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NEURAL MODEL OF SYNCHRONOUS GENERATOR WITH NONLINEAR MAGNETIZING CHARACTERISTIC

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Abstract: *The paper presents the proposal of using artificial neural networks for simulation investigations of synchronous generators working as autonomous supply sources. The comparative analysis of the neural model and that based on the synchronous generator R-L parameters is performed. A three-stage hybrid algorithm consisting of genetic, Nelder-Mead and gradient algorithms was applied to learning the artificial neural network.*

Key words: *synchronous generator, neural model*

INTRODUCTION

The development in the field of computer science engineering makes it possible to use advanced procedures for optimal selection of supply systems (for instance polyoptimisation [7]), in particular automatic control ones. Analytical methods for selecting regulation systems are insufficient. Due to it, iterative algorithms requiring accurate and time-consuming computer simulations are used in most procedures for optimal choice of these systems.

The accuracy of simulation computations depends, first of all, on two factors: the kind of the mathematical model applied (for instance: linear or nonlinear) and the accuracy of identifying the used model parameters.

The paper presents results of the analysis of the synchronous generator model taking into account nonlinearity of the generator magnetizing characteristic.

The proposed synchronous generator model is based on the theory of recurrent, multilayer neural networks [5]. The comparative analysis of the neural model worked out and circuit models of the synchronous generator was performed. In the investigations presented the voltage waveforms of a Gce32b salient pole generator of 4 kW power and 400 V rated voltage at 3000 rot/min were assumed to be the standards for the neural model.

1 SYNCHRONOUS GENERATOR CIRCUIT MODEL

The basis of a mathematical circuit model is the synchronous generator physical model [3, 6] – Fig.1. It can be assumed, generally, that two processes: mechanical and electromagnetic, related to each other, occur in the generator [3, 6]. They are connected with rotation of the driving motor shaft and flow of currents in the synchronous generator windings.

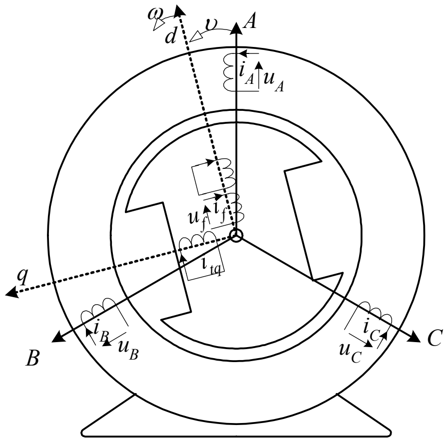

Fig.1: Synchronous generator physical model

In order to simplify the analysis, the following assumptions were taken [6]: the symmetric, three-phase stator winding is sinusoidally distributed, magnetic permeability of the stator and rotor cores is constant, losses in the stator and rotor cores can be neglected, the rotor is of two-axis symmetry, the rotor has a damper cage in d and q axis, interactions of eddy currents in the rotor are replaced with the increased interactions of damper cages in the particular machine axis, the generator is loaded with a symmetric, three-phase load, the rotation speed is constant.

It is convenient to write the equations of state of the synchronous generator in the cartesian coordinate system d, q rotating with the rotor electric angular speed, and so motionless in relation to the rotor. For the physical model the d and q axes are the magnetic symmetry axes.

$$\mathbf{U} = \mathbf{R} \cdot \mathbf{I} + \frac{\mathrm{d}}{\mathrm{d}t}\mathbf{\Psi} + \mathbf{\Omega} \cdot \mathbf{\Psi} \tag{1}$$

$$\mathbf{\Psi} = \mathbf{L} \cdot \mathbf{I} \tag{2}$$

Graphical interpretation of the equations of state of the synchronous generator (1) and (2) is the so-called circuit model presented for particular model types in Fig. 2. In the paper there are analysed the model of type: (2, 1) – i.e. with one damper circuit in the d and q axis.

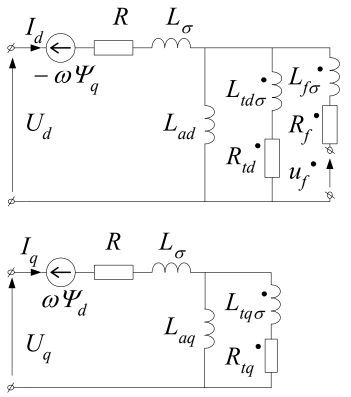

Fig.2: Synchronous generator circuit models

In simulation investigations the circuit models of the type presented above were implemented in the Matlab-Simulink program. The simulation model were constructed basing on matrix and integration operation blocks (Fig. 3).

