

# Comparative study of neural networks used in modeling and control of dynamic systems

**Abstract:** In this paper, a diagonal recurrent neural network that contains two recurrent weights in the hidden layer is proposed for the designing of a synchronous generator control system. To demonstrate the superiority of the proposed neural network, a comparative study of performances, with two other neural networks, has been made. The investigated neural networks were: a feedforward neural network (FFNN), a first-order diagonal recurrent neural network (1\_DRNN) and the proposed second-order diagonal recurrent neural network (2\_DRNN). Moreover, to confirm the superiority of the proposed 2\_DRNN, the results obtained with this network were also compared with those of the IEEE recommended conventional excitation control system (CECS).

**Streszczenie:** W artykule przedstawiono diagonalną rekurencyjną sieć neuronową do projektowania układu regulacji generatora synchronicznego. Proponowana sieć posiada dwie rekurencyjne wagi w warstwie ukrytej. Aby wykazać wyższość proponowanej sieci dokonano analizy porównawczej efektywności z dwoma innymi sieciami neuronowymi. Badanymi sieciami neuronowymi były: jednokierunkowa sieć neuronowa (FFNN), diagonalna rekurencyjna sieć neuronowa pierwszego rzędu (1\_DRNN) oraz proponowana diagonalna rekurencyjna sieć neuronowa drugiego rzędu (2\_DRNN). Ponadto, aby potwierdzić wyższość proponowanej sieci (2\_DRNN), uzyskane wyniki dla tej sieci porównano z wynikami uzyskanymi dla konwencjonalnego układu regulacji (CECS) zalecanego przez IEEE. (Studium porównawcze sieci neuronowych używanych w modelowaniu i sterowaniu systemami dynamicznymi)

**Keywords:** feedforward neural network, diagonal recurrent neural network, neurocontrol, turbogenerator.

**Słowa kluczowe:** sieci neuronowe, modelowanie.

## Introduction

In the last three decades various neural network architectures have been used in modeling and control of dynamic systems [1÷16]. In most of these works feedforward neural network (FFNN), combined with tapped delays and using backpropagation algorithm for weight adaptation have been used successfully [1÷11]. However, the FFNN is a static network and without tapped delays it does not represent a dynamic system mapping. On the other hand, the recurrent neural network (RNN) has advantages that FFNN does not possess [12÷16]. Among these advantages we can mention the ability to store information for later use. Therefore the RNN is more suitable for dynamical systems than the FFNN. In this paper, diagonal recurrent neural networks (DRNN) are used to form the neuro-identifier (NI), which provides information about the plant to be controlled, and the neuro-controller (NC), which provides the necessary control signal to the plant. The DRNN can be made equivalent to a fully connected recurrent neural network (FCRNN). Contrary to FCRNN, in the DRNN there is no links between neurons in the hidden layer. Therefore, the DRNN has fewer weights than the FCRNN and shorter training time.

The paper is organized as follows. In the section II, a neural network based excitation control system is presented. In the section III, the training process for the considered neural networks is described. In the section IV, a generalized dynamic backpropagation algorithm (GDBPA) used in the training process is developed. In this same section are presented the structures of the studied neural networks: FFNN, first-order DRNN and second-order DRNN. In the section V, simulation tests are described and the results are illustrated and discussed. Finally, section VI gives the conclusion of the paper.

## Neural network based excitation control system

The block diagram of the investigated neural network based excitation control system is shown in figure 1. It consists of two subnetworks: the first network, named neuro-identifier (NI), provides information about the plant to be controlled and the second, named neuro-controller (NC), provides the necessary control signal to the plant such that the error between plant and desired output is minimized.

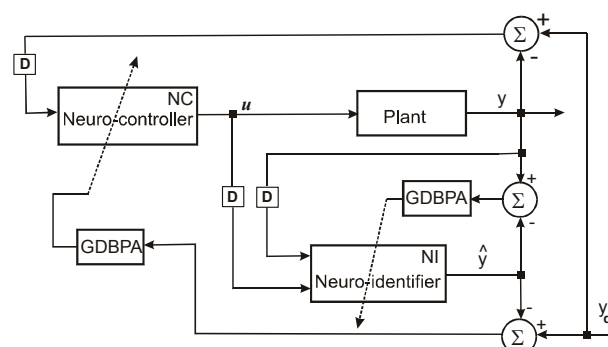


Fig. 1. Block diagram of neural network based excitation control system

The NI is a two-layered neural network with nine inputs: three delayed signals of the terminal voltage deviation ( $U_{ref} - U_g$ ), three delayed signals of the active power deviation ( $P_{ref} - P_g$ ) and three delayed signals of the controller output signal  $u$ . The hidden layer contains twelve neurons. The output layer has two neurons whose output are the predicted value  $U_g^*$  of terminal voltage and the predicted  $P_g^*$  of generator active power.

