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Estimating Rotor Angle and Stability of Synchronous Generator using Neural Network Modeling

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Abstract

There are several methods to study the stability and to estimate parameters of synchronous generators in different models[1,2,3]. In these methods, it is assumed that the rotor angle is measurable, while the lack of some signals in transmission line is possible[4]. The main approach of this paper is to estimate rotor angle in a synchronous generator using an artificial neural network (ANN) and dynamic parameters of generator such as electromagnetic torque, mechanical speed, generator current and generator voltage. This way, it is plausible to predict the stability of every generator with a system under error probability. Error has been tested in two ways in this system: first, increased torque load, and second, 3-phase short circuit error. The proposed method has been applied successfully. The simulation results completely confirm the proposed method.

Keywords: *synchronous generator, rotor angle, artificial neural network, stability.*

1. Introduction

Synchronous machine models play an important role in most studies, including stability and control, and are regarded as an advanced model [8]. In most cases synchronous machine is used as a generator and its dynamic behavior and steady state can be predicted by *qd* axis [6]. In majority of synchronous machine models the behavior of rotor windings, magnetic saturation and saliency had complex circuits, which had provided an integrated behavior for modeling the synchronous machine. This fact satisfies our need to modern computational tools. In [1, 3, 8] artificial neural network (ANN) has been used as a stable and appropriate method and a highly modern modeling technique that is able to model nonlinear functions easily. ANN can also model nonlinear functions with several variables and big sizes in Curse Dimension problems [9]. In recent years, due to their simple computations and adaptive capacities, ANNs have been developed in electrical machines [1,3]. We use them in this paper because of their high response rate [1]. Since power system security considers an extensive range of applications, we divide them into dynamic and static applications. System stability falls in dynamic category [1]. rotor angle in synchronous machine has been emphasized in several references as an important problem in power system dynamic problems, and is regarded as a nonlinear function of machine variables [1,2,3]. The proposed approach of this paper is to use *feed-forward* neural network and *back-propagation* supervised algorithm. The error rate is calculated through ANN and, if needed , the essential measures to command protective equipments of power plant can be taken. In next sections, the synchronous generator model and its dynamic efficiency are described briefly through a change in input torque. Then we will investigate the structure of ANN and stability.

2. Synchronous generator model

The synchronous machine rotor is equipped with a excitation winding and one or more damper windings. In addition, the rotor of a salient pole synchronous machine is magnetically asymmetric. In most cases, stator variables are transferred to the fixed reference system in rotor (Park equation)[6]:

$$f_{qd0s}^{r} = K_s^r(\theta_r) f_{abcs} \tag{1}$$

$$K_s^r(\theta_r) = \frac{2}{3}\begin{bmatrix} cos\theta_r & cos\left(\theta_r - \frac{2\pi}{3}\right) & cos\left(\theta_r + \frac{2\pi}{3}\right) \\ sin\theta_r & sin\left(\theta_r - \frac{2\pi}{3}\right) & sin\left(\theta_r + \frac{2\pi}{3}\right) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \tag{2}$$

In this section, first, we state the voltage and electromagnetic torque equations in machine variables. Then, we use Park's reference system to determine machine equations with stator variables in rotor reference system. The differential equations for synchronous generator are as follows [6]:

$$v_{abcs} = -r_s i_{abcs} + p\lambda_{abcs} \quad (3)$$
$$v_{qdr} = r_r i_{qdr} + p\lambda_{qdr} \quad (4)$$

Lower indices *s, r* are the variables related to stator and rotor windings, respectively. Where:

$$(f_{abcs})^T = [f_{as} \quad f_{bs} \quad f_{cs}] \quad (5)$$
$$(f_{qdr})^T = [f_{kq1} \quad f_{kq2} \quad f_{kd} \quad f_{kd}] \quad (6)$$

Equation for linkage fluxes is:

$$\begin{bmatrix} \lambda_{abcs} \\ \lambda_{qdr} \end{bmatrix} = \begin{bmatrix} L_s & L_{sr} \\ (L_s)^T & L_r \end{bmatrix} \begin{bmatrix} -i_{abcs} \\ i_{qdr} \end{bmatrix} \quad (7)$$

It is negative due to generator operation. Voltage and torque equations in rotor reference system are:

$$v_{qd0s}^r = -r_s i_{qd0s}^r + \omega_r \lambda_{qds}^r + p\lambda_{qd0s}^r \quad (8)$$

$$V_{qdr}'^r = r'_r i_{qdr}'^r + p\lambda_{qdr}'^r \quad (9)$$

Upper index *r* means rotor reference.