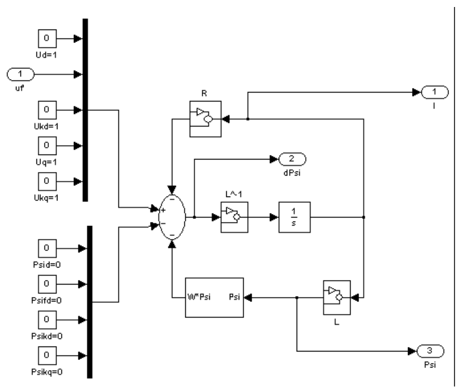

Fig.3: Synchronous generator simulation model

2 SYNCHRONOUS GENERATOR NEURAL MODEL

Artificial neural networks (ANN) are nowadays widely used in control and modelling technique. Different kinds of networks, including unidirectional and recurrent ones, are used for modelling physical phenomena [1, 2, 5, 8].

In modelling with the use of ANN there is usually employed the neural network ability to approximate and generalise, whereas the modelled object is treated as a black box. During the learning process there are used supervising learning algorithms [5], whereas the signals to be learned are the input and output signals of the modelled object. The generator model applied to the voltage regulator optimisation has the following input parameters: the field voltage and load impedance while its output is the armature voltage [5]. With so defined input and output parameters, during the initial tests it was stated that treating the synchronous generator as a black box and learning the network basing only on the input and output signals do not deliver satisfactory results. The supervising learning process in spite of the correct functioning (i.e. obtaining the satisfactory error value of reconstructing the given signals) did not always result in obtaining the network operating correctly, since the learned network was unstable in some cases.

In the presented investigations there was proposed a neural model being combination of two models learned independently of each other [8]. It was assumed that the synchronous generator armature voltage can be reconstructed on the basis of two voltages, namely: the armature voltage in no-load state $U_{0\mathrm{ANN}}$ and virtual voltage drop along the generator internal impedance U_{wANN} (Fig. 4, where the virtual voltage drop cannot be physically interpreted for a real generator.

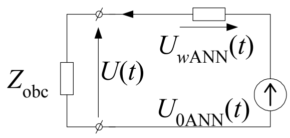

Fig.4: Circuit interpretation of the neural model

According to Fig. 4, the armature voltage $U(t)$ is given by:

$$U(t) = U_{0\mathrm{ANN}}(t) - U_{w\mathrm{ANN}}(t) \tag{3}$$

where

$$\begin{aligned} U_{0\mathrm{ANN}}(t) &= \int f_{0\mathrm{ANN}}(t)\mathrm{d}t, \\ U_{w\mathrm{ANN}}(t) &= \int f_{w\mathrm{ANN}}(t)\mathrm{d}t, \end{aligned} \tag{4}$$

where $f_{0\mathrm{ANN}}$ and $f_{w\mathrm{ANN}}$ are unknown functions represented by artificial neural networks.

The actual value of the function $f_{0\mathrm{ANN}}$ is determined by a neural network on the basis of information on the field voltage u_f and the difference (in the previous computation step) between the field and reconstructed voltage relative values. Whereas the actual value of the function f_{wANN} depends on the load impedance value Z_{obc}, the voltage value in no-load state U_{0ANN} and the armature voltage value in the previous computation step. For reconstruction of the searched functions there were used networks with one hidden layer with three neurons of sigmoidal activation function [5]. The model assumed for reconstruction of the synchronous generator armature voltage is shown in Fig. 5.

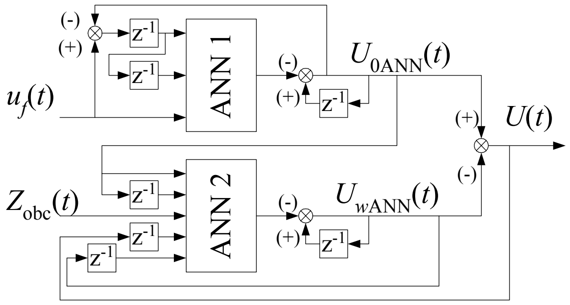

Fig.5: Circuit interpretation of the neural model

It was stated that the commonly used algorithm of back error propagation [5] did not deliver the correct results in the case analysed. Despite obtaining the satisfactory value of the reconstruction error of waveforms to be learnt, the learnt recurrent network was not always stable. Due to it, a sequent, hybrid algorithm was applied to the learning of the both component models of the generator.

The proposed sequent algorithm consisted of three stages. The first one was a genetic algorithm used for initial determining the neural network parameters. The second stage was the Nelder-Mead algorithm, while the final values of the network parameters were determined at the third stage by the Newton gradient algorithm. Such algorithm structure allowed combining the advantages of the particular algorithms while their basic disadvantages could be eliminated.

Application of the genetic algorithm at the first step enables initial searching the range of predicted values of the network parameters. Meeting the number of generations (50 generations for population of 20 members at 10-bit chromosome) was assumed to be the stopping condition of the genetic algorithm. For such genetic algorithm parameters, the algorithm result was the optimal solution approximation. The solution delivered by the genetic algorithm was the starting point for the Nelder-Mead algorithm. The use of the Nelder-Mead algorithm improved the result obtained from the genetic algorithm bringing it closer to the optimal solution in such a way that the final gradient algorithm could quickly deliver the satisfactory solution. Meeting 500 computational loops was assumed to be stopping condition at the second and third stage of computations.

