Paper No. T3-1.3, pp. 1-5

14th INTERNATIONAL SYMPOSIUM on POWER ELECTRONICS - Ee 2007
XIV Međunarodni simpozijum Energetska elektronika – Ee 2007
NOVI SAD, REPUBLIC OF SERBIA, November 7th - 9th, 2007

VARIATIONS OF RBF NETWORK IN ROTOR TIME CONSTANT ADAPTATION

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Abstract: *This paper presents the results of the rotor time constant adaptation method with the application of artificial neural network. The estimation of the rotor time constant for adaptive model of MRAS is realized by the help of PI-controller and then is replaced by the Radial Basis Function network. The estimated rotor time constant is then used in the vector control of electrical drive. There were discussed the different architectures of RBF network in the field of adaptation of rotor time constant parameter. Simulations have been performed in the Matlab-Simulink.*

Key Words: ***Induction motor/ Vector control/ Radial Basis Function/Adjustable speed drive***

1. INTRODUCTION

Artificial neural networks (ANN) are mainly used in these types of application where the realization of another methods would be very difficult, expensive or even unrealizable. In these applications there is possible to take the advantage of the main features of neural networks, namely: approximation ability of different nonlinear functions, possibility to set their parameters in virtue of the experimental or learning data set, the quickness of information processing and their robustness. There is no necessary mathematical or structure description, there is possible to solve the problem just like the black box task with their inputs and outputs.

The Radial Basis Functions (RBF) emerged as a variant of artificial neural network (ANN) in late 80`s by Broomhead and Love and their work opened another ANN frontier. RBF network is a type of ANN for applications to solve problems of supervised learning regression, classification and time series prediction. The radial basis functions have been applied in the area of neural networks where they may be used as a replacement for the sigmoid hidden layer transfer function in multilayer perceptrons. The radial basis functions are powerful techniques which are built into a distance criterion with a respect to the centre. Such networks have 3 layers, the input layer, the hidden layer with the RBF non-linearity and the linear output layer. RBF networks have the advantage of non suffering from local minima in the same way as multilayer perceptrons. The most popular choice for the non-linearity is the Gaussian. The output layer is in regression problems a linear combination of hidden layer values representing mean predicted output. The RBF architecture is discussed in [1] and the training algorithms and methods are mentioned in paper [2].

In most cases, it presents higher training speed when compared with ANN based on back-propagation training methods, easier optimization of performance since the only parameter that can be used to modify its structure is the number of neurons in the hidden layer etc…

Rotor time constant adaptation methods are used in the modern control of induction drive. The value of rotor resistor changes in dependence on drive load. To improve the motor power its necessary the identification of these parameters and adjusts them.

2. ADAPTATION METHOD

The adaptive reference system model is based on comparison of two estimators. The first one, so-called the reference model doesn't include rotor time constant. The other, which contains rotor time constant, is the adaptive model. The error between them is used to derive an adaptation algorithm that produces the estimated value of rotor time constant in current model, which is used in vector control of induction motor drive (Fig.1). This model contains the rotor time constant which is a changing parameter. In order to ensure the optimal vector control of induction motor, the rotor time constant has to be adjusting continuously.

To derive adaptation algorithm there were used equation of voltage model of rotor flux and the equations of current model of rotor flux. It was well described in the work [3] and the adaptation algorithm it's described by the following equations:

$$\Phi(e) = e_\alpha \left(L_m i_{S\alpha} - \hat{\Psi}_{R\alpha}\right) + e_\beta \left(L_m i_{S\beta} - \hat{\Psi}_{R\beta}\right) \qquad (1)$$

$$e_\alpha = \left(\Psi_{R\alpha} - \hat{\Psi}_{R\alpha}\right), \quad e_\beta = \left(\Psi_{R\beta} - \hat{\Psi}_{R\beta}\right) \qquad (2)$$

$$\frac{1}{\hat{T}_R} = K_1 \Phi(e) + K_2 \int \Phi(e)\, dt \qquad (3)$$

,where $K_1 > 0$, $K_2 > 0$ (4)

