Australian Journal of Basic and Applied Sciences, 5(3): 442-451, 2011
ISSN 1991-8178

On-line Estimation of Synchronous Generator Dynamic Parameters by Ann Observer Based on One Statistic Feature Extraction from the Operating Data

[1]H. Chahkandi Nejad, [2]R. Jahani, [2]S. Zarrabian, [2] H. A. Shayanfar

[1]Electrical Engineering Department Islamic Azad University, Birjand Branch, Birjand, Iran.
[2]Electrical Engineering Department Islamic Azad University, South Tehran Branch, Tehran, Iran.

Abstract: This paper presents a new method for implementing Artificial Neural Network (ANN) observers in estimating and identifying synchronous generator dynamic parameters based on one statistic feature extraction from the operating data using obtained measurements from time zone information. Required data for training the neural network observers are obtained through off-line simulations of a synchronous generator operating in a one-machine-infinite-bus environment. Optimal components of the patterns are segregated from many learning patterns based on a new method called "normalized variance". Nominal values of parameters are used as a deviance index in the machine model. Finally, neural network is tested through online simulated measurements in order to estimate and indentify synchronous generator dynamic parameters.

Key words: Artificial Neural Networks; Dynamic Parameters; On-line Estimation, Operating Data; Synchronous Generator;

INTRODUCTION

Security is one of the essential requirements in power systems operation and dynamic security is a field of power systems security, which the operators continuously try to improve it. From frequency point of view, this domain contains low-frequency oscillations and the relative fluctuations are classified as parameter alteration group. Along with power systems developments, the importance of dynamic researches has enormously increased. Synchronous generators have a key role in this field and its pertinent studies. The power system operators need simulations in order to have a certain view of system behavior during different operating conditions because most of possible disturbances cannot be applied to the real network. Simulations consist of several steps that the most important of them is the identification of grid parameters because simulation softwares must have the parameters of powers system components in order to simulate the behavior of the system. Generator dynamic parameters change due to aging and inner faults; therefore continuous examination and identification is needed. In recent years, there has been a considerable interest in on-line estimation of synchronous generator parameters because maintenance has been provided during the operation. On-line methods are particularly attractive since the machine service need not to be interrupted and parameter estimation is performed by processing measurements obtained during the normal operation of the machine. It is obvious that identification of generator parameters based on operation information, requires an estimator system and Artificial Neural Networks (ANN) are high capable to achieve this case. In this paper, an ANN observer is developed to map sequences of the measured machine outputs to dynamic parameters by processing data acquired during transient disturbances. Over the past years, significant advances have been made to accurately model synchronous generators, based on well-established modeling techniques. Also during training, all the dynamic parameters of the machine are assumed to be measurable. This would correspond to the stage when simulations are carried out to obtain a sufficiently accurate observer model. After developing the neural network observer, it can be used to estimate generator dynamic parameters by processing measurements acquired on-line in an operating environment.

II. Machine Model Description:

For every electric power system dynamic study, a proper mathematical model must be chosen. Fundamental equations of synchronous machines were obtained by Park and some years ago. Park model is the best known and simple model for synchronous generators. Park's voltage equations are described by a coordinate system consisting of two axes: d-axis or direct axis fixed on the field winding axis and q-axis or

Corresponding Author: H. Chahkandi Nejad, Electrical Engineering Department Islamic Azad University, Birjand Branch, Birjand, Iran.

quadratic axis perpendicular to the d-axis. Park model for synchronous generator has been shown in Fig.1.