The NC is also a two-layered neural network with just six inputs: three delayed signals of the terminal voltage deviation ( $U_{ref} - U_g$ ), three delayed signals of the active power deviation ( $P_{ref} - P_g$ ). In the case of a feedforward neural network the hidden layer contains nine neurons and in the case of diagonal recurrent neural network six recurrent neurons. The NC output layer has one simple neuron whose output  $u$  provides the signal for the generator's excitation control.

The proposed controller 2\_DRNN must ensure two functions: the function of an automatic voltage regulator (AVR) to maintain terminal voltage at the desired value  $U_{ref}$ , and the function of a power system stabilizer (PSS) for damping electromechanical oscillations. Therefore, its input signals are the voltage deviation and the active power deviation. The inputs of the two subnetworks NI and NC are time delayed by the sample period of 20 ms to create dynamic properties of the plant. For each input actual value and two previously delayed values are considered.

All neurons of both subnetworks NI and NC, with the exception of those in output layers, are nonlinear with the sigmoidal activation function:

$$(1) \quad \sigma(x) = \frac{1}{1 + e^{-\beta x}}$$

where  $x$  represents the sum of the neuron input signals and  $\beta$  is the activation gain and has a constant value. The internal structures of the used neurons are given in figures 2, 3 and 4.

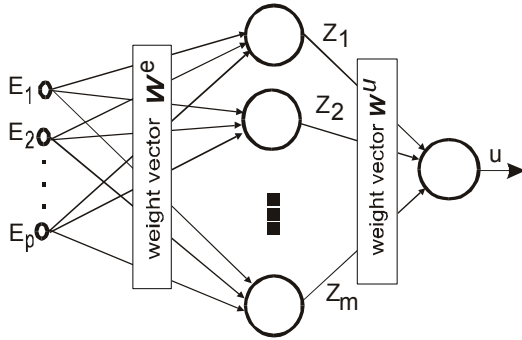


Fig. 2. Feedforward neural network structure

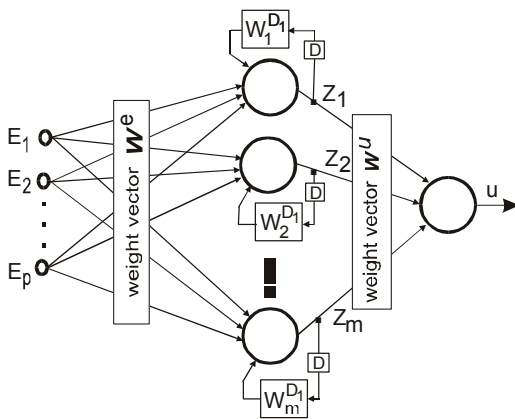


Fig. 3. First-order diagonal recurrent neural network structure

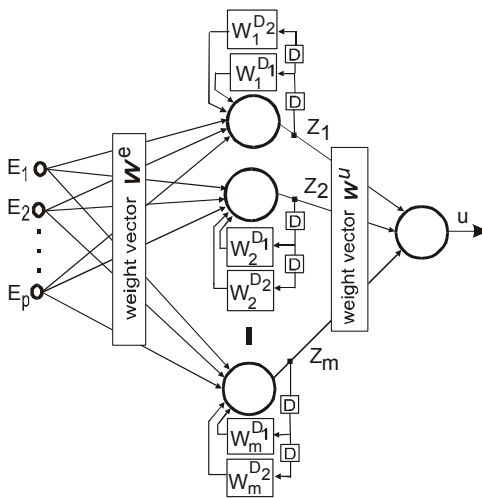


Fig. 4. Second-order diagonal recurrent neural network structure

The number of neurons in the hidden layers for both NI and NC are determined by using trial and error method.

There is no theoretical considerations that can help to establish this parameter. Moreover, for the study of the transient stability there is no need to consider more than one hidden layer for both NI and NC. Nor, there is no need to consider more than three time delays for input signals [9].