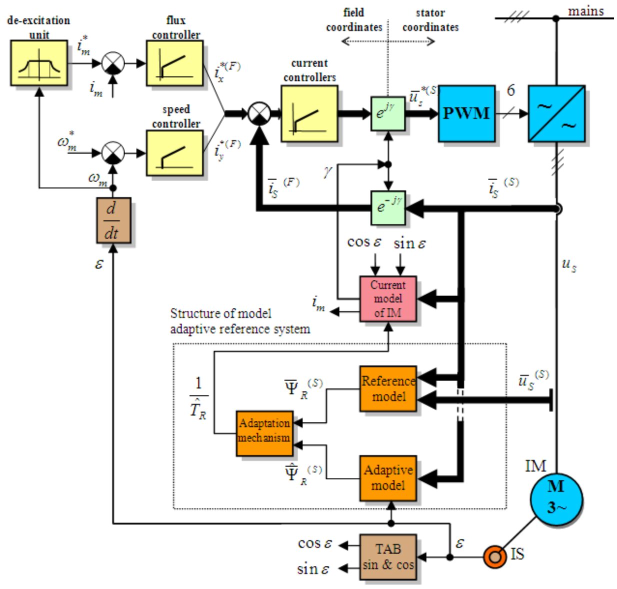

Fig. 1. *Control structure with adaptive system*

The adaptation mechanism consists of evaluation of adaptation signal (Eq.1) and its sequential minimalization by the help PI-controller (Eq.3). Figure 2 shows the structure of model adaptive reference system and also the substitution of the adaptation mechanism with the artificial neural network.

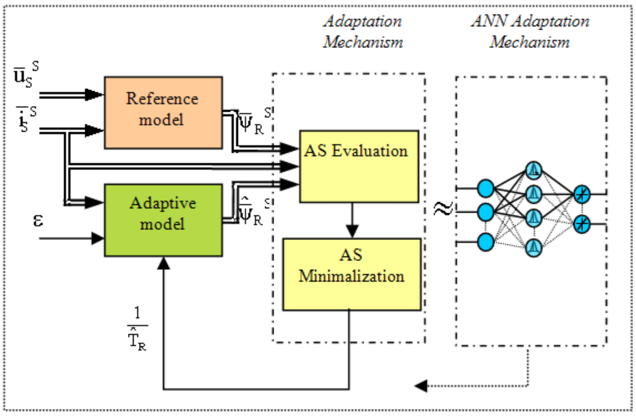

Fig. 2. *Adaptation mechanism*

3. RADIAL BASIS FUNCTION NETWORK

The aim of this work was to compare the features of Radial Basis network with different architectures. There was no intention to compare training algorithms. That was described in the paper [2]. In this paper the effort focused in different architectures of RBF, also there was added white noise, which is very useful in the application of feed-forward neural networks.

There was realized comparative procedure. At first there was realized common RBF network with the appropriate architecture, it mean with one, two or without feedback, etc… Then there was changed the field of coverage from one RBF unit. That was mathematical described in [1]. In fact it means more sporadic or densely lay-out of the RBF units, which is expressed by lower or higher number of RBF units.

Figure number 3 depicts the data acquisition of training data set for the off-line neural network training.

The start of the motor was set without load and in the time 0.5 seconds with the load. The model was always adjusted according to the actual architecture of tested RBF network. Then there were used Forward Subset Selection training algorithm and all of this was done in Matlab-Simulink software.