There are three armature phase winding a, b and c on the stator of the machine, which have been replaced by two equivalent armature phase windings, a winding on the d-axis and a winding on the q-axis. There are two damper windings on the rotor, D on the d-axis and Q on the q-axis which are permanently short-circuited. There is also a field winding F on the d-axis, which is DC-excited. The equations can be written as: (A. keyhani. *et al.* 1999)

$$V_d = R_a\left(-I_d\right) + p\lambda_d - \lambda_q p\theta \tag{1}$$

$$V_q = R_a\left(-I_q\right) + p\lambda_q + \lambda_d p\theta \tag{2}$$

$$V_F = R_F I_F + p\lambda_F \tag{3}$$

$$0 = R_D I_D + p\lambda_D \tag{4}$$

$$0 = R_Q I_Q + p\lambda_Q \tag{5}$$

In this path, equations can be written in per unit of value. During the development of the synchronous machine theory, many reactances and time constants have been defined. They include the synchronous reactance for the steady-state analysis, the transient reactance, which includes the field winding effect for electric transient analysis and other dynamic studies, and the transient and sub-transient time constants associated with the reactances. Now, the flux leakages can be presented as follows:

$$\begin{bmatrix} \Psi_d \\ \Psi_F \\ \Psi_D \end{bmatrix} = \frac{1}{\omega_0}\begin{bmatrix} x_d & x_{md} & x_{md} \\ x_{md} & x_F & x_{md} \\ x_{md} & x_{md} & x_D \end{bmatrix}\begin{bmatrix} -i_d \\ i_F \\ i_D \end{bmatrix} \tag{6}$$

$$\begin{bmatrix} \psi_q \\ \psi_Q \end{bmatrix} = \frac{1}{\omega_0}\begin{bmatrix} x_q & x_{mq} \\ x_{mq} & x_Q \end{bmatrix}\begin{bmatrix} -i_q \\ i_Q \end{bmatrix} \tag{7}$$

According to these equations, the d- and q-axis equivalent circuit for the synchronous machine, similar to those of the three-winding transformer and the two-winding transformer, maybe drawn as in Fig.2. Under these circumstances, we can provide a new collection of synchronous machine parameters called "operational parameters" which can be defined as:

X_d : Unsaturated d axis synchronous reactance.
X'_d: Unsaturated d axis transient reactance.
X''_d: Unsaturated d axis sub-transient reactance.
X_q : Unsaturated q axis synchronous reactance.
X''_q: Unsaturated q axis sub-transient reactance.
T'_d: d axis transient open circuit time constant.
T''_d : daxis sub-transient open circuit time constant.
T''_q :q axis sub-transient open circuit time constant.
H: Inertia constant

III. Estimating Synchronous Generator's Dynamic Parameters Based on Artificial Neural Network:

There are six processing elements in the ANN observer input layer and 1 element in its output layer. The number of inputs is obtained from the studies which have been performed on the synchronous generator dynamic parameters observability during its measurable output variables. On the other hand, the ANN with one output helps us to have a more clear view about the ANN ability in estimating dynamic parameters. Therefore, by applying artificial neural networks, the variables representative of generator operating conditions are mapped to each generator dynamic parameter being modeled and a total of ten ANNs are used to model

generator dynamic parameters. Today it is specified that an ANN with one hidden layer is suitable enough to impersonate all nonlinear performances. Thus, each model consists of a single hidden layer having optimal number of neurons. The structure of this ANN is shown in Fig.3.
As shown in Fig. (3), components of neural network input vector consist of output signals samples of some sample generators.

IV. Simulation Studies:

Extensive simulations have been performed to investigate the performance of the proposed ANN observer in order to estimate synchronous generator dynamic parameters. In order to achieve necessary data required for testing and training the ANN observer, dynamic simulations have been performed on the three hundred synchronous generator models connected to an infinite bus. All disturbances that occur during synchronous generator operation are subdivided to three fields, which include:

- Excitation faults
- Prime-mover torque faults
- Connected grid faults

Optimal weights of neural network is separately calculated and investigated for all disturbance categories. Then, it helps us to have a clear view about accuracy of estimated parameters based on obtained information corresponding to each disturbance. Therefore, the measurements accomplished during each disturbance are recorded separately and consequently, the trained network corresponding to each disturbance can be used to estimate the parameters online when a disturbance occurs. Operational data generating process has been shown in Fig.4.