The electromagnetic torque equation and rotor angle in rotor reference is:

$$T_e = \left(\frac{3}{2}\right)\left(\frac{p}{2}\right)\left(\lambda_{ds}^r i_{qs}^r - \lambda_{qs}^r i_{ds}^r\right) \quad (10)$$

$$\dot{\omega}_r = \frac{1}{2H}(T_1 - T_e) \quad (11)$$

$$\dot{\delta} = \omega_r - \omega_e \quad (12)$$

3. Generator dynamic performance

Figures 1 to 5 show the dynamic behavior of generator during a change in input torque from 0 to 27.6x10^6 N.m using MATLAB software. These dynamic responses are calculated using a full set of nonlinear differential equations. Information related to these machines is presented in Appendix 1 [6].

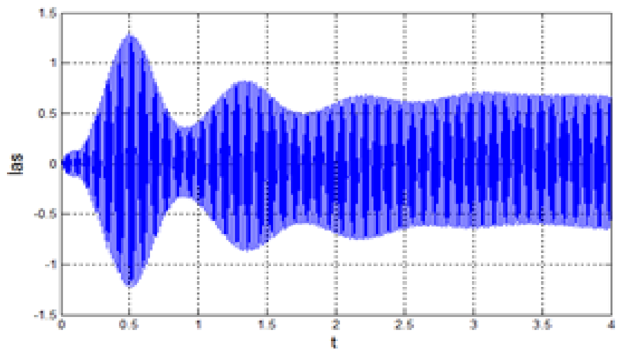


Fig.1 Stator axis current

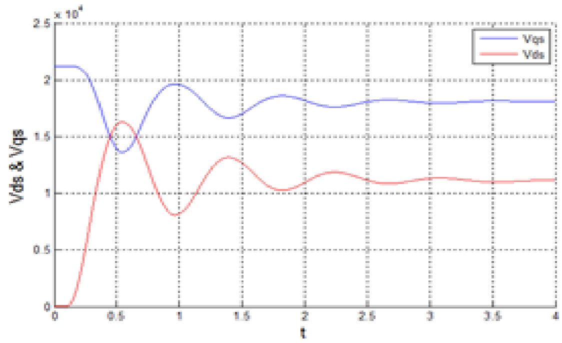


Fig.2 q.d axis voltage

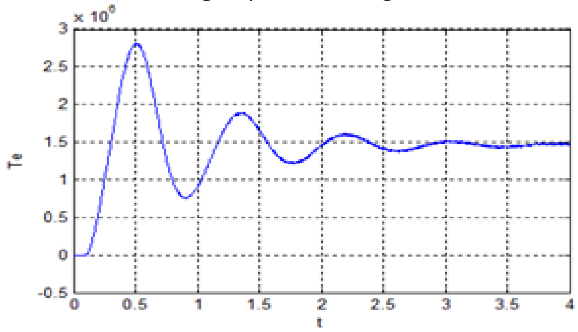


Fig.3 Electromagnetic torque

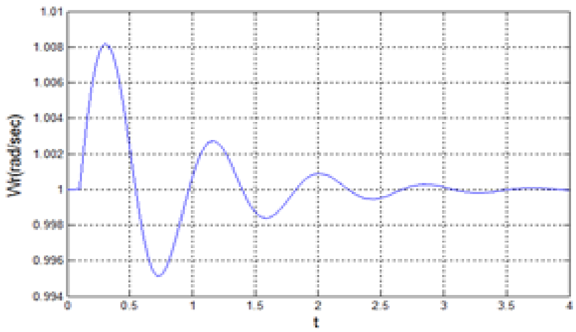


Fig.4 Rotor speed

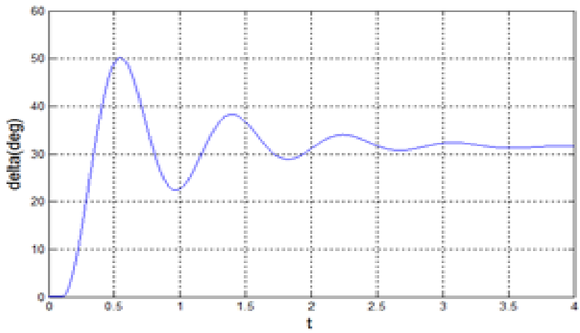


Fig.5 Rotor angle (stable state)

As can be seen from the responses, where the machine is exposed to step change in input torque from 0 to 27.6x10^6, rotor speed and rotor angle increase immediately after step increase in input torque. The rotor accelerates until the machine is stable.