### Training process

The algorithm used to adjust the weights for both subnetworks NI and NC is the generalized dynamic backpropagation algorithm (GDBPA) developed in the next section.

### Offline training of the neuro-identifier

Training process is accomplished by switching on the neuro-identifier (NI) to operate in parallel with the synchronous generator, which is controlled by a conventional excitation control system [17], named (CECS). Small random signals are included as noise to the reference voltage. The differences between the respective outputs of the turbogenerator model ( $U_g, P_g$ ) and the outputs of NI ( $U_g^*, P_g^*$ ) generate the error signals for updating the NI weights which initially were set to small random values. The offline training is stopped when the mean square error between the identified output signals ( $U_g^*, P_g^*$ ) and the actual plant output signals ( $U_g, P_g$ ) reaches a small number (in this case 0.0001). The identifier training is usually achieved after 1250 s training.

### Offline training of the neuro-controller

For the neuro-controller (NC) offline training, a conventional AVR with PSS is used to control the plant. The plant output signals ( $U_g, P_g$ ) fed to the neuro-controller with the previous two values. The NC output  $u$  is compared to the conventional excitation control system (CECS) output. The deviation between the two signals is used to update the neuro-controller weights. The NC training has been performed for various load conditions and disturbances. The weights are adjusted till the mean square error obtained has been reduced to a minimum value of 0.0001.

### Online training of the neuro-identifier and the neuro-controller

When the offline trainings of the neuro-identifier NI and the neuro-controller NC are terminated, these two subnetworks are switched on to replace the conventional excitation control system (CECS): the NI is used to learn the plant dynamics and the NC to control the plant. The online training of the subnetworks is illustrated in figure 1. The error between the plant output signal and the neuro-identifier output signal is propagated to adjust the NI weights. The error between the desired values of plant output and the neuro-identifier output is used to update the NC weights.

In this paper, three types of neural networks are separately considered, to design the neural network based excitation control system: a feedforward neural network (FFNN), a first-order diagonal recurrent neural network (1\_DRNN) and a second-order diagonal recurrent neural network (2\_DRNN). The structures of these networks are presented in figures 2, 3 and 4.

### Generalized dynamic backpropagation algorithm for diagonal recurrent neural network training

The mathematical model for the second-order diagonal recurrent network (2\_DRNN) of figure 4 is as follow:

$$(2) \quad u(k) = \sum_{j=1}^q w_j^u Z_j$$

$$(3) \quad Z_j = \sigma(S_j(k))$$

$$(4) \quad S_j(k) = w_j^{D1} Z_j(k-1) + w_j^{D2} Z_j(k-2) + \sum_{i=1}^p w_{ij}^e E_i(k)$$

where for each discrete time  $k$ ,  $E_i(k)$  is the  $i$ -th input to the DRNN,  $S_j(k)$  is the sum of inputs to  $j$ -th recurrent neuron,  $Z_j(k)$  is the output of the  $j$ -th recurrent neuron, and  $u(k)$  is the output of the DRNN.  $w^e$ ,  $w^{D1}$ ,  $w^{D2}$  and  $w^u$  are respectively input, first-order recurrent, second-order recurrent and output weight vectors.  $\sigma(\cdot)$  is the sigmoid function given in equation (1).

Let  $y_d$  and  $y(k)$  be the desired and the real plant output respectively. The error cost function is defined by

$$(5) \quad J(k) = \frac{1}{2} (y_d - y(k))^2$$

The gradient of error in equation (5) with respect to an arbitrary weight vector  $w \in \mathbb{R}^n$  is represented by:

$$(6) \quad \frac{\partial J}{\partial w} = \frac{\partial}{\partial w} \left[ \frac{1}{2} (y_d - y(k))^2 \right] = -\Delta y(k) \frac{\partial y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial w}$$

where  $\Delta y(k) = y_d - y(k)$  is the error between the desired value and the output of the plant. The factor  $\partial y(k)/\partial u(k)$  represents the sensitivity of the plant with respect to its input.