It is obvious that when a disturbance occurs in a power system, all sample generators' outputs have individual oscillations due to their individual dynamic parameters. We use the deviation of each output from its origin as an input of the neural network. Network training process has been shown in Fig.5.

We can observe that weights of network are tuned corresponding to difference between real and estimated value of the parameters. Also, neural network test process is shown in Fig.6.

V. Neural Network Training:

Regarding to the goal of this research, the training data consist of different synchronous generators' performance data such as: fossil steam units, combustion turbine units, hydro units, etc. The simulation models are developed in MATLAB environment. The operating data of synchronous generators during any kind of disturbances are used for training and testing the ANN, independently. Also, a total of 10 ANNs are trained to estimate all of the ten mentioned synchronous generator dynamic parameters on the basis of each training data bank. The training data set for each ANN consists of 225 synchronous generators operating data (%75 of total patterns). All ANN models are trained using Levenber-Marquardt algorithm. Here, due to extension of simulation environment (30 parameters because of 10 parameters for each disturbance zone), only the simulation results of one parameter among 30 parameters is presented during its training period. The rest of 29 parameters are simulated similarly and the results will be shown in tables 1- 4 at the end of the paper. Now, we describe the simulation results of ANN training for inertia constant (H) which is one of the mentioned parameters. A sudden reduction of %10 in generator input power is considered as a disturbance in this case. It is important that a disturbed generator's output swings are depend on dynamic parameters which are obtained from generator's nature. Therefore, to generate input space (input components) for ANN estimator, sample data of disturbed generators' outputs has been used. In this way, the outputs have been sampled with sampling rate of 0.0150 during 15 seconds. The sampling interval ([0, 15] seconds) is obtained based on researches implemented on synchronous generator dynamic parameters observability. (S. Ahmed-Zaid. *et al*. 1995) Now, we have thousand samples on the interval of [0, 15] seconds which some of them must be chosen between all training patterns. In this paper, there are six generator's outputs as the inputs of ANN which are chosen from following outputs:

1) Electrical active power
2) Electrical reactive power
3) Mechanical speed
4) Power angle
5) d-axis component of the stator current
6) q-axis component of the stator current
7) d-axis component of the stator voltage
8) q-axis component of the stator voltage

In Fig. 7, for instance, d axis component of the stator current is shown versus disturbance of pattern 110 on the interval of [0, 15] seconds.

Therefore, input space of ANN includes 6 outputs, each in 10 samples. Hence, input vector of the network will have sixty components. The number of samples is obtained by trial and error method to minimize fault and network size.

VI. How to Select ANN Input Vector Components:

It is known that a neural network will be suitable for online applications when its input vector components and processor elements are minimized because in case of excess neurons, the weights of the ANN increase and direct emission of the ANN decreases.(In this paper, optimal number of neurons has been obtained by trial and error method on 7 neurons). According to previous section, the number of total patterns (test and train) are 300 and for each generator's outputs, 1000 samples with constant step are selected during [0, 15] seconds. Therefore, only 6 outputs (1,2,4,5,7,8), mentioned in previous section, are selected here and some optimal samples are chosen between all generators to decrease the weights of ANN. It must be noted that these samples must be recorded in periods which represent generator characteristics and separate generators based on their responses against disturbances. Consider three hundred generators as 300 points in a 1000-dimensional space such that some dimensions in this space can be chosen as the best inputs of the ANN and by drawing all three hundred points on these dimensions, the least overlap occurs for selected generators. These dimensions are sampling times which are the best to separate and choose three hundred points. Therefore, to identify these dimensions, we calculate the normalized variance of all data (300 generators) correspond to all dimensions (1000 dimensions) and then, choose some dimensions as the input of ANN such that the map of all data (300 generators) on these dimensions maximize the normalized variance index. The normalized variance of data along jth-axis can be defined as:

$$\frac{VAR_j(data)}{MAX(data_j) - MIN(data_j)} \tag{8}$$

In equation (8), the numerator is the data variance along jth-axis and denominator is the difference between maximum and minimum data along jth-axis. Since the large scales cause the large variances, they are normalized along their related axis in order to avoid making mistakes in extraction of optimal input vector components.