4. Artificial neural network (ANN)

4.1 estimating rotor angle and the proposed method

It is difficult to obtain the rotor angle of a synchronous time frame through direct examinations; on the other hand, it can be estimated from voltage and current of the machine [4]. Since the system is nonlinear, it is suggested to use an automatic learning technique, like ANN. In fact, it has been known that ANNs are generally automatic learning and can afford nonlinear systems easily[3]. The aim of ANN in this paper is to estimate the rotor angle using machine torque, speed, voltage and current measurements.

4.2 Artificial neural network model and learning algorithm

ANN consists of a few simple elements called neuron. Its input is multiplied by weight (w) and is passed through a nonlinear filter in order to estimate the activity level of neurons. Neurons usually have an order, topologic and very strong interrelation in ANN [9]. In this paper we use the *feed-forward* neural network with *Levenberg-Marquardt* algorithm that has a few advantages over other learning algorithms including, advantage in input and system noise, learning from samples and the ability to keep results [3]. In the following figure the *feed-forward* neural network of the paper is presented.

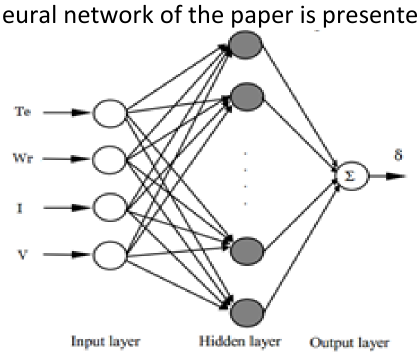


Fig.6 the structure of artificial neural network

ANN inputs includes : Te, Wr, I and v, respectively, and in output the load angle δ is estimated. In the output layer 1 purelin linear neuron and in the hidden layer 30 tansig neurons are used.
p=[Te Wr I v]'

5. Simulation results

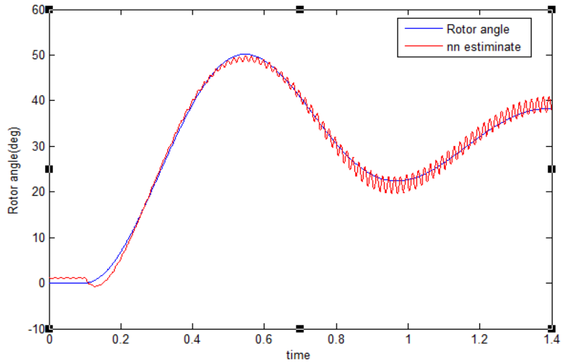
5.1 Simulation training and testing

The number of hidden layers is obtained with trial-and-error and studying the network behavior during learning process.

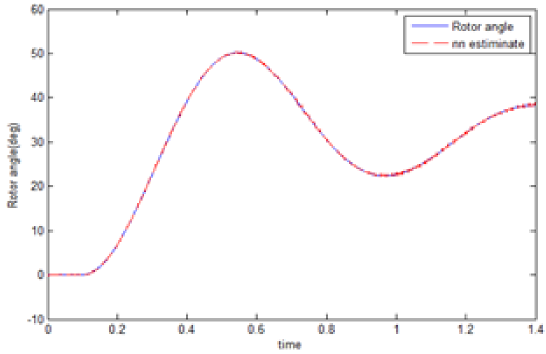
Table 1: The structure of artificial neural network with different hidden layers

TEST	ANN_NEFF	MSE	CORRELATION FACTOR	CYCLES
1	4-2-δ	1.55	0.9972	72
2	4-10-δ	0.105	0.9998	79
3	4-20-δ	0.029	0.9999	289
4	4-30-δ	0.012*	0.9999	192

Various states were tested, the best of which was considered 30 neurons in the layer. To do so, MATLAB Neural Network Toolbox was used. The results of simulation are presented in the following figures.



a: 2 neurons in the hidden layer



b: 30 neurons in the hidden layer

Fig.7 Estimation in two states

The *mse* error rate is presented in different states in the following table.

As can be seen, the utmost error rate between artificial neural network and the real value is 0.012 degrees.