The output gradient  $\partial u(k)/\partial w$  needs to be computed for both NI and NC. Its computation is summarized as follows. The output gradients with respect to output, recurrent, and inputs weights, respectively, are given by:

$$(7) \quad \frac{\partial u(k)}{\partial w_j^u} = Z_j(k)$$

$$(8) \quad \frac{\partial u(k)}{\partial w_j^{D1}} = w_j^u \frac{\partial Z_j(k)}{\partial w_j^{D1}}$$

$$(9) \quad \frac{\partial u(k)}{\partial w_j^{D2}} = w_j^u \frac{\partial Z_j(k)}{\partial w_j^{D2}}$$

$$(10) \quad \frac{\partial u(k)}{\partial w_{ij}^e} = w_j^u \frac{\partial Z_j(k)}{\partial w_{ij}^e}$$

Let

$$(11) \quad P_{ij}(k) = \frac{\partial Z_j(k)}{\partial w_{ij}^e}$$

and

$$(12) \quad Q_{ij}(k) = \frac{\partial Z_j(k)}{\partial w_j^{D1}}$$

Then:

$$(13) \quad P_{ij}(k) = \frac{\partial Z_j(k)}{\partial S_j(k)} \frac{\partial S_j(k)}{\partial w_{ij}^e} = \sigma'(S_j(k)) \frac{\partial S_j(k)}{\partial w_{ij}^e}$$

$$= \sigma'(S_j(k)) \frac{\partial}{\partial w_{ij}^e} \left[ \sum_{l=1}^p w_{lj}^e E_l + \sum_{m=1}^2 w_j^{Dm} Z_j(k-m) \right]$$

$$= \sigma'(S_j(k)) \left[ Z_j(k-i) + \sum_{m=1}^2 w_j^{Dm} \frac{\partial Z_j(k-m)}{\partial w_{ij}^e} \right]$$

$$= \sigma'(S_j(k)) \left[ Z_j(k-i) + \sum_{m=1}^2 w_j^{Dm} P_{ij}(k-m) \right]$$

$$(14) \quad Q_{ij}(k) = \sigma'(S_j(k)) \frac{\partial S_j(k)}{\partial w_j^{D1}}$$

$$= \sigma'(S_j(k)) \frac{\partial \left[ \sum_{l=1}^p w_{lj}^e E_l + \sum_{m=1}^2 w_j^{Dm} Z_j(k-m) \right]}{\partial w_j^{D1}}$$

$$= \sigma'(S_j(k)) \left[ E_i + \sum_{m=1}^2 w_j^{Dm} \frac{\partial Z_j(k-m)}{\partial w_{ij}^e} \right]$$

$$= \sigma'(S_j(k)) \left[ E_i + \sum_{m=1}^2 w_j^{Dm} Q_{ij}(k-m) \right]$$

where  $\sigma'(\cdot)$  is the derivative of the function  $\sigma(\cdot)$  defined in equation (1).

To calculate  $P_{ij}(k)$  and  $Q_{ij}(k)$  we suppose the following initial values:

$$(15) \quad P_{ij}(0)=0, \quad P_{ij}(1)=0,$$

$$(16) \quad Q_{ij}(0)=0, \quad Q_{ij}(1)=0.$$

Therefore, the weights are adjusted by the following equation:

$$(17) \quad w(k+1) = w(k) + \eta \left( -\frac{\partial J(k)}{\partial w(k)} \right)$$

where  $\eta$  represents the learning rate whose the value is determined empirically so that a compromise between the training time and the accuracy of the network is achieved.

The above algorithm can be used not only to adjust the DRNN weights but also to adjust the FFNN weights. In the case of FFNN all the weight vectors  $w^{D1}$  and  $w^{D2}$  must be equal zero.

### Simulation tests

In order to evaluate and compare effectiveness of each previously described neural controllers (FFNN, 1\_DRNN, 2\_DRNN), simulation tests have been carried out for the single machine infinite bus power system of figure 5. This system consists of a three-stage turbine that provides a mechanical power, a synchronous generator that transforms mechanical power in an electrical active power  $P_g$  and a reactive power  $Q_g$  and provides an output voltage  $U_g$ . The generator is connected to an infinite bus system through a step-up transformer and parallel transmission lines. The differential equations and parameters used to simulate the dynamic behavior of the synchronous generator are presented in Appendix A1. However, the mathematical models of the governor and turbine, of the conventional automatic voltage regulator (AVR) with PSS and excitation system are given in [17].

In the performed simulation tests different loading conditions and disturbances have been considered. Due to limited space, only the results for loading condition  $P_g=0,8$  in p.u. and  $Q_g=0,2$  in p.u., with a leading power factor, are

presented in this paper. The applied disturbances are as follows:

- 5% step increase at  $t=0s$  and 5% step decrease at  $t=5s$  in the infinite bus voltage;
- three phase short circuit at  $t=0s$  and cleared 200ms later;
- 20% step decrease in the reference power.