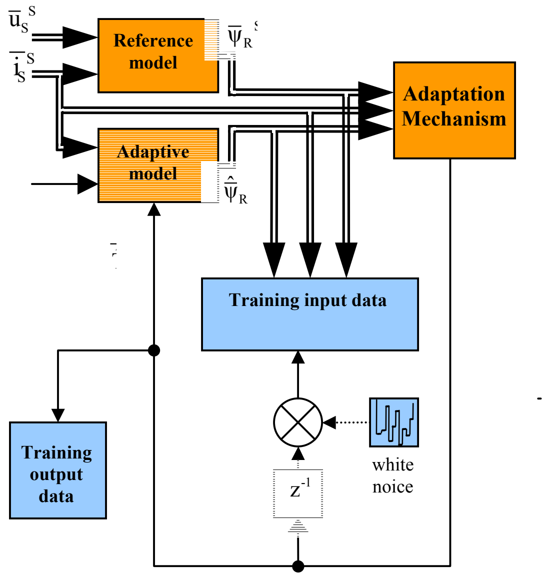

Fig. 3. *Block structure of the in-out data training acqusition*

3.1. RBF network with one feedback

The first type is the most used and common. RBF network with one feedback without scaling and without the white noice. The figure 4 depicts the RBF architecture with the appropriate input variables. There are always three layers: input, hidden layer with the non-linear activation function and the output linear layer.

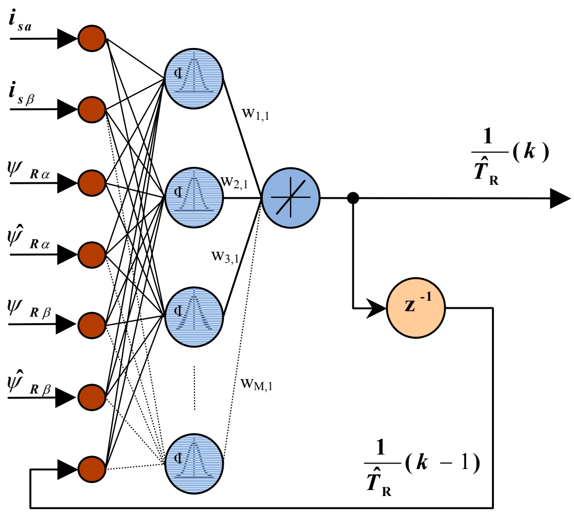

Fig. 4. *Architecture of RBF neural network*

There are the input data for the adaptation mechanism, which were also used like an input training data set for the neural network, in the figure 5. Output or we can say the desired output time behavior is always depicted in the figures by the red dotted line.

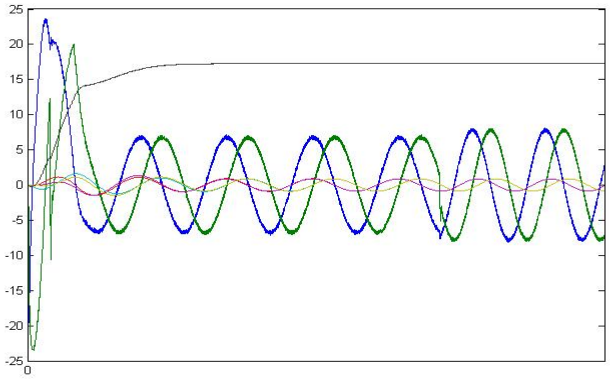

Fig. 5. *Input training data set*

In the first RBF neural network there were used 97 RBF units. The output time behavior is perfect as we can see in the figure 6, the difference between the adaptation mechanism and the RBF network is really neglect able (Fig.7).