5.2 Error application results

When generator is operating, the effects of factors such as short circuit, peak hours, power lines cut, etc , on the rotor angle can be observed. In this paper, this feature was modeled by artificial neural network. The network should be capable of controlling the rotor angle momentarily. However, if it exceeds the standard limit (minimum change for rotor angle in steady state is usually between 10-80 degrees [3]), protective equipments decrease or increase the rotor speed, or can stop the generator if necessary.

5.2.1 Increased input torque error

If the input torque from driving motor increases to an amount higher than the maximum limit, the machine cannot keep its steady state performance, because the machine is not able to transfer the fed power from the shaft. In this situation, theoretically, the system accelerates toward infinite speed. Nevertheless, the usual protections disconnect the machine from the system and decrease the input torque. For example, the existing protections operate when speed exceeds 3 or 5% higher than synchronous speed. Thus, this detection using ANN is as follows:

1. Error application as increased input torque to $55.6x10^6$ NM
2. Training the network by weights and biases from the best training with 30 neurons.

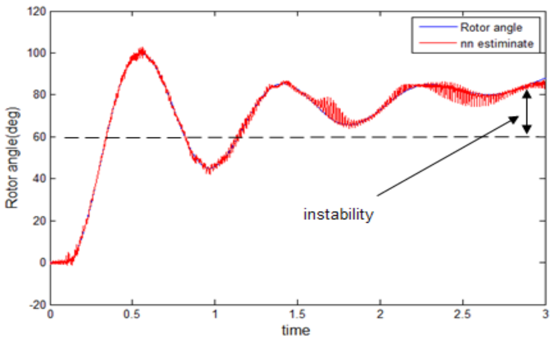


Fig.8 estimation in two states applying increased input torque error

In this state the number of data is 2682 samples for each input (inputs as 4x2682) and 2682 samples are considered for the output. Between [0, 0.1] the input data were applied without error, and between [0.1, 3] a torque equal to $55.6x10^6$ NM was applied to the network. Given the fact that we applied the error in 0.1 second to the generator, from Fig. 8 it is clear that the error is revealed after 2 seconds. In these errors, the rotor angle becomes unstable after a stable oscillation.

5.2.2 Three-phase error

In this section, we have focused on three-phase error for ANN learning and testing. All the three-phase errors occur in 0.01 second [1]. Since the terminal voltage is zero during three-phase error, the machine cannot transfer any power to the system.

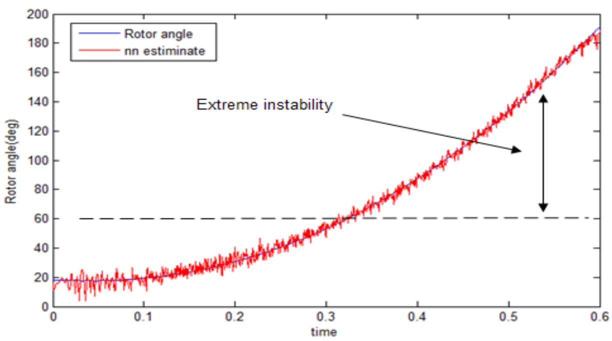


Fig. 9 estimation in two states applying three-phase error in terminals

So, it leads to motor acceleration. If the error stays a bit more on the system, the machine becomes unstable. In simulating in 0.02 second, we apply a three-phase error to the terminal. Between [0, 0.02] the same data are used and between [0.02, 0.6] the three-phase error data are applied. Fig. 9 shows the network performance after applying the error in 0.02 second. A network with 30 neurons in hidden layer is assumed. In this state, a total of 1202 sample data are considered for each input (input as 4x1202) and 1202 samples are considered for the output.

Conclusions

In this paper a system was designed for estimating rotor angle using artificial neural network. By measuring torque, speed, voltage, and current, this system estimated rotor angle easily. Then, stability in ANN was discussed using two error samples: increased input torque error and three-phase error. The advantage of the proposed design was error detection from generator signals including torque, speed, stator current, and stator voltage, without computing linear parameters. The results are worked out by MATLAB Neural Network Toolbox that confirms the proposed method.

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Appendix 1

0.480	Xq	325 MVA	Nominal power
0.85	Xd	20 kv	VL-L
0.0136	r'_{kq2}	0.85	Power Factor
0.1029	X'_{lkq2}	112.5 r/min	Speed
0.0005	r'_{fd}	$35.1\times10^6 J.s^2$	J
0.0141	r'_{kd}	7.5 s	H
0.160	X'_{lkd}	0.0019	rs
0.2049	X'_{lfd}	0.12	Xls