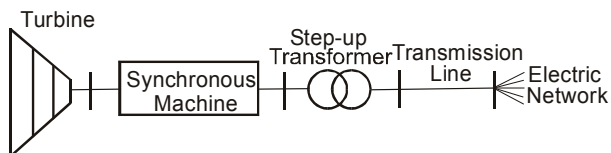


Fig. 5. Schematic diagram of the power system model

The results with each disturbance are depicted in figures 6÷11. Figures 6, 7 and 8 show the responses of the turbo-generator unit with each of the considered neural networks: FFNN, 1\_DRNN and 2\_DRNN. In each figure, terminal voltage variations and angular speed variations are presented. The responses with diagonal recurrent neural networks are indicated by solid lines of different thickness and those with feedforward neural network by dashed lines.

Figure 6 shows system responses to  $\pm 5\%$  step changes in infinite bus voltage, figure 7 the system responses to three phase short circuit and figure 8 the system responses to 20% step decrease in reference power.

It can be seen from figure 6 that the angular speed overshoot during the first alternance is more damped with 2\_DRNN than with 1\_DRNN and FFNN. Therefore the voltage overshoot during this period is a little bit higher with 2\_DRNN than with the two other neural networks. Figure 7 shows clearly that the voltage control and the damping of angular speed oscillations with 2\_DRNN and with 1\_DRNN are much better than with FFNN. In this case the damping with 2\_DRNN is even slightly higher than with 1\_DRNN. In figure 8 the voltage overshoot and the angular speed overshoot with 2\_DRNN are more damped that with the two other neural networks.

The described above simulation results show that the proposed 2\_DRNN is more efficient comparatively to 1\_DRNN and to FFNN. To confirm the superiority of the proposed 2\_DRNN, an additional study was performed: the performance of the 2\_DRNN has been compared with the performance of IEEE 1S excitation control system with conventional PSS [17] designated by CECS. In this study, the same disturbances as previously were applied. The results with both control systems are illustrated in figures 9, 10 and 11. It show once again that the proposed 2\_DRNN yields much better voltage control and much higher damping of electromechanical oscillations.

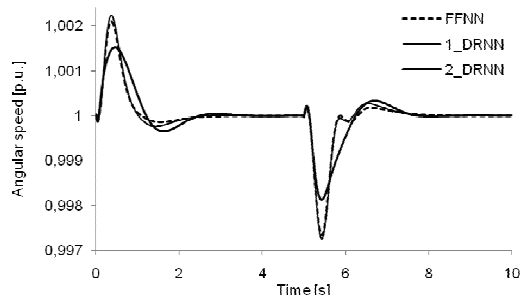
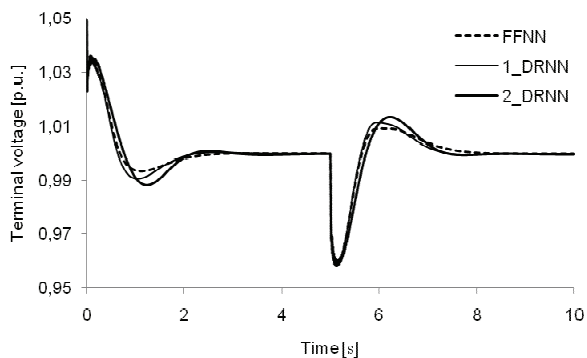