VII. Results of ANN Training:

In this paper, the number of 225 Templates from 300 Templates (75% patterns) were considered for the training that the results of training are shown in following figures. Since the error function according to the weight vector components has many local minimums and also because of the process of minimizing the error depends strongly on the initial values of weight vectors, the results have been obtained after several runs, there is no reason these results are the best and it is possible to obtain better results in the next performances. The abundance of training patterns (225 patterns) in different disturbance periods is shown in Fig. 8.

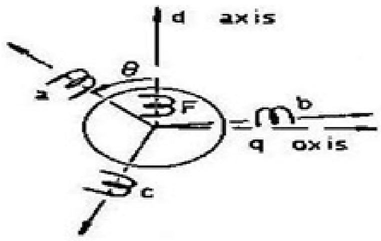
It can be found from Fig. 9 that the estimation error of almost all 217 patterns is zero. The maximum error index can be determined from Fig. 9 during training process which is 0.25.

VIII. Results of ANN Observer Testing:

To test the effectiveness of the trained ANN observers in estimating dynamic parameters under on-line conditions, simulated measurements are generated with the machine operation in a one–machine–infinite bus environment. The test data set for each ANN consists of 75 synchronous generator's operating data, which are not considered for the training stage. Now, we describe the simulation results of the test period for the trained parameter H. The abundance of testing patterns (225 patterns) in different disturbance periods is shown in Fig. 10. As it can be seen from Fig. 10, the errors of 69 patterns (test patterns) are in the interval of [-0.14, +0.14] and the error of rest of them (6 remainder patterns) is less than 0.7.

Fig. 11 also shows the real error of the parameter H and its estimation error corresponding to testing patterns and the deviation from real value in each pattern can be seen separately. It can be found from Fig. 11 that the estimation error of almost all 69 patterns is zero. The maximum error index can be determined from Fig. 11 during test process which is equal to 0.7. The results summary for estimating of all parameters in each three disturbance zones is shown in Table 1.

In Table 1, the maximum error for each parameter corresponding to its related disturbance has been calculated. Also in Table 2, the patterns abundance with absolute error more than 0.05, is shown.



Three-Phase Winding Synchronous Machine.

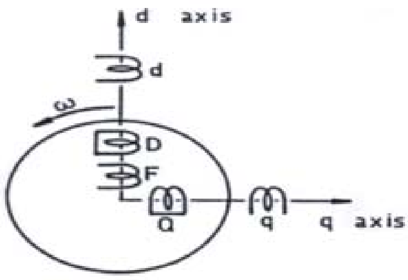
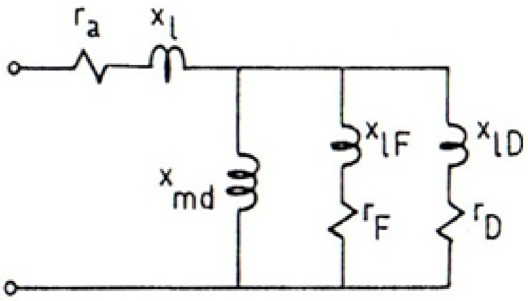
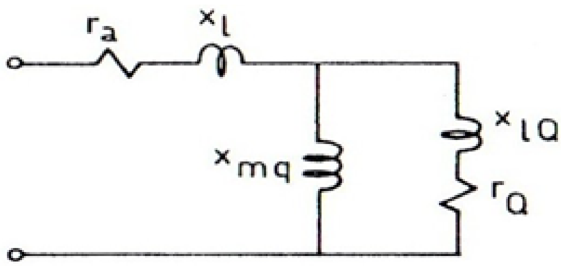


Fig. 1: Park's Synchronous Machine.



(a) d axis



(b) q axis

Fig. 2: The d- and q-axis Equivalent Circuits of the Synchronous Machine.

