal. The reference model, usually expressed by the voltage model, your equation in stationary reference frame is given by

$$\hat{\bar{\Phi}}_r = \frac{1}{k_r}\left(\int(\bar{V}_s - R_s\bar{I}_s)dt - \sigma\ell_s\bar{I}_s\right) \quad (1)$$

Where

$$k_r = \frac{M}{\ell r}, \quad \sigma = 1 - \frac{M^2}{\ell_s\ell_r}$$

The rotor flux can be estimated using (1). However the integration voltage model produces a problem of dc offset and drift component in low speed region. Therefore, a negative low-gain feedback is therefore added that stabilizes the integrator and prevents its output from increasing without bounds. The feedback signal converts the integrator to a first-order delay, designed to have a low corner frequency $\frac{1}{\tau_1}$.

The reference model (1) thus becomes

$$\hat{\bar{\Phi}}_r = \frac{1}{k_r}\left(\hat{\bar{\Phi}}_s - \sigma\ell_s\bar{I}_s\right), \tau_1\frac{d\hat{\bar{\Phi}}_s}{dt} + \hat{\bar{\Phi}}_s = \tau_1\left(\bar{V}_s - R_s\bar{I}_s\right) \quad (2)$$

The adaptive model, usually represented by the current model, describes the rotor equation where the rotor flux vector is expressed in terms of stator current and the rotor speed. The rotor flux vector obtained from the adaptive model in stationary reference frame is given by

$$\tau_r\frac{d\hat{\bar{\Phi}}_r}{dt} + \hat{\bar{\Phi}}_r = j\hat{\omega}\tau_r\hat{\bar{\Phi}}_r + M\bar{I}_s \quad (3)$$

The adaptive model generates the rotor flux estimate from the measured stator current and a tuning signal $\hat{\omega}$. A tuning signal $\hat{\omega}$ is obtained through a proportional –integral (PI) controller.

$$\hat{\omega} = \left(kp + \frac{ki}{s}\right)\left(\hat{\Phi}_r^S \otimes \hat{\Phi}_r^R\right) \tag{4}$$

The superscript S and R indicates that $\hat{\Phi}_r$ originates from the stator model or rotor model.

4. 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 approximate function to represent functions with weighted sums of nonlinear terms [8]. 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 activation function as shown in Fig.3.

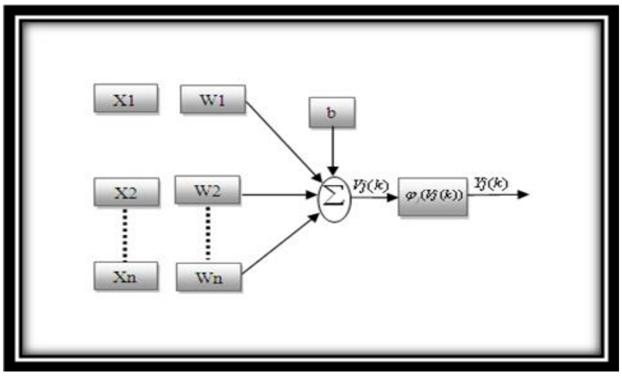


Fig. 3 Representation of the Artificial Neurone

The artificial neuron illustrated in Fig.3 can be modeled mathematically as follows:

$$Vj(k) = \sum_{i=1}^{n} XiWi + b \tag{5}$$

$$Yj(k) = \varphi_j\left(Vj(k)\right) \tag{6}$$

Where:

n : is the number of input signals of the neuron;

Xi : is the i -the input signal of the neuron;

Wi : is the weight associated with the i -th input signal; b : is the threshold associated with the neuron;

$Vj(k)$: is the weighed response (summing junction) of the j -th neuron with respect to the instant k ;

$\varphi j(.)$: is the activation function of the j -th neuron; $Yj(k)$ is the output signal of the j -th neuron with respect to the instant k .

A. Training Neural Network

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 [9].