Fig. 6. Responses to step changes in infinite bus voltage

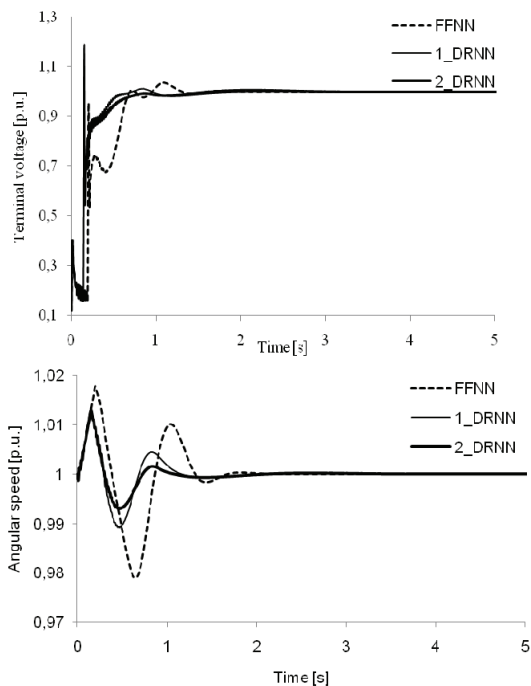


Fig. 7. Responses to three phase short circuit

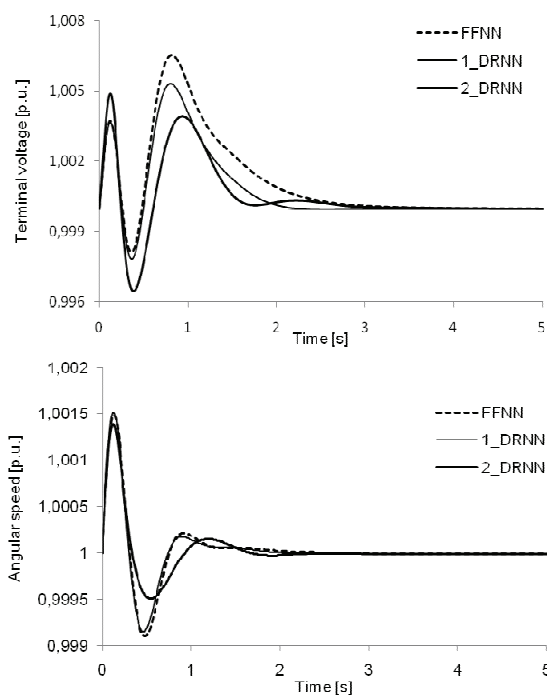


Fig. 8. Responses to step decrease in reference power

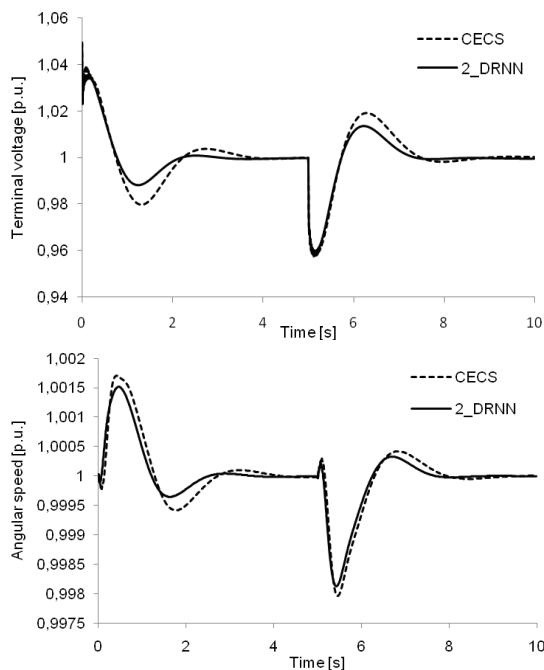


Fig. 9. Responses to step changes in infinite bus voltage

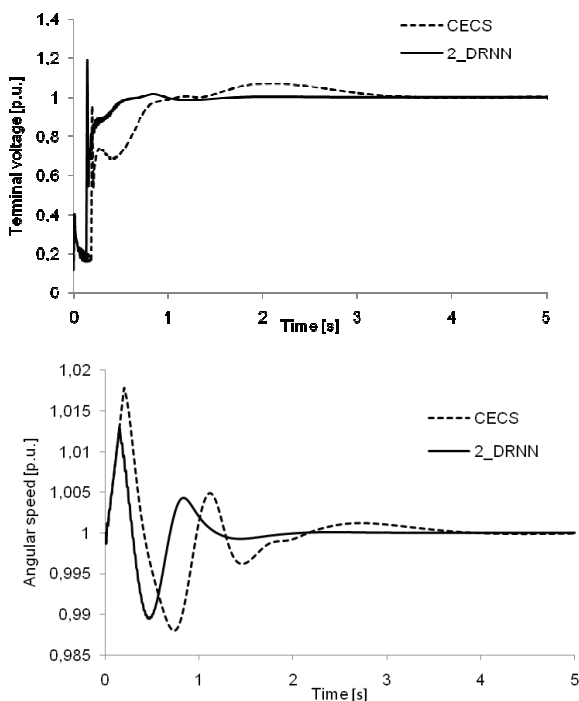
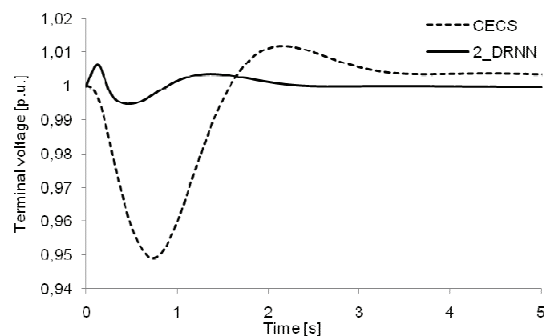


