On-line determination of salient-pole hydro generator parameters by neural network estimator using operating data (PEANN)

IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 10, 2021, accepted September 18, 2021, date of publication September 27, 2021, date of current version October 6, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3115783

On-Line Determination of Salient-Pole Hydro Generator Parameters by Neural Network Estimator Using Operating Data (PEANN)

O. SHARIATI[1], (Member, IEEE), M. R. AGHAMOHAMMADI[2], (Member, IEEE), AND B. POTTER[1], (Member, IEEE)

[1]School of Construction Management and Engineering, University of Reading, Reading RG6 6AH, U.K.
[2]Faculty of Electrical Engineering, Shahid Beheshti University, Tehran 19839 69411, Iran

Corresponding author: O. Shariati (o.shariati@reading.ac.uk)

This work was supported in part by the University of Reading.

ABSTRACT A novel application of Artificial Neural Network (ANN) to estimate and track Hydro Generator Dynamic Parameters using online disturbance measurements is presented within this paper. The data for training ANN are obtained through off-line simulation of the generators modelled in a one-machine-infinite-bus environment using the parameters sets that are representative of practical data. The Levenberg-Marquardt algorithm has been adopted and assimilated into the back-propagation learning algorithm for training feed-forward neural networks. The inputs of ANN are organized in coordination with the results obtained from the observability analysis of synchronous generator dynamic parameters in its dynamic behaviour. A collection of 10 ANNs with similar input patterns and different outputs are developed to determine a set of dynamic parameters. The trained ANNs are employed in a real-time operational environment for estimating generator parameters using online measurements acquired during disturbance conditions. The ANNs are employed and tested to identify generator parameters using online measurements obtained during different disturbances. Simulation studies demonstrate the ability of the ANNs to accurately estimate dynamic parameters of hydro-generators. The results also show the impact of test conditions on the accuracy degree of estimation for these parameters. The optimal structure of ANNs is also determined to minimize the error in estimating each dynamic parameter.

INDEX TERMS Salient-pole, hydro generator, dynamic parameters, artificial neural network, online estimation, operating data.

I. INTRODUCTION

Hydroelectric power plants constitute a major part of the generation in electric power systems, which contribute to system dynamics with dominating effect on system stability. The identification of generators' dynamic parameters is an important step in ensuring an accurate power system simulation and valid dynamic assessment; especially because the dynamic oscillations are categorized as a parameter-alternating group.

Various research and studies discuss the identification of electrical machine parameters, especially synchronous generators. There are powerful off-line methods such as Stand Still Frequency Repose (SSFR) [1], [2], Flux Decay [3] and Finite Element [4]. These methods can also be categorized into harmless methods [5], [6] and harmful tests such as load rejection [7] and short circuits [8], [9]. Some of these methods are focused on static parameters or immeasurable rotor body current. Reference [10] is a critical review that shows the advantages and disadvantages of the aforementioned methods and their objectives in detail. Regarding this review, there is an opportunity for presenting new harmless methods with a focus on estimating the dynamic parameter of synchronous generators.

There has been considerable interest in the online estimation of synchronous generator parameters in recent times [11]–[15]. These methods are practical for use with existing installation since the machine service does not need to be interrupted, and parameter estimation can be obtained

The associate editor coordinating the review of this manuscript and approving it for publication was Haruna Chiroma.

in a real-time environment during the normal operation of the machine [16]. The online methods should be capable enough to identify a complete set of parameters with a high degree of accuracy by using operating data.

The need for online parameter estimation arises due to the deviation of generator parameters from their nominal values obtained in offline testing. Although the procedure of estimating system dynamic parameters via processing its measurable outputs is essentially a system identification task, incipient faults can typically be detected by continuous or periodic monitoring of characteristic quantities. Incipient faults, which refer to internal damage in mechanical or insulation characteristics of generator, can lead to eccentricity in electrical machines and consequently gradual change in dynamic parameters of generator [17]–[19]. In this regard, parameter identification by the neural network can offer promising tools for damage prediction.

The success in the application of artificial neural networks to estimate the state vector of the induction motor, rotor body parameters [20]–[22] strongly corroborates this work.

Whilst the success of ANNs in identifying the dynamic parameters of synchronous generators has been established, hydro and steam generators present additional challenges that are yet to be resolved. The distinct parameter sets that are employed in the simulation of hydro and steam generators, and their different amounts, require separate ANNs for parameter estimation [23], [24].

