# COMPARISON OF DIFFERENT TYPES OF NEURAL SPEED ESTIMATORS FOR THE INDUCTION MOTOR DRIVE

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Abstract: New control methods of the induction motor drives require knowledge of motor state variables, especially rotor speed. Various schemes of the rotor speed estimation were recently used, based on the mathematical models of the induction machine, on nonlinear phenomena of the motor and based on neural network concept. This papers deals with the application of neural networks approach to induction motor speed estimation under various operating conditions, including frequency control. Two kinds of neural speed estimators were compared in simulation and real experiments performed with help of TMS320C31 digital signal processor. Experimental results were presented and the speed estimation quality was evaluated. 

Keywords: Induction motor, neural networks, speed estimation, digital signal processors

## 1. INTRODUCTION

In the recent years there is a big interest in the development of new methods for the induction motor (IM) speed estimation for the sensorless induction motor drives. Various methods of the rotor speed estimation were used, based on the mathematical models of the induction machine (Joetten and Maeder, 1983; Tamai, *et al.*, 1987; Orlowska-Kowalska, 1992; Kim, *et al.*, 1994) or nonlinear phenomena caused by rotor eccentricity or other motor saliences (Jansen and Lorenz., 1995). Neural networks (NN) offer a promising alternative way to handling this problem.

Because of the well-known advantages of NN, they are used now also in power electronics and motion control systems (Bose, 1994; Orlowska-Kowalska and Kowalski, 1996). The main methods of IM speed estimation developed in the last years were presented in Fig.1, including theirs main features.

Few authors (Ben-Brahim and Kurosawa, 1993; Simoes and Bose, 1995; Fodor, *et al.*, 1996; Orlowska-Kowalska and Kowalski, 1997; Orlowska-Kowalska and Migas, 1998) have reported the application of NN for the reconstruction of induction motor state variables. These applications were based on neural modelling or neural identification methods.

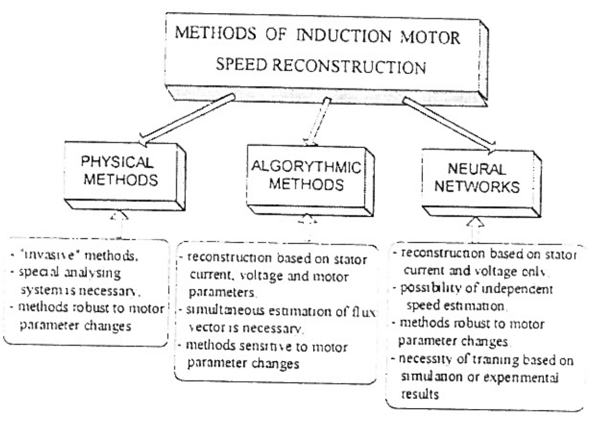


Fig.1. Methods of speed reconstruction for induction motor drive

This paper deals with the comparison of two kinds of neural network approaches for on-line speed estimation of the induction motor drive. All concepts were verified by simulations as well as by real experiments, realised with help of a digital signal processor.

## 2. NEURAL NETWORK APPROACH TO SPEED ESTIMATION PROBLEM

Two kinds of neural network approaches can be used for speed estimation of the induction motor:

- a method based on neural modelling,
- a method based on neural identification.

The first method is based on an analogy between mathematical description of a simple perceptron and the differential equation for rotor flux simulator, written in a discrete form. This method was described first by Ben-Brahim and Kurosawa (1993) and its idea is demonstrated in Fig.2a.

a)

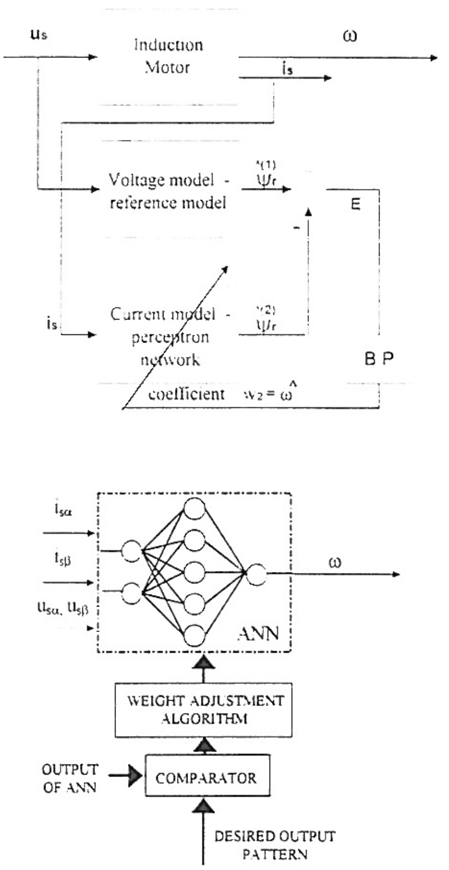


Fig.2. Different concepts of neural speed estimators: a) based on neural modelling; b) based on neural identification