Fig. 10. Responses to three phase short circuit



11. Responses to step decrease in reference power

## Conclusion

In this paper three types of neural networks, used for modeling and control of turbogenerator unit connected to an infinite bus power system, have been investigated. These neural networks are: the Feedforward Neural Network (FFNN), the first-order Diagonal Recurrent Neural Network (1\_DRNN) and the proposed second-order Diagonal Recurrent Neural Network (2\_DRNN). Each of the neural networks has first been subjected to an offline training process using the generalized dynamic backpropagation algorithm (GDBPA) developed in this paper. Once the training process terminated, the neural network has been switched on to replace the conventional excitation control system with PSS.

The performances of the neural networks have been evaluated through simulation tests, under various operating conditions and disturbances. The test results have been compared and the proposed 2\_DRNN has proved to be more efficient. Moreover, to confirm the superiority of the 2\_DRNN, its dynamic and transient operation was also compared to the operation of the IEEE conventional excitation control system (CECS). Here also, the 2\_DRNN beats the CECS in terms of offering better voltage control and better damping of electromechanical oscillations.

Moreover, it is important to mention that the proposed 2\_DRNN performs two functions simultaneously: that of Automatic Voltage Controller (AVR) and that of Power System Stabilizer (PSS). Its architecture is very simple.

## REFERENCES

- [1] Mohammadzahi M., Member L.C.: A design approach for feedback-feedforward control systems, *American Control Conference (ACC)*, 2010.
- [2] Ting-Li C., Chung-Cheng C., Yi-Chieh H., Wen-Jiun L.: Stability and almost disturbance decoupling analysis of nonlinear system subject to feedback linearization and feedforward neural network controller, *Neural Networks, IEEE Transactions on*, volume 19, 2008.
- [3] Min H., Wei G., Jincheng W.: Predictive control based on feedforward neural network for strong nonlinear system, *Neural Networks, 2005 IJCNN'05, Proceedings, 2005 IEEE International Joint Conference*, Volume 4, 2005, 2266-2271.
- [4] Parisini T., Zoppoli R.: Neural networks for feedback feedforward nonlinear control systems, *Neural Networks, IEEE Transactions on*, Volume 5, issue 3, 1994, 436-449.
- [5] Kuschevski, J.G., Hui, S., Zak S.H.: Application of feedforward neural networks to dynamical system identification and control, *Control Systems Technology, IEEE Transactions on*, Volume 1, Issue 1, 1993, 37-49.
- [6] Thomas R.J., Sakk E.: On using an artificial feedforward neural network as a controller in large-scale power systems, *Circuits and Systems, IEEE International Symposium on*, vol. 2, 1991, 1133-1136.
- [7] Tiliouine H.: A modified neural network controller configuration, *14th International Conference on Methods and Models in Automation and Robotics, Międzyzdroje, Poland*, Volume 14, part I, August 2009.

[8] Sumina, D., Bulic, N., Erceg, G.: Simulation model of neural network based synchronous generator excitation control, *Power Electronics and Motion Control Conference, 2008. EPE-PEMC 2008. 13<sup>th</sup>*, 556-560.

[9] Venayagamoorthy G.K., Harley R.G.: A continually online trained neuro-controller for excitation and turbine control of a turbogenerator, *IEEE Transactions on Energy Conversion*, 16 (16), 2001, 261÷269.

[10] Salem M.M, Zaki A.M., Mahgoub O.A., Abu El\_Zahab E., Malik O.P.: Studies on a multi-machine power system with a neural network based excitation controller, *Power Engineering Society Summer Meeting, 2000 IEEE*, Volume 1, 105 ÷ 110.

[11] Lubošny Z.: Adaptacyjny neuronowy regulator generatora synchronicznego, *Przegląd Elektrotechniki R.80*, nr 10, 2004, 971÷974.

