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Adaptive neural voltage controller with tunable activation gain

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Abstract

In this paper an adaptive neural voltage controller (ANVC) for turbogenerator, with tunable activation function gain is developed. It combines both traditional neural model and neural model with activation gain depending on the operating conditions of the plant. Simulation results evaluating the performance of the ANVC under different operating conditions and disturbances are presented. These results are compared to that obtained with a fixed activation gain neural controller (the traditional one) and to that obtained with conventional (analog) controller.

Keywords: turbogenerator, adaptive neural voltage controller (ANVC), activation gain.

Adaptacyjny neuronowy regulator napięcia z nastrojonym współczynnikiem wzmocnienia funkcji przynależności

Streszczenie

W artykule przedstawiono model adaptacyjnego neuronowego regulatora napięcia dla turbogeneratora z nastrojonym współczynnikiem wzmocnienia funkcji przynależności. Ten model jest kombinacją klasycznego neuronowego modelu i neuronowego modelu z współczynnikiem wzmocnienia funkcji przynależności zależnym od warunków pracy obiektu. Przedstawiono, także wyniki symulacji mające na celu badania efektywności proponowanego regulatora dla różnych zakłóceń i różnych warunków pracy turbogeneratora. Te wyniki porównano z wynikami uzyskanymi z regulatorem o stałym współczynniku wzmocnienia funkcji przynależności oraz z wynikami uzyskanymi z regulatorem analogowym.

Słowa kluczowe: Turbogenerator, adaptacyjny neuronowy regulator napięcia, współczynnik wzmocnienia aktywacji.

1. Introduction

The increasing complexity of electric power systems and the demands of economic and operational requirements emphasize the need for continuing improvements in power plant and control.

Turbogenerators are major components in electric power systems, and their performance is directly related to security and stability of power system operations. A turbogenerator is a highly nonlinear system, subject to large changes of operating conditions. Conventional controllers with fixed parameters cannot provide the most effective plant and system control under these circumstances. Consequently, there has been a growing interest in adaptive control. Since more than one decade numerous studies [1, 2, …, 14] on the using neural networks in control field have been made and demonstrated that adaptive neural control is particularly suitable for controlling highly uncertain, nonlinear, and complex systems.

In the design of neural network controller a multilayer feedforward structure, with nonlinear outputs of the neurons, is the most utilized [2, 3, …, 6]. In general, we use the logistic or the hyperbolic tangent functions to introduce the nonlinearities of the used neurons (fig. 1), and during the training process, the weights between neurons are tunable while the activation function gain is fixed. In this paper it is demonstrated that a neural model with fixed activation function gain is obviously a simplified one. Its capability is limited. To tune just the neurons weights is insufficient to give satisfactory results. In the proposed neural voltage controller, besides tuning weights, the activation function gain is made depending on the operating conditions of the synchronous generator.

2. Design of the proposed neural voltage controller

The architecture of the proposed controller is shown in fig. 2. The controller uses the indirect adaptive control method [13]. It consists of three subnetworks: the neural identifier (NI) which identifies the plant, the adaptive neural voltage controller (ANVC) which provides the necessary control of the excitation system, and the third subnetwork named TAG (tunable activation gain) which defines the gain value α of the activation functions. Each of the three subnetworks is a feed-forward three-layer network. All the neurons in the subnetworks are with sigmoid non-linearity (fig. 1). The controller ANVC has five inputs based on the deviation between the synchronous generator voltage U_g and the reference voltage Vr. However, the neuro-identifier NI has ten inputs, based on the generator voltage and on the control signal Uc. The inputs of the TAG subnetwork are the components of the vector X: the active power P_g, the reactive power Q_g and the terminal voltage U_g. All these components represent synchronous generator quantities which are used to detect the generator operating conditions. On the basis of this information the subnetwork TAG selects the activation function gain α. The output of the TAG subnetwork is filtered through a first order inertial element which provides the activation gain.
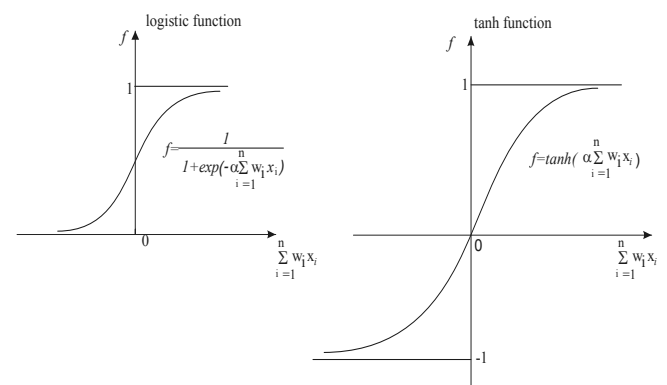