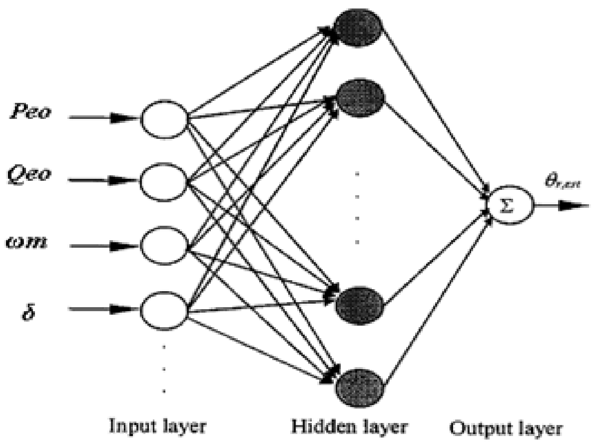


Fig. 3: ANN observer structure.

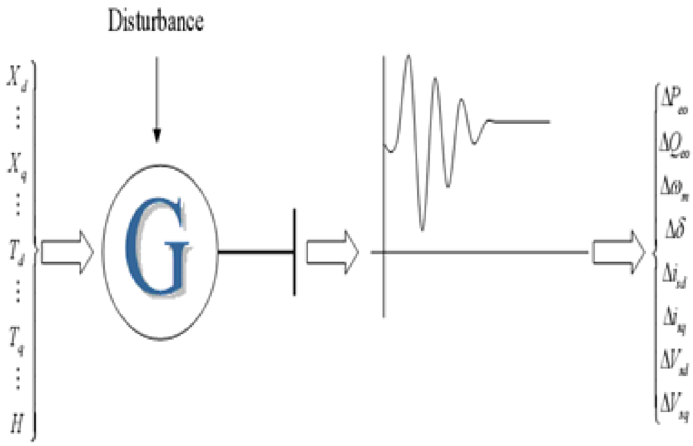


Fig. 4: Operational data generating process.

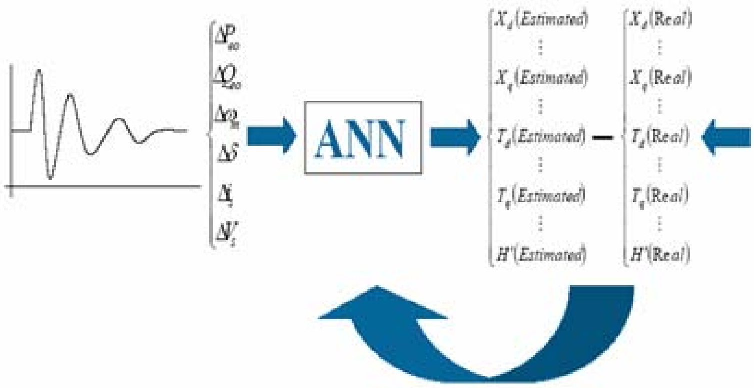


Fig. 5: ANN training process.

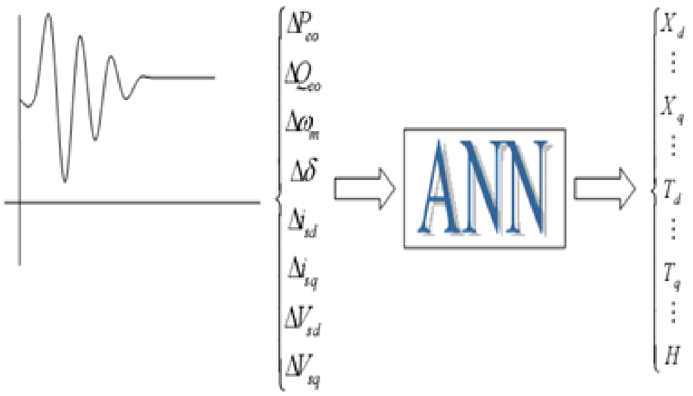


Fig. 6: ANN observer test process.