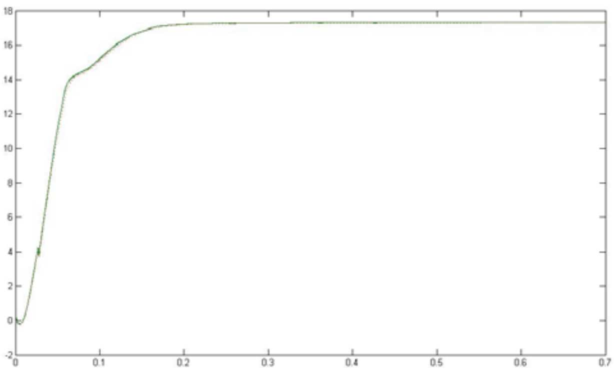

Fig. 6. *Output $1/T_R$ from RBF and AM*

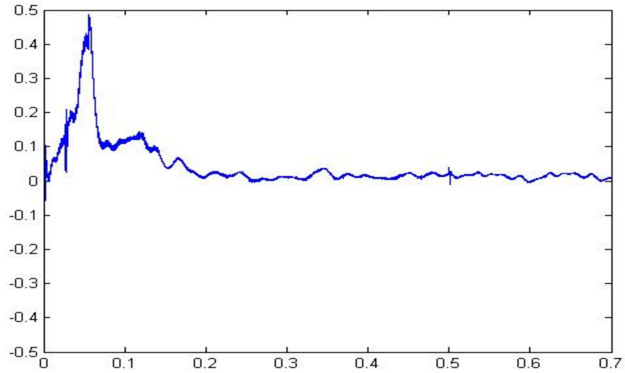

Fig. 7. *Difference between RBF and AM output*

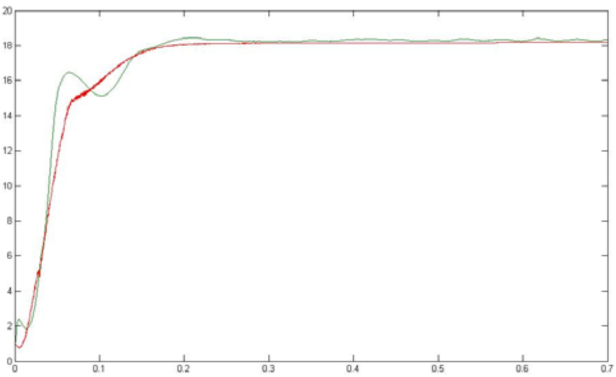

Fig. 8. *Output $1/T_R$ from RBF and AM*

Next network was used with thinly lay-out of 33 RBF units and the response is also quite good (Fig.8). Last one was used with denser lay-out of 365 RBF units and the output was almost the same like with the 96 RBF units. Then is no reason to use this kind of structure because of higher memory demand and higher computation time.

3.2. RBF without feedback connection

Next architecture of RBF network didn't include the feedback. In the figure 10 there is possible to see that this output behavior is not the expected one. The network contains 81 RBF units. In the next figure there is obvious improvement of the output curve, but the price was higher number (261) of the RBF units.