The concept of such neural speed estimator is based on the comparison of two well known rotor flux models: 1 – the traditional rotor flux simulator based on the stator differential equation and algebraic dependence between stator and rotor flux vectors: 2 - model based on the rotor differential equation, which involves one of its parameters - rotor speed – as a state variable. This second model may be regarded as a perceptron model with adjustable weight, which is simply related to the rotor speed. Perceptron neural network is connected to the voltage flux model and trained on line with help of back propagation method, based on the error between network and voltage model outputs, as shown in Fig.2a.

The second method, based on neural identification principle, requires a different approach with help of multilayer feedforward or recurrent networks, as it was shown in Fig.2b. In the recent paper of the authors (Orlowska-Kowalska and Kowalski, 1997; Orlowska-Kowalska and Migas, 1998), they have used feedforward and recurrent NN for the rotor speed and flux estimation. It was proved that these networks enable the reconstruction of rotor speed in various operating conditions of the induction motor, even based on measurements of stator phase currents only. It was possible in the case, when stator current values in few previous steps were introduced to the network input. Better results were obtained when additional pre-processing input values, like stator current and/or voltage magnitude were introduced to the network input.

In the paper both estimation methods were compared in simulation tests from the point of view of sensitivity to motor parameter changes. Neural modelling as well as neural identification approaches were described, including neural networks structures and their training methods. Some simulation and experimental results were presented.

## 3. COMPARISON OF THE SPEED ESTIMATION METHODS

### *3.1. The neural modelling method*

As it was described above, the neural modelling method is based on the comparison of two well-known flux models of the induction motor. The rotor flux simulator based on the stator voltage equation (voltage model) is the following:

$$\frac{d}{dt}\underline{\Psi}_r^{(1)} = \frac{X_r}{X_M}\left(\underline{u}_s - R_s\underline{i}_s - X_s\sigma T_N\frac{d\underline{i}_s}{dt}\right)\frac{1}{T_N} \quad (1)$$

Respectively, the second model of the rotor flux simulator based on the current model is:

$$\frac{d}{dt}\underline{\Psi}_r^{(2)} = \left[\frac{R_r}{X_r}\left(X_M\underline{i}_s - \underline{\Psi}_r^{(2)}\right) + j\omega\,\underline{\Psi}_r^{(2)}\right]\frac{1}{T_N}, \quad (2)$$

where: $T_N = 1/2\Pi f_{sN}$, $\sigma = 1-(X_M^2/X_rX_s)$, $R_s$, $R_r$, $X_s$, $X_r$ - stator and rotor resistances and reactances respectively, $X_M$ - magnetising reactance,

$\underline{u}_s$, $\underline{i}_s$ – stator voltage and current vectors, $\underline{\psi}_r$ - rotor flux vector, $\omega$ - rotor speed.

The current model can be written in the discrete form in following way for neural modelling purposes:

$$\hat{\underline{\Psi}}_r^{(2)}(k) = (w_1\mathbf{I} + w_2\mathbf{J})\,\hat{\underline{\Psi}}_r^{(2)}(k-1) + w_3\underline{i}_s(k-1), \quad (3)$$

where: $\mathbf{I} = \begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}$, $\mathbf{J} = \begin{bmatrix}0 & -1\\ 1 & 0\end{bmatrix}$.