Several training algorithms have been proposed to adjust the weight values in dynamic recurrent neural network. Examples for these methods are the dynamic back propagation from Narendra and Patthasarathy; 1991.The cost function being minimized is the error between the network output and the desired output given by equation (7):

$$E(k) = \frac{1}{2}\sum_j \varepsilon_j^2(k) = \frac{1}{2}\sum_j \left[Y_j^*(k) - Y_j(k)\right]^2 \tag{7}$$

$Y_j^*(k)$ is desired response to the j -th output put neuron.

For an optimum weight configuration, $E(K)$ is minimized with respect to the synaptic weight W_{ji}. The weights associated with the network output layer are therefore updated using the following relationship [10]:

$$W_{ji}(k) = W_{ji}(k-1) - l_r \frac{\partial E(k)}{\partial W_{ji}(k)} \tag{8}$$

Where:

W_{ji} is the weight connecting the *j*-th neuron of the output layer to i -th neuron of the previous layer, and l_r is a learning rate of the back propagation algorithm.

5. Neural Network MRAS Speed Observer

The MRAS-based scheme described in the previous section contains a reference model and an adaptive model. However, greater accuracy and robustness can be achieved if the mathematical model is partially replaced by a neural network. It is then also possible to eliminate the need of the separate PI controller, since this can be integrated into the tuning mechanism of the neural network-based model. The neural network-based model can take various forms: it can be an artificial neural network (ANN) or a fuzzy neural network etc. and there is also the possibility of using different types of speed tuning signals. It is believed that some of these solutions can give high accuracy and are relatively robust to parameter variations even at extremely low stator frequency [11]. Among these models we choose the NN rotor flux observer. It can be represented by a linear two layer NN where the motor speed is expressed as one of its weights.

B. Neural Network Rotor Flux observer

The bloc diagram MRAS speed observer was shown in Fig. 2. The adaptive model represented by (3) can be replaced by two layer linear neural network.So equation (3) becomes:

$$\hat{\bar{\Phi}}_r(k) = W_1\hat{\bar{\Phi}}_r(k-1) + W_2 j\hat{\bar{\Phi}}_r(k-1) + W_3\bar{I}_s(k-1) \quad (9)$$

Where:

$$W_1 = \left(1 - \frac{T}{\tau_r}\right)$$

$$W_2 = \hat{\omega}T$$

$$W_3 = \frac{MT}{\tau_r}$$

T is the sampling time for the rotor flux observer.

Equation (9) can be rewritten as:

$$\hat{\bar{\Phi}}_r(k) = W_1X_1 + W_2X_2 + W_3X_3 \quad (10)$$

Where:

W_1, W_2, W_3 are the weights of the neuron.
$X1$, $X2$, $X3$ are the three inputs to the neuron.

In equation (10) W_1 and W_3 are already known and W_2 need to be updated. The weight of the network W_2 is found from training, so as to minimize the cumulative error function $E(k)$,

$$E(k) = \frac{1}{2}\sum \varepsilon^2(k) = \frac{1}{2}\left(\bar{\Phi}_r(k) - \hat{\bar{\Phi}}_r(k)\right)^2 \quad (11)$$

The error in rotor flux is back propagated to adjust the weight of the neural network. The weight adjustment using generalized delta rule is given by:

$$\Delta W_2 = -\frac{\partial E(k)}{\partial W_2} = -\left(\hat{\bar{\Phi}}_r(k) - \bar{\Phi}_r(k)\right)^T X_2 \quad (12)$$

The new weight can be written as:

$$W_2(k) = W_2(k-1) + \Delta W_2 \quad (13)$$

To ensure accelerated convergence, the last weight change is added to the weight update as [12]:

$$W_2(k) = W_2(k-1) + l_r\Delta W_2(k) + m\Delta W_2(k) \quad (14)$$

Where m is positive constant called the momentum constant.

Then the rotor speed can be estimated from the weight W_2 as:

$$\hat{\omega} = \frac{W_2}{T} \quad (15)$$

The block diagram of the NN-based rotor flux MRAS scheme is shown in Fig. 4.