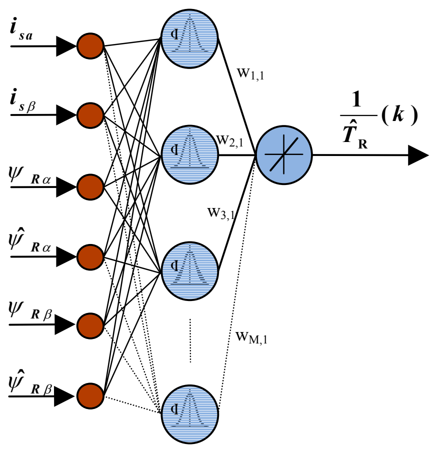

Fig. 9. *Architecture of RBF neural network*

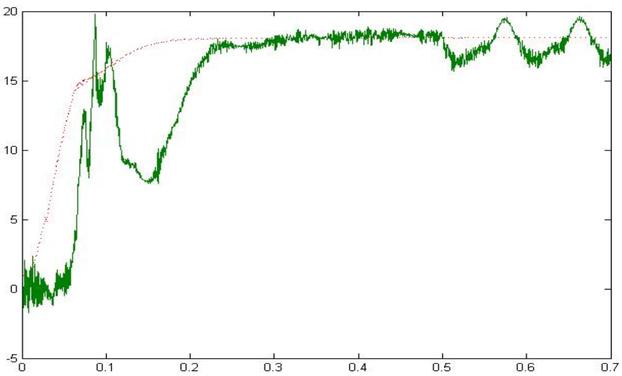

Fig. 10. *Output $1/T_R$ from RBF and AM*

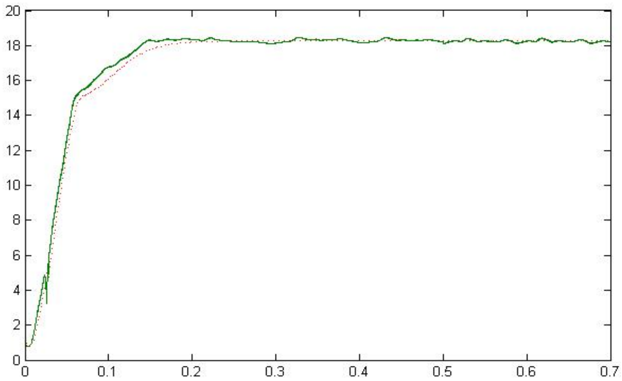

Fig. 11. *Output $1/T_R$ from RBF and AM*

3.3. RBF with two feedback connection

There is described the RBF architeucture with two feedbacks connections. As we can see the output time behaviour is also very good (Fig.12 & Fig. 13) like in the first case. There were used 120 RBF units and the next was used with thinly lay-out of 51 RBF units and the response is also quite good (Fig.14). Denser lay-out of RBF network disposes with 261 RBF units and this is the same problem like with network with one feedback.