This model, transformed to α-β stationary coordinate system, can be treated as a simple connection of two neurons with linear activation functions. One of the weight coefficients of these neurons – $w_2$, is in fact the rotor speed. It can be derived with help of back propagation method (BP) of the error $E$ and thus the speed estimate can be obtained:

$$w_2(k) = w_2(k-1) + \eta\,\Delta w_2(k),$$

where: $\eta$ - learning coefficient, $\alpha$ - momentum factor. (4)

$$\Delta w_2(k) = -\eta\,\delta\,\mathrm{J}\,\hat{\Psi}_r^{(2)}(k-1) + \alpha\,\Delta w_2(k-1),$$

$$\delta = \frac{\partial E}{\partial\,\hat{\Psi}_r^{(2)}(k)};\quad E = \frac{1}{2}\varepsilon^2(k) = \frac{1}{2}\left(\hat{\Psi}_r^{(1)}(k) - \hat{\Psi}_r^{(2)}(k)\right)^2.$$

After using of two (α, β) components of the rotor flux vectors, for voltage and current models respectively, the back propagation algorithm for $\omega$ modification can be obtained:

$$\hat{\omega}[k] = \hat{\omega}[k-1] - \eta\left(-e_\alpha \Psi^{(2)}{}_{r\beta} + e_\beta \Psi^{(2)}{}_{r\alpha}\right)[k-1] + \alpha\Delta\omega[k-1], \quad (5)$$

where:

$$e_\alpha = \psi_{r\alpha}{}^{(1)} - \psi_{r\alpha}{}^{(2)}$$
$$e_\beta = \psi_{r\beta}{}^{(1)} - \psi_{r\beta}{}^{(2)}.$$

As it was proved by Ben-Brahim and Kurosawa (1993), this neural identifier works very well for nominal parameters of the induction motor used in both models. In the case when rotor resistance is varying, the estimation errors occur, especially in the low speed region. But mathematical model (1) and (2) used in the estimation scheme depend on the other motor parameters also. In the case when activation function of the each neuron is linear, as it was proposed originally, it is hardly to consider this estimator as real neural network with all its advantages, especially with robustness to noise and parameter disturbances. So, in this paper, the proposed estimator was also checked to the changes of other motor parameters used in the voltage and current flux models.

The neural speed estimator was trained in the wide range of speed and load torque changes, on the base of simulation results, obtained with help of MATLAB-SIMULINK, for inverter-fed induction motor. Then the trained network was tested for speed and load torque reference signal different than used in the training procedures. The testing speed reference was increased linearly form 0 to 1 [p.u.] and then at t = 0.5[s] it was changed to 0.5 [p.u.] (in the duration of 0.25[s]). The load torque initially was set up to 0, then, at t = 0.4[s], it was changed to 1 [p.u.] and at t = 0.7[s] it was changed to 0.5 [p.u.]. In the simulation the Euler method with an integration step equal 0.0001[s] was used, to have the similar conditions as in the real experiment. The transient and average estimation errors were checked and presented in the case of all parameter changes. It was proved that for optimal choice of η and α coefficients, it is possible to obtain low sensitivity of the estimator to motor parameter changes. Some transients of the speed estimation results were presented in the following figures.

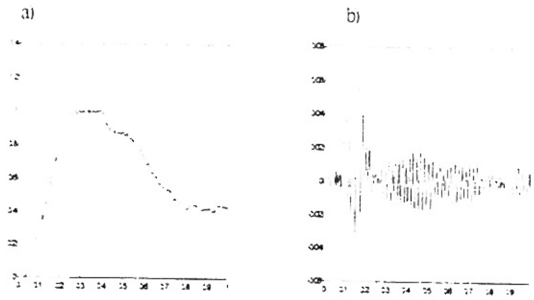

Fig.3. Rotor speed, its estimate (a) and speed estimation error (b) for $\eta_e = 0.08$, $\alpha_e = -0.00008$, $Rr = Rr_N$ (with filter)

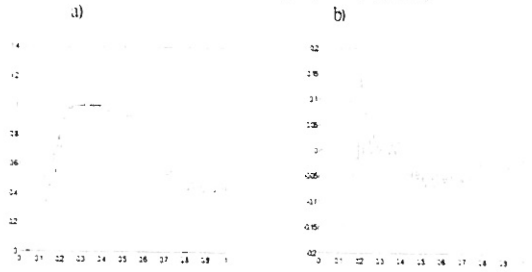

Fig.4. Rotor speed, its estimate (a) and speed estimation error (b) for $\eta_e = 0.08$, $\alpha_e = -0.00008$, $Rr = 1.5Rr_N$ (with filter)

In Fig.3 and 4 the results obtained for neural modelling method were presented in the case of nominal and higher values of rotor resistance used in the estimator model (at all figures the rotor speed and the estimation error were demonstrated in the vertical axis and the time (in [s]) was presented in the horizontal axis).

Mathematical models (voltage and current flux models, respectively) used in this estimation scheme depend on the other motor parameters also. So, the speed estimator was checked out to all motor parameters changes. It was shown, that significant speed reconstruction errors occur in the case of motor parameters changes or theirs bad identification.