3 COMPARATIVE ANALYSIS OF SYNCHRONOUS GENERATOR NEURAL AND CIRCUIT MODELS

For the analysis of the neural generator models there were learnt 10 different models reconstructing the voltage in no-load state and 10 models reconstructing the virtual voltage drop along the generator internal impedance. Each of the models was learnt for a randomly generated starting point. At the second stage there were generated 10 complete models of the synchronous generator by combination of component models (Fig 5).

The bands of the reconstructed quantity waveforms were determined by recording the waveforms of the armature voltage modeled during repeated simulations of the generated models. The errors for the standard and test waveforms differing from the waveforms applied to the neural model learning process were analysed. The results obtained are shown in Figs. 6 and 7.

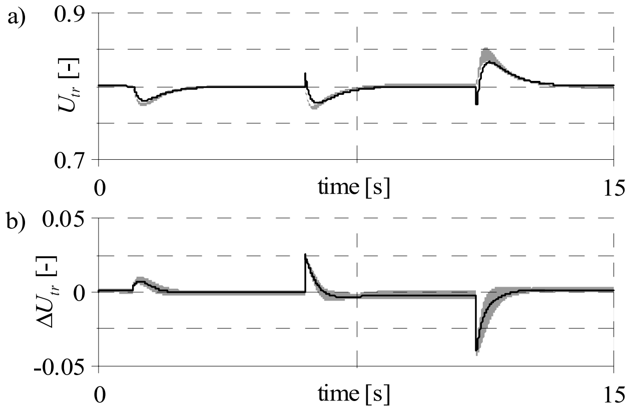

Fig.6: Bands of standard voltage waveforms (a) and their reconstruction errors (b) for the complete generator model

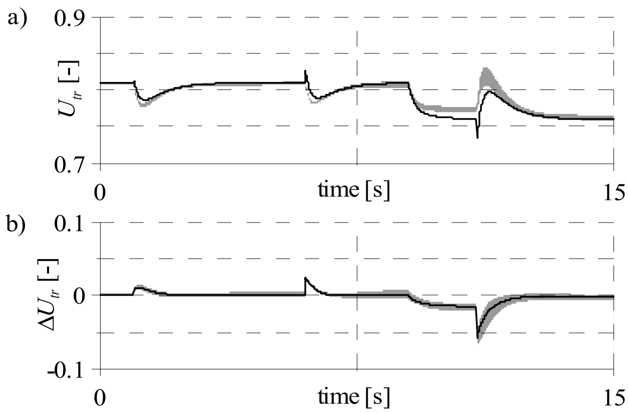

Fig.7: Bands of test voltage waveforms (a) and their reconstruction errors (b) for the complete generator model

In order to compare the results obtained for the neural model, the analysis of the circuit model was carried out. The results obtained (for the test waveform) are shown in Fig. 8.

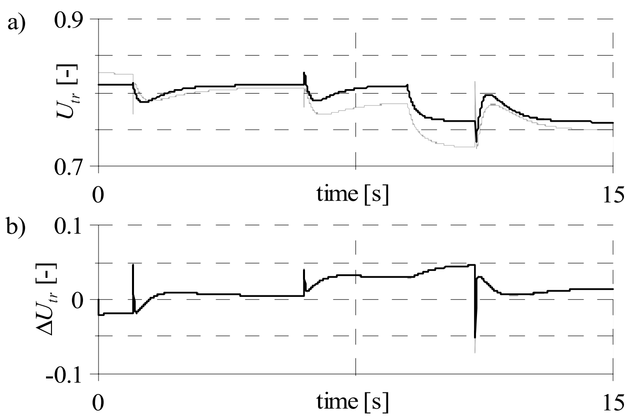

Fig.8: Bands of test voltage waveforms (a) and their reconstruction errors (b) for the complete generator model

4 SUMMARY

The following conclusions can be drawn from the analysis results presented above:

- The algorithm applied to determining the neural model parameters delivers correct results. The limitation of the iteration number of the particular algorithm steps does not considerably influence the quality of the model obtained.

- The cascade neural model structure used is stable and enables independent learning of component models, which reduces the number of simultaneously searched parameters and shortens the time of their determination.

- The error values for the neural model obtained from investigations do not exceed 5% for the learning voltages (Fig. 6b) and 6% for the test ones (Fig.7b). They are comparable with the errors of the circuit model (which does not take into account nonlinearity of the magnetizing characteristic) regarding the maximum values (Fig. 8). However, the average values and error waveforms are considerably better for the neural model.

On the basis of the results presented above one can state that the neural model described in the paper is an alternative for circuit models.

However, the use of the neural model requires the application of the complex and time-consuming algorithm for determining the neural network parameters which, next, limits the range of the model use for computations requiring large number of simulations (for instance polyoptimisation [7]).

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