Furthermore, the dynamic performance of the machine and its nonlinearity have a close relationship with the disturbance type. The observability of different dynamic parameters is considerably affected by the disturbance type. Thus, in continuation of the related studies [25], [26], the other aspect that has been taken into consideration by this research is the analysis of disturbance impacts on the degree of accuracy of parameter identification.

In this paper, a set of ANN observers has been developed to map sequences of measurable machine outputs to the dynamic parameters of hydro generators by processing data acquired during transient disturbances. The measurements have been obtained online in an operating environment. In order to estimate the dynamic parameters of hydro generators based on the online measurable machine outputs, a set of ANN estimator are developed. The proposed Parameter Estimator ANNs (PEANN) are able to estimate dynamic parameters of generators based on the operational data measured during dynamic behaviour following a large or small disturbance. For each machine's parameter, an individual PEANN is developed and trained.

II. MACHINE MODEL DESCRIPTION

As a common practice in the operation of power systems, hydro generators use the salient-pole synchronous machines for energy conversion. This machine type is used due to the high consistency between the technical specifications of this type of generator with the operation condition of hydro units (i.e., low rotation speed and therefore high number of poles).

Synchronous generators can be modelled using the Park machine model in terms of voltage-current-reactance which is applicable for modelling mid-term and long-term transient behaviour of generator following the occurrence of a fault or disturbance. It is worth noting that most power system behaviours like rotor angle stability, frequency stability and voltage stability are expressed and evaluated in terms of Root Mean Squarer (RMS) variables [27], [28]. Therefore, RMS modelling of synchronous generators in terms of dynamic parameters is essential for power system simulation. In this paper, based on the above requirement of the power system and the related IEEE Standard [29], the RMS model of a synchronous generator in terms of dynamic parameters is investigated.

The synchronous machine equations are developed in related references [29]–[33] and the schematic view of the three winding and the Park's transformed model are respectively presented in Figure 1 (a) and (b). The inductances and resistances of the stator and rotor circuits constitute the parameters of this formulation. These are known as fundamental or basic parameters [34].

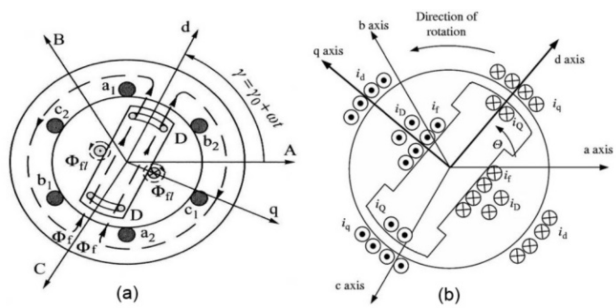


FIGURE 1. (a) Three-phase winding and (b) Park's synchronous machine.

While the fundamental parameters completely specify machine electrical characteristics, they cannot be directly determined from measured responses of the machine. Therefore, a convenient method for identifying the electrical characteristic of a machine is its representation in terms of operational parameters. These are related to the armature and field windings quantities.

Referring to Figure 2, the relationship between the incremental values of armature quantities may be expressed as follows [34]:

$$\Delta\Psi_d(S) = G(S)\,\Delta e_{fd}(S) - L_d(S)\,\Delta i_d(S) \tag{1}$$

$$\Delta\Psi_q(S) = -L_q(S)\,\Delta i_q(S) \tag{2}$$

where:

G armature to field transfer function
L_d d-axis operational inductance
L_q q-axis operational inductance
ψ_d d component of armature flux linkage

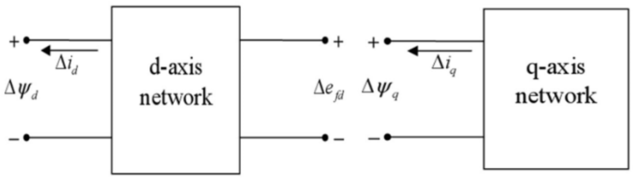
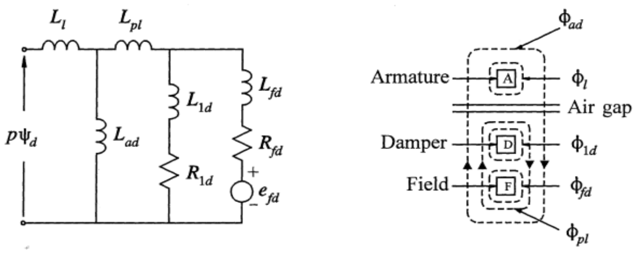


FIGURE 2. The d- and q-axis networks identifying armature quantities.