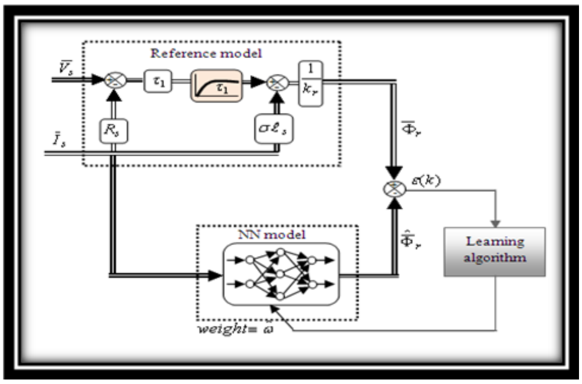


Fig. 4 Representation of the NN Rotor Flux MRAS for Speed estimation

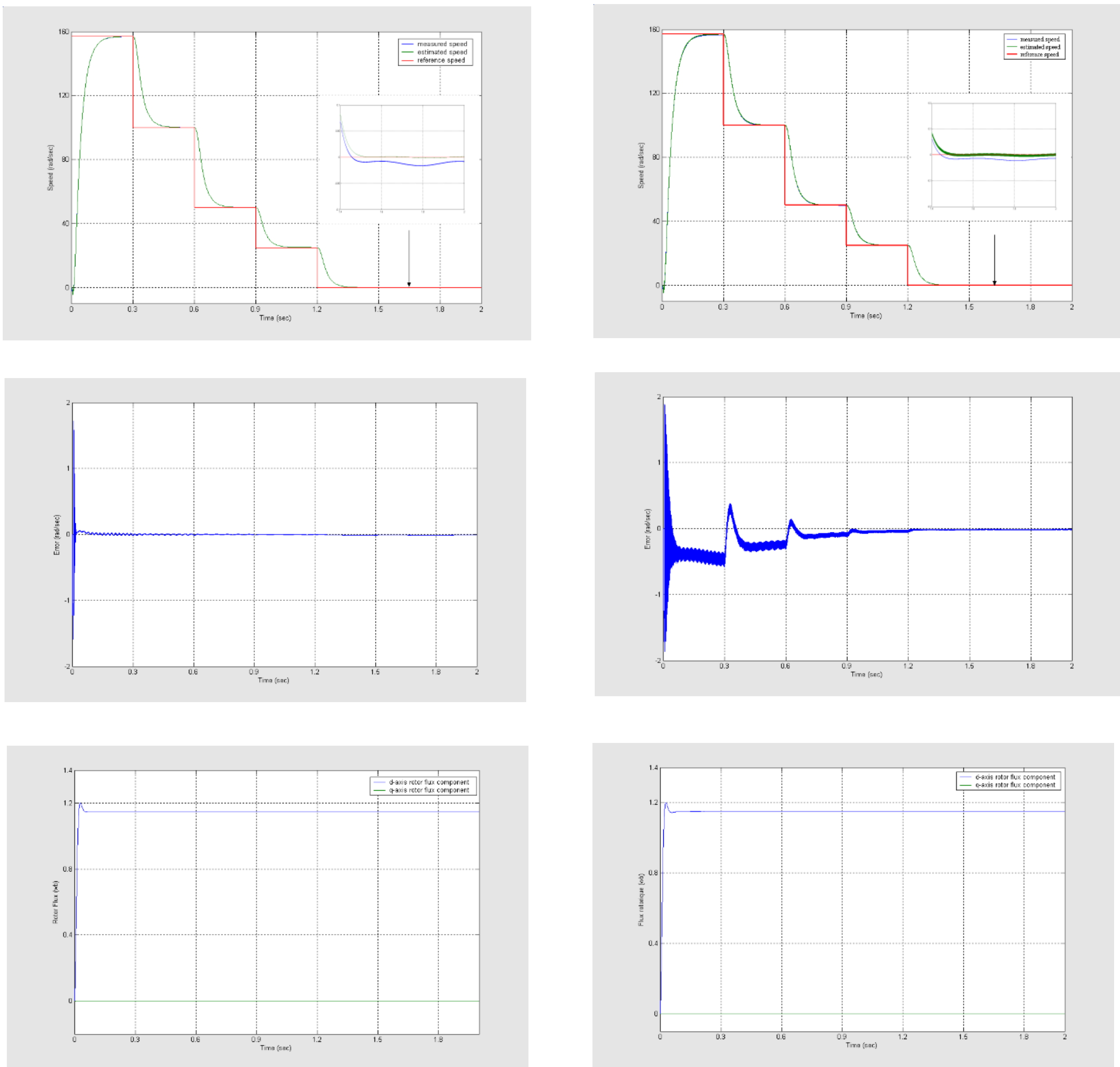
6. Results And Discussion

The simulation phase is very important to verify correctness of theoretical assumptions and to find behavior of the drive. To study the performance of the two proposed schemes MRAS speed observer, an induction motor with parameters given in table I is simulated using Matlab-simulink. Two MRAS schemes will be compared: the first scheme uses the conventional current model (3) as an adaptive model whereas the other scheme makes use of NN rotor flux observer instead. Through next test the comparison will be done to verify the performance of previous MRAS schemes.

In the following test, the estimated speed is used for speed control and field orientation, where the drive is working as sensorless direct rotor flux oriented. The encoder speed is used for comparison purposes only. The test is conducted in the low speed and around the zero speed regions. It concerns a speed starting with a (at t = *0*) with $\omega_{ref} = 157 rad/\sec$ and 100% load torque then the speed reference decreases to values ω_{ref}=100, 50, 25 et 0 rad/sec at respectively t = 0.3, 0.6, 0.9 and 1.2 sec.

The Fig. 5 shows the simulation results of the sensorless direct rotor flux oriented control using the classical MRAS and NN MRAS speed estimator for a variable speed command. The measured speed of induction motor and estimated speed using a classical MRAS and NN MRAS are practically same. It is clear that the estimated speed tracks well the trajectory of the reference one with good accuracy over the whole speed range this for both of classical MRAS and NN MRAS. It can be seen also that the classical MRAS observer demonstrates a better transient error than NN MRAS observer but both the two scheme errors converge to zero in steady state.