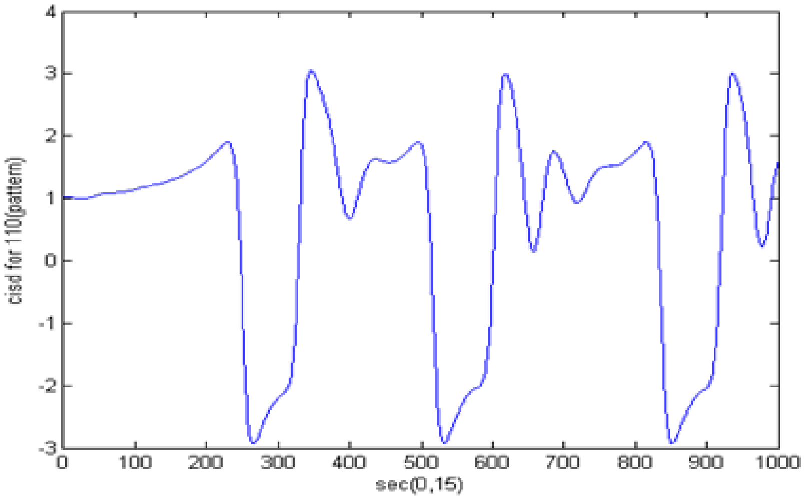


Fig. 7: A sample output (generator number 110).

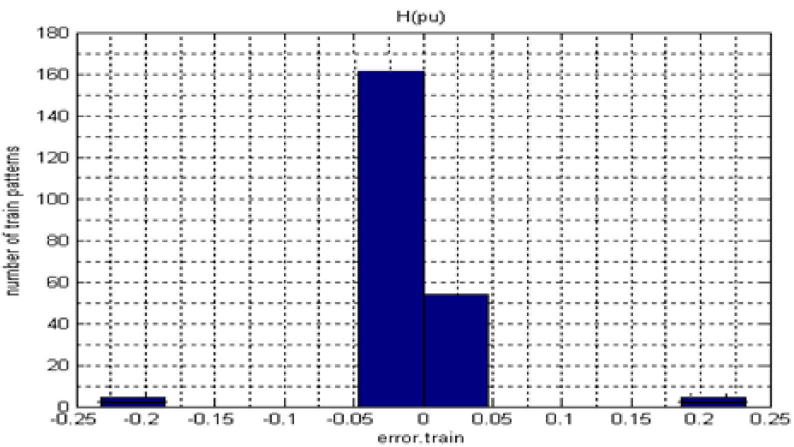


Fig. 8: Abundance of training patterns in different disturbance periods.

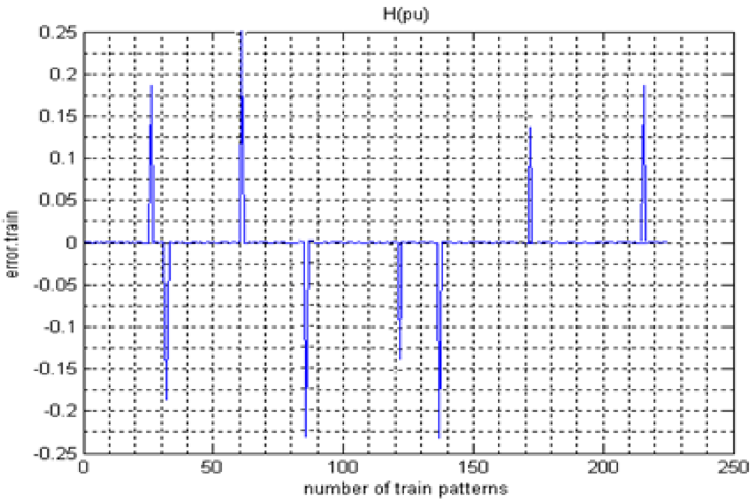


Fig. 9: Real error of the parameter H and its estimation error corresponding to training patterns.