[12] Chun-Jung C., Tien-Chi C., Hung-Jung H. and Chin-Chih O.: PSS design using adaptive recurrent neural network controller, *Fifth International Conference on Natural Computation*, Volume 2, 2009, 277÷281.

[13] Yingyi J., Chengli S.: Adaptive model predictive control using diagonal recurrent neural network, *Natural Computation, ICNC '08. Fourth International Conference on*, Volume 2, 2008, 276÷280.

[14] Xiaochen H., Yen, G.G.: Local signal based supplementary excitation controller for damping inter-area oscillations through recurrent neural networks, *Neural Networks, IJCNN 2007. International Joint Conference on*, 2007, 2498÷ 2503.

[15] Jeen-Shing W., Yen-Ping C.: A fully automated recurrent neural network for unknown dynamic system identification and control. *Circuits and Systems I: Regular Papers, IEEE Transactions on*, Volume 53, 2006, 1363÷1372.

[16] Chi-Huang L., Ching-Chih T.: Design and experimental evaluation of an adaptive predictive controller using recurrent neural network, *Systems, Man and Cybernetics, 2005 IEEE International Conference on*, Volume 1, 2005, 690÷695.

[17] IEEE Recommended practice for excitation system models for power system stability studies, *IEEE Std 421.5-2005 (Revision of IEEE Std 421.5-1992)*, 2006, 1÷85.

$S_n$  rated apparent power  
 $P_n$  rated active power  
 $U_n$  rated voltage  
 $I_n$  rated current  
 $\cos\varphi_n$  rated power factor  
 $r_s$  stator windings resistance  
 $x_s$  stator leakage reactance  
 $x_d$  direct axis synchronous reactance  
 $x_d'$  transient reactance in d axis  
 $x_d''$  subtransient reactance in d axis  
 $x_q$  quadrature axis synchronous reactance  
 $x_q''$  subtransient reactance in q axis  
 $T_d'$  transient time constant in d axis  
 $T_d''$  subtransient time constant in d axis  
 $T_q''$  subtransient time constant in q axis  
 $T_m$  mechanical torque  
 $T_e$  electrical torque  
 $J$  moment of inertia  
 $\omega_s$  synchronous angular speed

Table 1. Synchronous generator parameters

$S_n$	426 MVA
$P_n$	360 MW
$U_n$	22 kV
$I_n$	11.18 kA
$\cos\varphi_n$	0.85
$r_s$	0.00233 p.u.
$x_s$	0.199 p.u.
$x_d$	2.6 p.u.
$x_d'$	0.33 p.u.
$x_d''$	0.24 p.u.
$x_q$	2.48 p.u.
$x_q''$	0.25 p.u.
$T_d'$	1.1 s
$T_d''$	0.03 s
$T_q''$	0.03 s
$\omega_s$	$100\pi \text{ s}^{-1}$
$J$	$32300 \text{ kgm}^2$

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**A.1. Differential equations of synchronous generator**

$$(18) \quad \frac{1}{\omega_s} \frac{d\psi_d}{dt} = -u_d - \omega\psi_q - r_s i_d$$

$$(19) \quad \frac{1}{\omega_s} \frac{d\psi_q}{dt} = -u_q + \omega\psi_d - r_s i_q$$

$$(20) \quad \frac{1}{\omega_s} \frac{d\psi_f}{dt} = u_f - r_f i_f$$

$$(21) \quad \frac{1}{\omega_s} \frac{d\psi_{kd}}{dt} = -r_{kd} i_{kd}$$

$$(22) \quad \frac{1}{\omega_s} \frac{d\psi_{kq}}{dt} = -r_{kq} i_{kq}$$

$$(23) \quad \frac{1}{\omega_s} \frac{d\delta}{dt} = \omega - 1$$

$$(24) \quad \frac{d\omega}{dt} = \frac{1}{2H} (T_m - T_e)$$

**A.2. Nomenclature**

$\psi_d, \psi_q$  flux linkage in d q axis

$\psi_f$  field flux linkage

$\psi_{kd}, \psi_{kq}$  damping flux linkage in d q axis

$u_d, u_q$  generator voltage in d q axis

$i_d, i_q$  generator current in d q axis

$u_f$  field voltage

$i_{kd}, i_{kq}$  damping current in d q axis

$r_{kd}, r_{kq}$  damping windings resistance in d q axis