Fig. 1.   Example of used neuron activation functions [17]
Rys. 1.   Przykład stosowanych funkcji przynależności neuronów [17]

The plant represents a nonlinear system which can be expressed by [14]

$$Y(k+1) = f(Y(k), Y(k-1), ..., Y(k-m), U_c(k), U_c(k-1), ..., U_c(k-n)) \tag{1}$$

where f is the unknown nonlinear function to be estimated by the neural subnetwork NI, $Y(k)$ is the scalar output of the plant, and m and n are the known structure orders of the system. The purpose of the used control algorithm is to select a control signal $U_c(k)$, such that the output system $Y(k)$ is made as close as possible to a prespecified set point Vr. Since the input to the subnetwork NI is

$$P = [Y(k), Y(k-1),..., Y(k-n), U_c(k), U_c(k-1),..., U_c(k-m)] \quad (2)$$

The neuro model for the unknown system (1) can be expressed as

$$\hat{Y}(k+1) = \hat{f}(Y(k), Y(k-1),..., Y(k-n), U_c(k), U_c(k-1),..., U_c(k-m)) \quad (3)$$

where $\hat{Y}(k+1)$ is the output of the subnetwork NI and f the estimate $\hat{f}$.

For a voltage controller, **Y** represents the generator voltage U_g.

Using the backpropagation algorithm [15,16] the NI, the ANVC and the TAG have been initially trained off-line, over a wide range of operating conditions and a wide spectrum of possible disturbances. The neuron weights were updated as follows [15, 16]:

$$W_{ij}(k+1) = W_{ij}(k) + \eta \frac{\partial E}{\partial W_{ij}(k)} \quad (4)$$
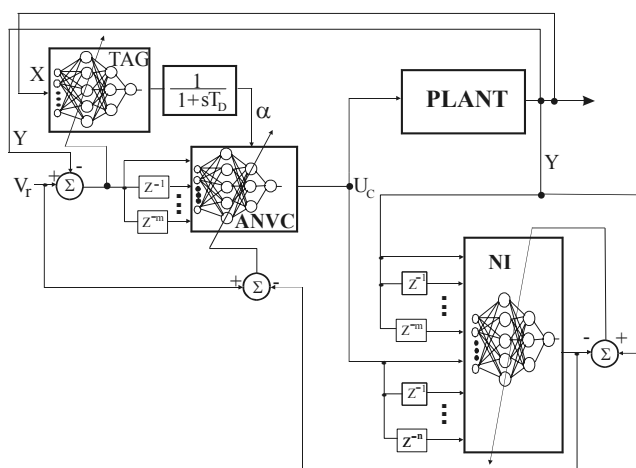

Fig. 2.　Neural control system structure
　　　　ANVC- adaptive neural voltage controller
　　　　NI- neuro identifier
Rys. 2.　Struktura neuronowego układu regulacji
　　　　NVC- neuronowy regulator napięcia
　　　　NI- neuronowy identyfikator

where $\boldsymbol{\eta}$ is a prespecified learning rate. The performance function **E** for training the neural network is defined as

$$E = \frac{1}{2}\sum_{l=1}^{p}\sum_{k=1}^{q}(d_k^l - u_k^l)^2 \quad (5)$$

where **d** is the desired output and **u** the output of the neural controller, **p** is the number of training samples and **q** is the number of the neurons in the output layer.