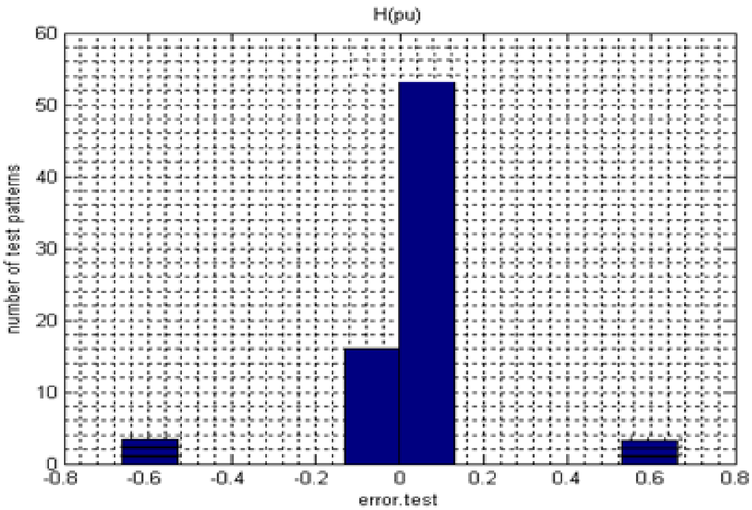


Fig. 10: Abundance of testing patterns in different disturbance periods.

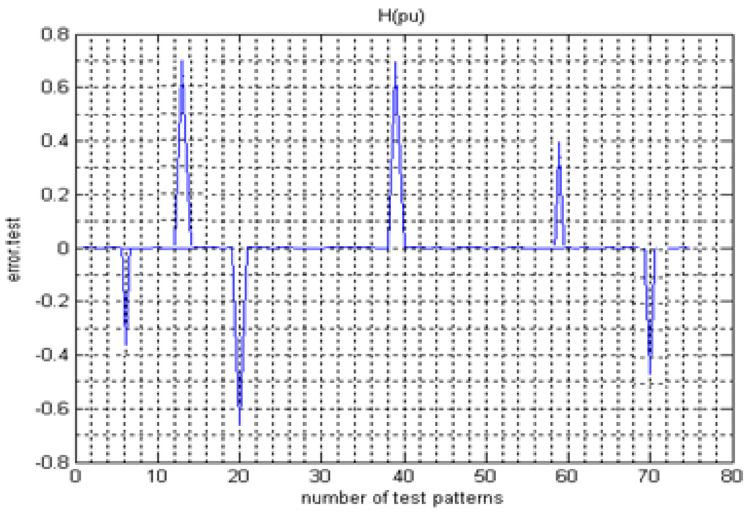


Fig. 11: Real error of the parameter H and its estimation error corresponding to testing patterns.

Table 1: Training period results (maximum error amplitude)

Disturbance/Parameter	Excitation faults	Prime-mover torque faults	Connected grid faults
Xd	0.563	0.259	0.145
X'd	0.145	0.178	0.363
X"d	0.124	0.749	0.145
Xq	0.455	0.669	0.145
X'q	0.356	0.189	0.362
X"q	0.14	0.441	0.145
T'd	0.61	0.541	0.144
T"d	0.154	0.491	0.114
T"q	0.329	0.111	0.699
H	0.218	0.250	0.290

Table 2: Training period results (error abundance)

Disturbance/Parameter	Excitation faults	Prime-mover torque faults	Connected grid faults
Xd	3	4	4
X'd	7	3	2
X"d	1	3	5
Xq	7	3	2
X'q	3	4	1
X"q	3	6	2
T'd	4	3	3
T"d	2	3	7
T"q	6	2	1
H	3	8	5

Table 3: Test period results (maximum error amplitude)