In order to obtain the brief answer to the problem of neural speed estimator sensitivity to the changes of all parameters of induction motor equivalent circuit, the average speed estimation errors were calculated in the following way:

$$Err\,[\%] = \sum_{k=1}^{n} \frac{e_{\omega_k}[\%]}{n}, \quad (6)$$

where:

$$e_{\omega_k} = \frac{|\omega_k - \hat{\omega}_k|}{\omega_k} \cdot 100\% \quad (7)$$

$\omega$ - rotor speed, $\hat{\omega}$ - estimated rotor speed, $n$ – number of all speed samples.

The average speed estimation errors were calculated for different changes of stator and rotor resistances as well as for stator, rotor and magnetising reactances. Examples of these average errors were shown in Fig.5. The speed estimation error increase significantly when the bad identification of the following motor parameters occurs:

- too low rotor resistance value;
- too high stator resistance value;
- too low magnetising reactance value.

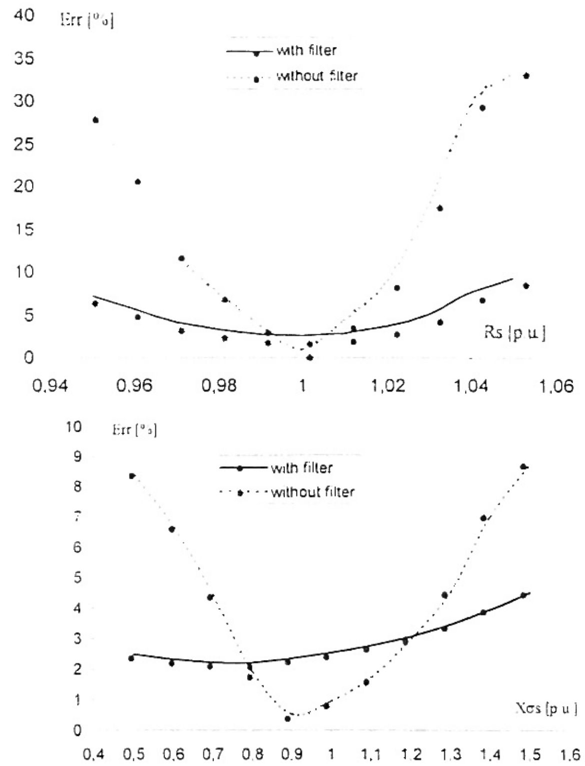


Fig.5. Dependence of average value of speed estimation error on stator resistance and leakage reactance, respectively

Identification errors of stator leakage reactance and stator resistance significantly influence the speed estimation errors, especially in the case when low-pass filters are not used.

### *3.2. The neural identification method*

In the case of neural identification of the nonlinear systems (like drive systems), the multilayer networks with nonlinear activation functions should be used. Various types of neural networks can be used for identification purposes of the dynamical plants:

1 – a feedforward ANN, which uses the measured outputs of the plant in few previous steps as inputs of the neural;

2 – a recurrent network (with feedback loop) which uses the estimated outputs of the network as its actual inputs.

Various structures of neural speed estimator were used in simulations and real experiments. The feedforward and recurrent networks (of Elman type) were tested in various operation modes of the drive system. The frequency control of the induction motor with changing speed reference was taken into account.

Networks with one or two hidden layers, with *tansig* neurons in the hidden layer and *purelin* neurons in the output layer were tested. The inputs of the networks were following: two stator currents $I_{s\alpha}$, $I_{s\beta}$ in stationary $\alpha-\beta$ coordinates and one pair or more theirs delayed values.

The input information about line currents only was insufficient to enable the proper speed reconstruction under stator frequency changes. So two solutions of additional input signals presented to the NN were tested:

1- The actual frequency of stator line current obtained from the additional I/f transducer, realised numerically (Orlowska-Kowalska and Migas, 1998);

2- the magnitude of stator current and voltage obtained by pre-processing of line currents and voltages. In both cases the neural estimators' sensitivity to an inaccuracy in motor parameters identification was tested by simulation and in the laboratory experiments.

In simulation tests the feedforward network with one hidden layer was not able to reconstruct the induction motor speed, even in the case of constant stator frequency. Only recurrent network of Elman type with one hidden layer has estimated motor speed with acceptable error in the range of 2-3% of rotor speed actual value. The best results were obtained for feedforward networks with two hidden layers and three pairs of delayed inputs.