- ψ_q q component of armature flux linkage
- i_d d component of the armature current
- i_q q component of the armature current
- Δ the symbol of incremental values
- S the Laplace operator

Equations (1) and (2) are applicable to any number of rotor circuits. In fact, Park [35] expressed the armature flux equations without specifying the number of rotor circuits.

The operational parameters may be determined either from design calculations or more readily from the tests on the actual machines. The d-axis equivalent circuit is presented in Figure 3. This figure shows unequal mutual effects and the related fluxes.



(a) Equivalent circuit (b) Flux paths

FIGURE 3. Unequal mutual effects in d-axis.

Assuming that $R_{fd} = 0$ during the sub-transient period and that $R_{1d} = 0$ during the transient period, the expressions for the standard parameters may be written by inspection of the equivalent circuit as follows [34]:

$$L_d = L_{ad} + L_l \tag{3}$$

$$L'_d = L_l + \frac{L_{ad}\left(L_{fd} + L_{pl}\right)}{L_{ad} + L_{fd} + L_{pl}} \tag{4}$$

$$L''_d = L_l + \frac{L_{1d}L_{fd}L_{ad} + L_{1d}L_{pl}L_{ad} + L_{ad}L_{fd}L_{pl}}{L_{ad}L_{fd} + L_{ad}L_{1d} + L_{1d}L_{fd} + L_{1d}L_{pl} + L_{fd}L_{pl}} \tag{5}$$

$$T'_{do} = \frac{L_{ad} + L_{fd} + L_{pl}}{R_{fd}} \tag{6}$$

$$T''_{do} = \frac{1}{R_{1d}}\left(L_{1d} + \frac{L_{fd}\left(L_{ad} + L_{pl}\right)}{L_{pl} + L_{fd} + L_{ad}}\right) \tag{7}$$

where:

- L_d d-axis operational inductance
- L_{ad} d-axis armature-damper mutual inductance
- R_{1d} d-axis damper resistance
- L_{1d} d-axis damper inductance
- L_{fd} field-damper mutual inductance
- L_l Potier inductance
- L'_d d-axis operational transient inductance
- T'_{do} d-axis transient open circuit time constant
- T''_{do} d-axis sub-transient open circuit time constant
- $L''d$ d-axis operational sub-transient inductance

and $L_{pl} = L_{f1d} - L_{ad}$ is series inductance correspond to field-damper peripheral leakage flux.

For a laminated Salient pole machine, the damper winding is the only rotor circuit in the q-axis; therefore, one q-axis rotor circuit is applicable. The parameters of this rotor circuit are such that it represents rapidly decaying sub-transient effects. The second rotor circuit, which is normally considered in solid rotor type, is ignored and no distinction is made between transient and steady-state conditions. Hence, the expressions for the common q-axis parameters of the salient pole machine are as follows [34]:

$$L_q = L_l + L_{aq} \tag{8}$$

$$L''_q = L_l + \frac{L_{aq}L_{1q}}{L_{aq} + L_{1q}} \tag{9}$$

$$T''_{qo} = \frac{L_{aq} + L_{1q}}{R_{1q}} \tag{10}$$

where:

- L_q q-axis operational inductane
- R_{1q} q-axis damper resistance
- L_l Potier inductance
- L''_q q-axis operational sub-transient inductance
- L_{aq} q-axis armature-damper mutual inductance
- T''_{qo} q-axis sub-transient open circuit time constant
- L_{1q} q-axis damper inductance

In per unit, the sub-transient, transient, and steady-state reactances shown in Table 1 are equal to the corresponding inductances. Hence, the practice is to identify synchronous machine parameters in terms of the reactances, instead of the inductances.

A high order model of salient pole synchronous machine uses all presently defined data; it is the most complex model currently available in large-scale stability programs. This research is built on the foundation of the above model. This approach is also compatible with IEEE standards [29] and the leading power system simulators, like DIgSILENT PowerFactory software.