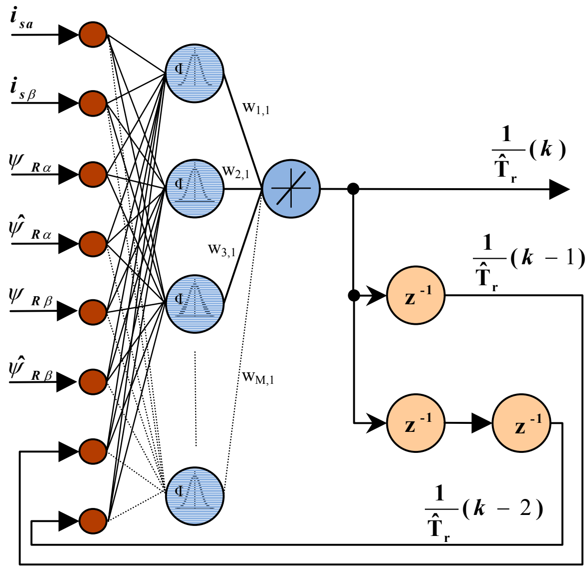

Fig. 12. *Architecture of RBF neural network*

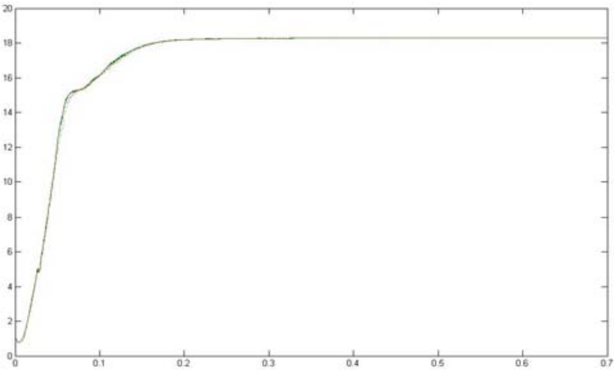

Fig. 13. *Output $1/T_R$ from RBF and AM*

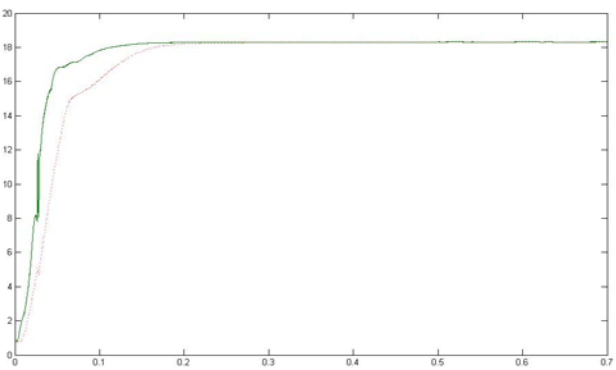

Fig. 14. *Output $1/T_R$ from RBF and AM*

3.4. RBF with the scaled input variables

The next architecture comes from idea of feed-forward architecture, where the input values must be scaled because of their activation function. In the figure 15 there are depicted input scaled trainig data set for RBF neural network.

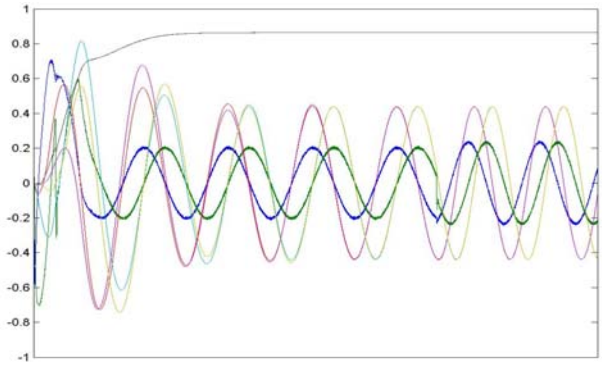

Fig. 15. *Input training data set*

Only the dense (436 units) RBF unit lay-out provide output curve (fig.18) like the unscaled networks. The classical one with 116 units we can also consider good enough(fig.16), but network with thin lay-out (32units) has low-quality output curve (fig.17).

There were one important difference in lower values of the inner network parametrs like radius, centers and weights.