Fig .5 shows also that the dynamics of the flux magnitude can highlight the decoupling role of the flux controller where the flux tracks its nominal value of 1.15 Wb for all speed ranges, we find this in both classical MRAS and NN MRAS.



(a) (b)

Fig. 5 Simulation results of the sensorless direct rotor flux oriented control at 100% load,
(a): conventional MRAS; (b): NN MRAS

TABLE I- INDUCTION MOTOR PARAMETERS

machine parameter	value	machine parameter	value
Rated Power	$4[KW]$	ℓ_s	$0.156\ [H]$
Pole number	2	ℓ_r	$0.156\ [H]$
R_s	$1.2[\Omega]$	M	$0.15\ [H]$
R_r	$1.8[\Omega]$	J	$0.05[kgm^2]$

7. Conclusion

Controlled induction motor drives without mechanical speed sensors at motor shaft have the attractions of low cost and high reliability. Several techniques have been proposed for rotor speed estimation in sensorless induction motor drives based on the machine model. The principal aim of this paper is to compare conventional MRAS and NN based MRAS for speed sensorless of induction motor drivers. The conventional MRAS based on rotor flux is proved that it can estimate a rotor speed with high accuracy in different speed range. The use of low pass filter improved the behavior of conventional MRAS. Nevertheless it can affect on estimated speed which becomes worse especially at low speed below the cut frequency. A NN rotor flux observer can replace the adaptive model in conventional MRAS it can ignore the PI controller and tuned by trial. For this propose a two layer NN is used. It estimates a speed rotor from weight of neuron which obtained through learning algorithm. The simulation results shows that the NN MRAS is also has ability to estimate a rotor speed and tracks well the trajectory of reference one moreover it can reach zero speed. To obtain better estimation by using NN the value learning rate must be chosen carefully to avoid instability. Because a large values of learning rate may accelerate the NN learning and consequently fast convergence but may cause oscillations in the network output whereas low values will cause slow convergence.

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