After this training stage, all three subnetworks NI, ANVC and TAG are hooked up in the system shown in fig. 3. On line, during the control process, the subnetworks are trained further in each sampling period. To update the neuron weights is used:

- for the neuro-identifier NI, the deviation between the generator voltage and the output signal of NI.
- for the controller ANVC and for the TAG subnetwork, the deviation between the generator voltage and the reference voltage. In the case of the TAG training the value of the learning rate $\boldsymbol{\eta}$ must be very small.

3. Simulation studies

A number of simulation experiments have been performed to investigate the effectiveness of the proposed neural controller. The neural controller has been tested on a turbogenerator unit (fig. 3) which consists of a synchronous generator, a static exciter, a turbine and a governor. The generator is connected, via a transformer unit and transmission line, to an infinite bus power.

Two variants of neural controllers have been considered :
- in the first variant ANVC1 the gain of the neuron activation function is maintained constant;
- in the second one ANVC2, this gain is made dependant on the generator load.

The responses of the system with the both neural model variants, and the conventional controller have been compared for various disturbances and various operating conditions. For the sake of brevity, results of only a representative set of studies are presented in this paper.
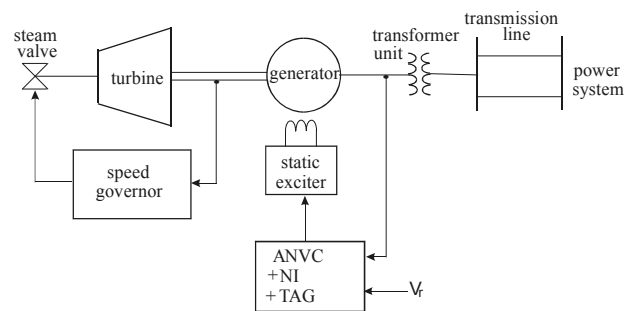

Fig. 3.　Schematic diagram of turbogenerator unit
Rys. 3.　Schemat blokowy turbozespołu

With the synchronous generator operating at the nominal set point, $P_g=P_{gn}=0.85$, $Q_g=Q_{gn}=-0.53$, a 5% increase of the infinite bus voltage was applied at time t=0s. After 5s, when the steady state is restored, a 5% decrease of the same voltage is simulated. The responses illustrating the dynamic behavior of the tested system are presented in fig. 4 and fig. 5. These results, obtained with the described above two neural model variants, are compared to that obtained with a conventional controller. After the first perturbation, the responses of the three controllers are close to each other, and the terminal voltage as well as the active power get back to their reference values when the transient state is achieved. However, after the second perturbation, which was applied under different value of the reactive power ($Q_g \neq Q_{gn}$), in the case of the neural controller with a fixed activation gain the terminal voltage does not rise to a reference voltage. To tune just the network weights proves to be insufficient to restore the desired voltage. However, the ANVC with updated activation gain restores the generator voltage exactly to its reference value. It demonstrates the importance of the activation gain α. Its tuning ensures a better control.
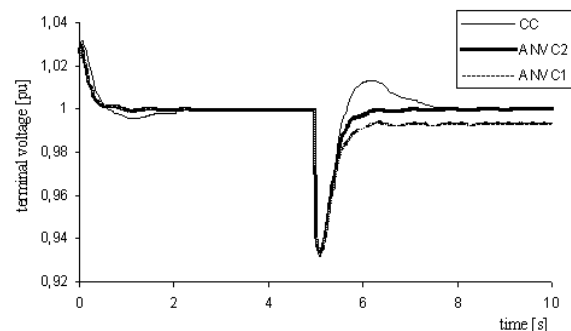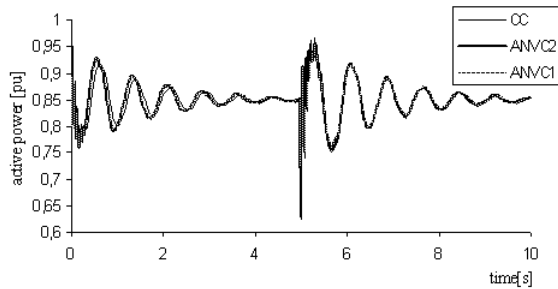