Disturbance/Parameter	Excitation faults	Prime-mover torque faults	Connected grid faults
Xd	0.572	0.322	0.365
X'd	0.125	0.112	0.144
X"d	0.324	0.114	0.387
Xq	0.488	0.579	0.195
X'q	0.456	0.669	0.172
X"q	0.676	0.448	0.445
T'd	0.112	0.65	0.141
T"d	0.673	0.114	0.564
T"q	0.759	0.536	0.095
H	0.572	0.322	0.365

Table 4: Test period results (error abundance)

Disturbance/Parameter	Excitation faults	Prime-mover torque faults	Connected grid faults
Xd	5	5	3
X'd	3	3	2
X"d	2	2	1
Xq	2	3	2
X'q	3	2	3
X"q	4	5	2
T'd	3	2	3
T"d	5	2	3
T"q	2	2	5
H	4	6	3

IX. Conclusion:

In this paper, for estimating the dynamic parameters of the synchronous generators a neural network based observer method based on fuzzy feature extraction was used. The exploited data has been collected in the cases of disturbances such as excitation, input power changes and short circuit occurrences. Validation studies show that ANN models can correctly interpolate between patterns which have not been used in training. It is expected that this improvements can enhance the performance of the used observer and makes it an efficient tool for estimating the dynamic parameters of the synchronous generators with acceptable error. Also, it is expected that steps as below can improve the performance:

1. Collecting richer data set
2. Applying separate ANNs to estimate dynamic parameters of solid rotor synchronous generators and salient pole rotor synchronous generators.
3. Optimizing estimated parameters using the difference between real generator performance and the performance of generators with estimated characteristics.

4. Optimizing Measurement times to have the best view of synchronous generators dynamic performance using minimum data value.

REFERENCES

Ahmed-Zaid, S. and N.A. Demerdash, 1995. "An Artificial-Neural-Network Method for the Identification of Saturated Turboganarator Parameters Based on a Coupled Finite-Element/State-Space Computational Algoritm" IEEE Transactions of Energy Conversation, 10(4): 625-633.

Anderson, P., 1984. "Power System Control and Stability" Galgoutilv Press,

Beye, K., R. Pintelon, J. schoukens, P. Lataire and P. Guillaume, 1994. "Identification of Synchronous Machines Parameters Using Broadband excitations" IEEE Transactions on Energy Conversation, 9(2): 551-558.

Edson da Costa Bortoni and Jose Antonio Jardini, 1997. "Synchronouse Machines Parameters Identification Using Load Rejection Test Data" IEEE Conference.

Henschel, S. and H.W. Dommel, 1999. "Noninterative Synchronous Machine Parameter Identification from Frequency Response Tests" IEEE Transactions on Power Systems, 14(2): 553-560.

Keyhani, A. and I. Kamwa,1999. "Neural Network Observers for On-line Tracking of Synchronous Generator Parameters" IEEE Transactions of Energy Conversations, 14(1): 23-30.

Khayat, O. and H.R shahdoosti, "using shahyat algorithm as a new method for pattern clustering and classification", lecture note in electrical engineering, 151-161: 28.

Keyhani, A. and G. Dayal, 1989. "Maximum Likelihood Estimation of Solide-Rotor Synchronous Machine Parameters from SSFR test Data" IEEE Tracsactions on Energy Conversation, 4(3).

Tumageanian, A. and A. Keyhani, 1992. "Synchronous Machine Parameter Estimation from Standstill Flux Decay Data" IEEE Conference.

Tsai, H., A. Keyhani, j. Demeko and R.G.Farmer, 1995. "On-Line Synchronous Machine Parameter Estimation from Small Disturbance Operating Data" IEEE Transactions on Energy Conversation, 10(1): 25-36.

Yao-nan Yu., 1983. "Electrical Power System Dynamics" Academic Press, INC. New York.

Xinqi Chen, Zhu. Shizhang, Pan. Quan, Qu. Lianxing, Zheng. Fengshi and Sun. Xudong, 1998. "On-line Identification of Synchronous Generator Parameter from Large Disturbance Testing Data" IEEE Conference.