



NEURONAL NETWORK SYSTEM TO IDENTIFY SPEED

TIRIAN Gelu Ovidiu

UNIVERSITY "POLITEHNICA" TIMIŞOARA FACULTY OF ENGINEERING HUNEDOARA

ABSTRACT:

The correction schema used is a direct vectorial correction schema, oriented after the rotor flux, without any speed transducer. The speed is being calculated "on-line" by means of a neuronal estimator. The algorithm of network training is the method of error backpropagation.

KEYWORDS:

neuronal network, identification, speed transducer

1. INTRODUCTION

Neuronal network can be made of simple processing elements, i.e. preceptrontype or neurons, making one-layer network, or of several elements of this type, which will make up multi-layer neuronal network. The paper suggests a neuronal network system, meant to identify speed. Starting from the idea of a direct vectorial control layout using two rotor flux estimators, we have built a neuronal network, which self trains in real time. The information retrieved from one of the weights of the neuronal network will be the very rotor speed and will constitute the basis of a control diagram without speed transducer for the asynchronous machine with short-circuited rotor.

2. THE STRUCTURE OF THE NEURONAL NETWORK

Specific training algorithms have to be applied in order to determine the values of these weights, which practically, represent the solution of the problem that has to be solved by the neuronal network. The training algorithms can be ranged into two categories, namely supervised-type and non-supervised-type training methods.

We have built a neuronal network, which self trains in real time. The data retrieved from one of the weights of the neuronal network will be the very rotor speed and will constitute the basis of a control diagram without speed transducer for the asynchronous machine with short-circuited rotor.

The state variable chosen to train the network is the rotor flux. In order to estimate it we can use the equation of the stator voltage reported to the stator mark:

$$\underline{\mathbf{u}}_{s} = \mathbf{R}_{s} \underline{\mathbf{i}}_{s} + \frac{d\underline{\Psi}_{s}}{dt}$$
(1)

The equation of the flux ψ_r (the desired value):

$$\frac{d\underline{\Psi}_{r}}{dt} = \frac{L_{r}}{L_{m}} \left(\underline{u}_{s} - R_{s} \underline{i}_{s} - \sigma L_{s} \frac{d\underline{i}_{s}}{dt} \right)$$
(2)

On the other hand, using the equation of rotor voltage reported to the stator mark one can calculate the rotor flux, this time called λ_r by means of the following:

$$\frac{d\underline{\lambda}_{r}}{dt} = -\frac{1}{T_{r}}I\underline{\lambda}_{r} + \frac{L_{m}}{T_{r}}\underline{i}_{s} + J\omega\underline{\lambda}_{r}$$
(3)

The diagram used to estimate the speed of the induction machine is the following:



Figure 1. The structure of the neuronal network system meant to identify the speed

Equation 3 can be written in view of numerical integration as follows:

$$\underline{\lambda}_{r}(\mathbf{k}) = \underline{\lambda}_{r}(\mathbf{k}-1) + (\mathbf{W}_{1}\mathbf{I} + \mathbf{W}_{2}\mathbf{J})\underline{\lambda}_{r}(\mathbf{k}-1) + \mathbf{W}_{3}\underline{\mathbf{i}}_{s}(\mathbf{k}-1) =$$

$$= \underline{\lambda}_{r}(\mathbf{k}-1) + \mathbf{W}_{1}\mathbf{X}_{1} + \mathbf{W}_{2}\mathbf{X}_{2} + \mathbf{W}_{3}\mathbf{X}_{3}$$
(4)

This model can be assimilate with a two-layer neuronal network, with weights W_1 , W_2 , W_3 and inputs X_1 , X_2 , X_3 .

The output error results from the flux estimated by equation 5 or the so-called UI estimator and the estimated flux of the neuronal network characterized by equation 5:

$$\underline{\varepsilon}(\mathbf{k}) = \Psi_{r}(\mathbf{k}) - \underline{\lambda}_{r}(\mathbf{k})$$
(5)

The algorithm of network training is the method of error backpropagation. In order to determine the weights in this case for the output layer only, we used one correction rule. In fact, the only adjusting weight is W_2 , as it is proportional to the magnitude that has to be identified, namely the rotor speed.

3. SCHEM OF CONTROL MRASNN

The correction schema used is a direct vectorial correction schema, oriented after the rotor flux, without any speed transducer. The speed is being calculated "on-

line" by means of a neuronal estimator, based on the structure given in figure 1. The flux estimator $I\omega$ is synthesized as a neuronal network and, by means of the "backpropagation"-type training algorithm, it is being trained in real time. The control schema regulates the speed with satisfactory results.



Figure 3. Schema de control MRASNN

Tests have been made for various speed profiles, both for the functioning in the linear zone, maintaining a constant rotor flux for low speeds, and for the de-fluxing area in order to obtain higher speeds.



Figure 4. Speed profile with slowing down from 500 rpm at –500 rpm



Figure 5. Speed profile with slowing down from at 1000 rpm at -1000 rpm

Figure 4 gives the complete speed profile, namely from 10 rpm to 500 rpm, functioning on a constant floor and slowing at time moment t = 4s m down to -500 rpm, functioning on a constant floor and slowing down to 10 rpm. Figure 5 gives the speed profile 1000 rpm, the schema functions under de-fluxing work conditions, due to the limited voltage of the DC circuit. The de-fluxing process starts around value 750 rpm and the reference flux is low and inversely proportional to the motor rotation rate.

4. CONCLUSIONS

Neuronal network system to identify speed, starting from the idea of a direct vectorial control layout using two rotor flux estimators. In this way we have built a neuronal network, which self trains in real time. The information retrieved from one of the weights of the neuronal network will be the very rotor speed and will constitute the basis of a control diagram without speed transducer for the asynchronous machine with short-circuited rotor.

REFERENCES / BIBLIOGRAPHY

- [1.] TIRIAN G.O.– Abordări moderne în estimarea și identificarea sistemelor, Referat doctorat, Universitatea "Politehnica" Timișoara, Facultatea de Automatică și Calculatoare, 2005.
- [2.] TIRIAN G.O.– High speed neuronal estimator for the command of the inductionmachine, Universitaria SIMPRO, pg.61...65, 2006
- [3.] CUIBUS M. Comanda sistemelor de acţionări electrice de curent alternativ utilizând reţele neuronale – Teză de doctorat, Universitatea "Politehnica" Bucureşti, Facultatea de Electrotehnică, 2004