For this type of neural speed estimator the obtained estimation errors are much smaller in the case of changing or bad identified motor parameters than for the simulator described in the chapter 3.1.

## 4. MICROPROCESSOR REALISATION OF NEURAL SPEED ESTIMATORS

The microprocessor implementation of neural speed estimators was realised with help of 32-bit digital signal processor TMS320C31 manufactured by dSPACE, in the laboratory rig presented in Fig.6.

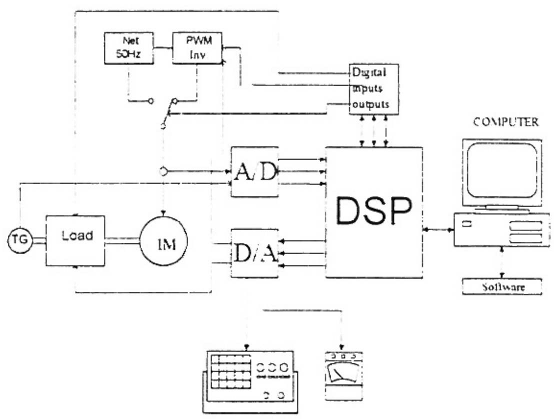


Fig.6. Laboratory rig with DSP realisation of IM neural speed estimation

Results of speed estimation obtained from trained NN were compared to the real motor speed measured by DSP (through tachogenerator and A/D converter). The measured and estimated speed transients as well as suitable errors were presented in Fig.7 and 8 for neural modelling method described in chapter 3.1.

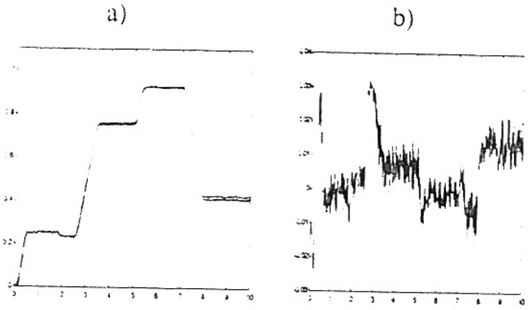


Fig.7. Experimental results for estimator based on neural modelling method : a) real motor speed and speed estimate; b) speed estimation error; nominal motor parameters

It can be seen from Fig.8 that transient and steady-state estimation errors occur in the case of motor parameter changes. The erros' range is +(3-5)% of the actual rotor speed. It means that this estimator presents results higher than real motor speed in the whole transient process, when motor parameter are different than nominal.

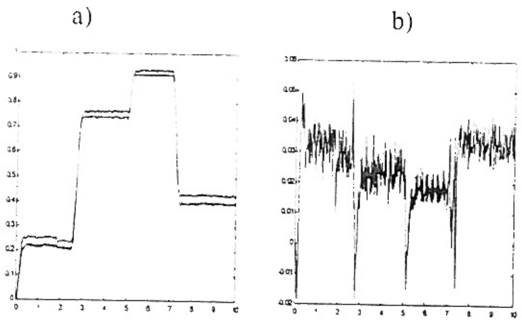


Fig.8. Experimental results as above: a) real motor speed and speed estimate; b) speed estimation error; $R_s=2\,R_{sN}$

For neural identification method different structures of neural networks, with various numbers of neurons in the hidden layers were realised numerically and results of the estimation of rotor speed were compared. To enable the proper speed reconstruction under stator frequency changes, the additional input signal was added to the NN input - it was the frequency of stator line current obtained from the additional I/f transducer realised numerically. In Fig.9 examples of speed estimation with help of digitally realised different structures of feedforward neural network during different modes of operation of the induction motor supplied from PWM inverter were presented.

From Fig.9c,d results, that in the case of feedforward NN with one hidden layer only, the obtained estimation errors are not greater than ±(3-4)%, what is almost the same result as in he case of two hidden-layer network (Fig.9a,b).