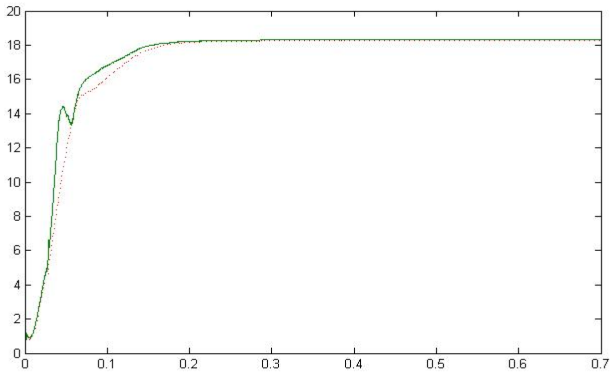

Fig. 16. *Output $1/T_R$ from RBF and AM*

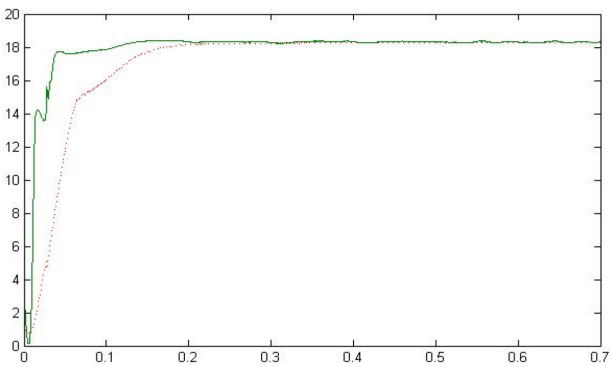

Fig. 17. *Output $1/T_R$ from RBF and AM*

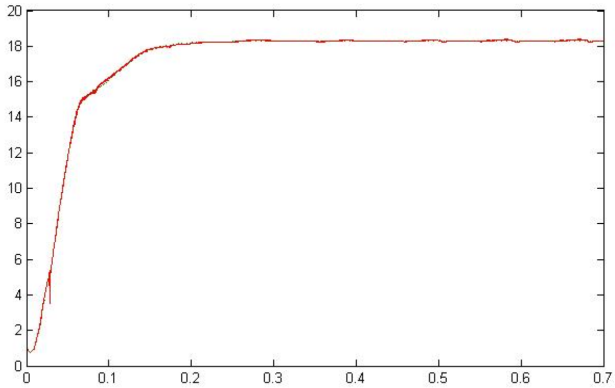

Fig. 18. *Output variables from RBF and AM*

3.5. RBF with the white noise

With an addition of the bounded white noise there were idea of reduce the weight and centers importance of the feedback connection. In the feed-forward neural networks it has the less neural hidden unit foundation. The input training data set is depicted in figure 19.

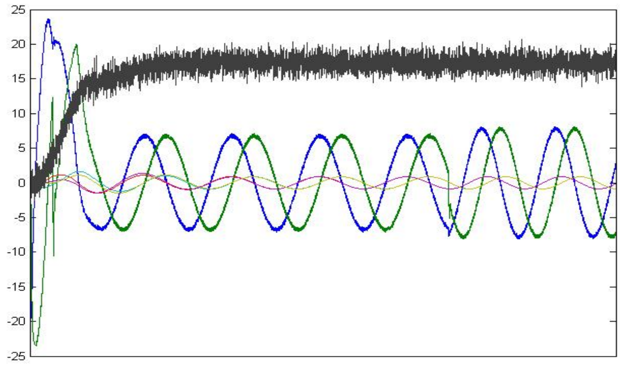

Fig. 19. *Input training data set*

There was used just only one type of RBF architecture with the classic lay-out of RBF units. The RBF neural network contains 215 activation units and then was useless to go on with this type. It will be discussed in the conclusion. Anyway, in the figure 20 there are depicted almost perfect output curves. It shows us that the difference between the "reference" adaptive model and the RBF network could be neglected.

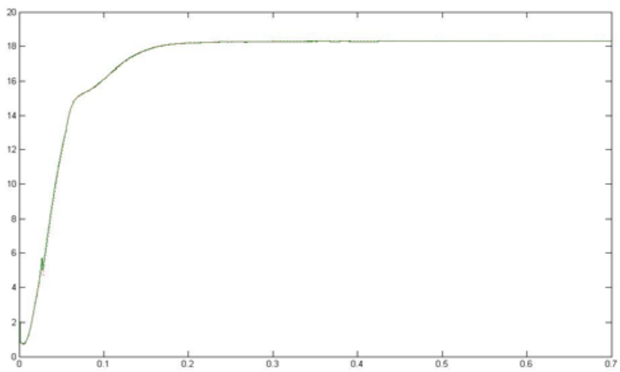
Fig. 20. *Output variables from RBF and AM*

4. CONCLUCION

The paper deals with different architectures of Radial Basis Function neural network. At the end of this work, there must be sad, that the most common architecture of RBF network with one feedback connection presents the best output time behavior in comparison with the others. RBF without feedback connection presents quite unstable and inaccurate output. The RBF with two feedbacks has very good output curves, but if we realize higher number of RBF units and more complicated connections then the result is also against this type. The next architecture with scaled input neither had better time behavior. The only result was lower values of the hidden layer variables like radius, centers and weights.

The last type with used white noise gives us lower number of hidden units in the feed-forward neural networks, but it doesn't work with RBF network. That's why there weren't used other types with different layout.

The result of this work is, that there could be use other types of RBF architecture if is necessary for some reason, like scaled input variables or non-present feedback connection, but then must be considerate the mentioned disadvantages.

This work has commitment to continue development and research of RBF neural networks for control electrical drives. In the near future there will be also done speed estimator by the use of this network and will be discussed the important features.

Some of these more interesting theoretical assumptions will be verified on real laboratory model with induction motor controlled by digital signal processor with the system for the training data acquisition.

5. REFERENCES

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ACKNOWLEDGEMENTS

In the paper there are the results of the project 102/05/2080 which was supported by The Czech Science Foundation (GA CR).