Fig. 4.　+5% and -5% step changes in infinite bus voltage
　　　　Pg=Pgn=0.85; Qg=Qgn=-0.53
Rys. 4.　Odpowiedzi na +5% i -5% skoków napięcia systemu
　　　　elektroenergetycznego Pg=Pgn=0.85; Qg=Qgn=-0.53

Fig. 5.   +5% and -5% step changes in infinite bus voltage
           Pg=Pgn=0.85; Qg=Qgn=-0.53
Rys. 5.   Odpowiedzi na +5% i -5% skoków napięcia systemu
           elektroenergetycznego Pg=Pgn=0.85; Qg=Qgn=-0.53

Further tests have been performed under other operating conditions, at $P_g=P_{gn}=0.85$ and $Q_g=0.2$ (capacitive). The same perturbations as above were applied. The obtained results are presented in fig. 6 and fig. 7. Under such operating conditions ($Q_g>0$), in the case of a step increase of the infinite bus voltage, the proposed ANVC2 is the one controller which could restore the steady state. Neither the traditional ANVC1 nor the conventional controller could avoid the synchronism loss.
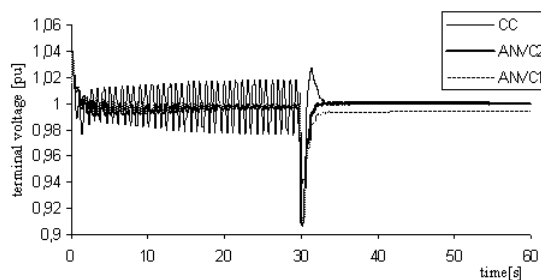

Fig. 6.   +5% and -5% step changes in infinite bus voltage
           Pg=Pgn=0.85; Qg=0.2
Rys. 6.   Odpowiedzi na +5% i -5% skoków napięcia systemu
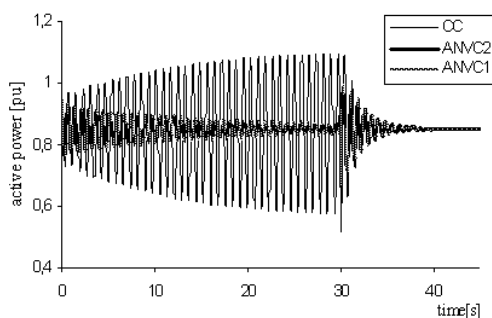   elektroenergetycznego Pg=Pgn=0.85; Qg=Qgn=0.2

Fig. 7.   +5% and -5% step changes in infinite bus voltage
           Pg=Pgn=0.85; Qg=0.2
Rys. 7.   Odpowiedzi na +5% i -5% skoków napięcia systemu
           elektroenergetycznego Pg=Pgn=0.85; Qg=Qgn=0.2

4. Conclusions

In this paper an adaptive voltage controller for turbogenerator using on-line trained neural network with tunable activation function gain is presented. It has following interesting properties:
- The proposed algorithm does not require the mathematic model of the plant.
- The controller considers the non-linear nature of the plant.

- The controller is adapted in an on-line mode to reduce the output error.

The performance of the proposed model has been evaluated under various operating conditions and disturbances. The simulation results demonstrated that the proposed controller provides a better control voltage and ensures a larger stability margin than a fixed activation gain model and than a conventional controller.

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