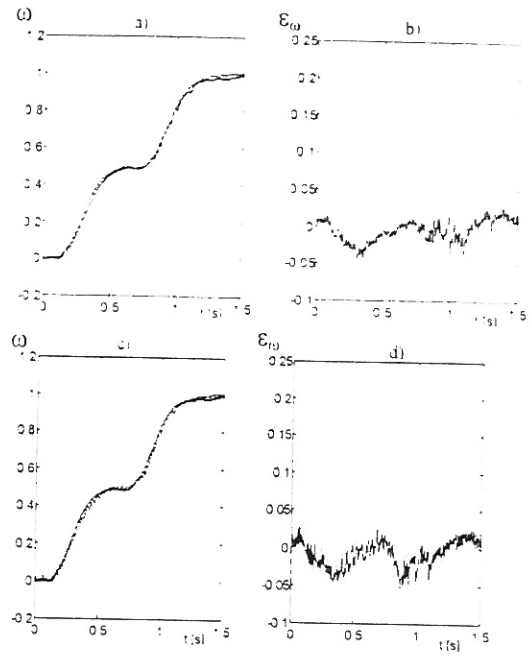

Fig.9. Transients of the motor speed, its neural estimate (a,c), the estimation error (b,d) during frequency changes: a,b - for 7-7-15-1; c,d - for 7-20-1 feedforward network

To improve the speed estimation results, the different concept was tested, which was mentioned earlier in chapter 3. As the additional NN input information, the stator current and voltage magnitudes were introduced, except of stator currents $I_{s\alpha}$, $I_{s\beta}$ in stationary $\alpha$-$\beta$ co-ordinates. It has significantly improved the speed reconstruction and the obtained average errors were in the range of ±(1-2)%. In Fig.10 the examples of such speed reconstruction were presented for feedforward network with one hidden layer only. The best results were obtained for neural network with two hidden layers, but even in the case of very simple one hidden layer network (4-5-1), speed estimation results were acceptable. It means that proposed concept with additional pre-processed input signals of neural networks is a good solution for induction motor speed reconstruction in the wide range of motor speed reference changes.

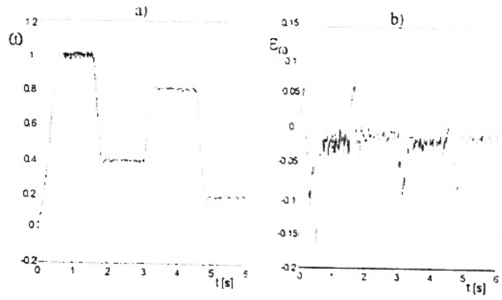

Fig.10. Transients of the motor speed, its neural estimate (a) and the estimation error (b) during frequency changes for NN 4-5-1

So, it could be said, that the "real" neural network speed estimators based on multilayer feedforward or recurrent neural networks, trained for changing motor parameters, are much robust than concept based on neural modelling method. They can perform the rotor speed estimation, after off-line training procedure, even for the motor with unknown parameters.

## 5. CONCLUSION

Two kinds of neural speed estimators were checked by simulation as well as by experiments in the real drive system. It was proved, that the speed estimator proposed by Ben-Brahim and Kurosawa (1993), based on neural network with linear activation function and back propagation algorithm, is sensitive to all motor parameters changes or bad identification of motor parameters, used in voltage and current flux models, which are components of the proposed speed estimation scheme. It seems that this kind of speed estimator is very similar to the MRAC method of the induction motor speed reconstruction, proposed by Tamai S. *et alt.*, (1987); the difference is only in the algorithm used for minimisation of the error between two flux models used in these schemes.

For the second solution based on multilayer feedforward or recurrent networks, it was proved by simulations, that in the case of changing parameters of the induction motor, the feedforward neural network with one hidden layer is not able to estimate properly the rotor speed based on stator current measurements only, when load-torque and parameter changes exceed the training rates. In the contrary, the one-hidden layer recurrent network reconstructs the motor speed with very low average error and is much more robust for parameter and load-torque changes.

But for neural networks trained by experimental patterns there is not big difference in the results of estimation between feedforward and recurrent networks with two hidden layers. So, for practical application the feedforward networks are much better, because of their simplicity and faster training process. It should be mentioned that in the case of frequency control of the induction motor, the neural estimator needs additional information about changing frequency of line stator currents or/and current and voltage magnitude. All proposed solutions based on multilayer networks (trained by simulation tests and by experiments) were robust to drive parameter changes as well as measurement disturbances in the opposite to the solution presented by Ben-Brahim and Kurosawa (1993). From the simulation and experiments results, that this kind of neural estimator seems to be an interesting solution for the sensorless induction motor drives as well as for on-line motor speed monitoring. It needs only two stator currents ($i_{SA}$ and $i_{SB}$) and two stator voltages ($u_{AB}$ and $u_{BC}$) measurements, as well as simple pre-processing of these variables, for the estimation of rotor speed, without any particular measurement or machine sensors. It does not need knowledge of any motor parameters, like in Ben-Brahim solution.

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