III. GENERAL OVERVIEW OF THE PROPOSED APPROACH

The principal concept of this research is based on the existing high correlation between the dynamic behaviour of a hydro generator and the related parameters. In other words, different disturbances are encountered normally during the operation of a generator and the generator response is consistent with its dynamic characteristics. Considering the validity of the

TABLE 1. Tabulated generator dynamic parameter.

X_d	Unsaturated d-axis synchronous reactance	pu
X_q	Unsaturated q-axis synchronous reactance	pu
X'_d	Unsaturated d-axis transient reactance	pu
X''_d	Unsaturated d-axis sub-transient reactance	pu
X''_q	Unsaturated q-axis sub-transient reactance	Pu
T'_{do}	d-axis transient open circuit time constant	Pu
T''_{do}	d-axis sub-transient open circuit time constant	S
T''_{qo}	q-axis sub-transient open circuit time constant	S
X_l	Leakage or Potier reactance	S
H	Inertia constant	--

nonlinear model in this operation condition [36], [37] and the high ability of ANN in modelling similar relationships, it is suitable to estimate the dynamic parameters of a generator by using its operating data. This concept is presented graphically in Figure 4.

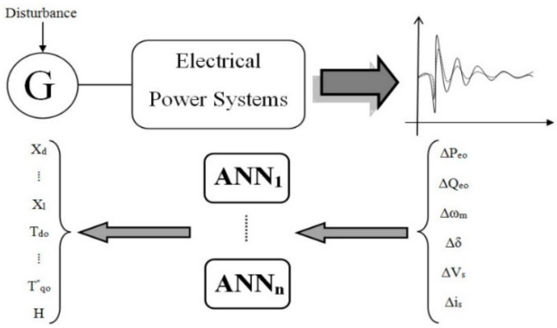


FIGURE 4. Conceptual structure of ANN application in the proposed parameter estimation.

Any change in dynamic characteristics of the generator leads to a variation in its transient behaviour [38]. Changes in the parameters can be due to the ageing of the generators, and internal faults. ANN is sufficiently capable to estimate the parameter variation in the generator dynamic performance. This fact is proven not only by the mathematical nature of ANN with optimized weight coefficients but also via its practical background in similar cases [39], [40].

An artificial neural network consists of a number of computing units, neurons, connected together according to some pattern of connectivity. The strength of a neural network derives from its capacity to learn from a nonlinear relationship between inputs and outputs without any underlying analytically model. The objective of this work is to develop a set of estimators (10 PEANNs for 10 parameters) that can map sequences of measurable operating data to the standard dynamic parameters. The schematic structure of the multi-layer feed-forward perceptron is visualized in Figure 5.

Each PEANN consists of n processing elements in the input layer, in coordination with the machine variables

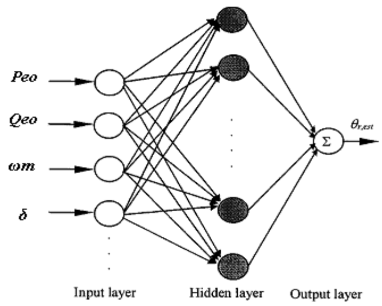


FIGURE 5. Input/output structure of PEANN.

describing the generator dynamic performance, and a single processing element in the output layer according to the machine parameter being modelled.

The naturally arising question is which variables to be used as inputs, in order to obtain a high level of sensitivity in the model. Answering this question is key in designing a good architecture for ANN.

Extensive research has been conducted by the research group members on the observability of synchronous generator dynamic parameters during its measurable output variables [25], [26]. The network with six inputs consisting of active and reactive power, rotor speed, load angle, stator voltage and current of each generator, obtained from these studies, can incorporate available meaningful generator measurements for this task.

There are two ways to develop a PEANN for this application. One approach is by having a single multi-input multi-output estimator. Although this approach will simplify the estimator configuration and training process, the interconnection of the neurons for various outputs will result in difficulty in achieving training convergence due to the masking effect [41]. Thus, inaccurate results can be expected. The next approach, employed by this research, is the application of an individual PEANN for each parameter.

To develop this approach, a collection of 10 PEANNs with similar inputs, but different outputs are employed at the same time for estimating 10 dynamic parameters. All elements of the input and output layers have linear transformations. As is common practice in power system studies, the measurements are performed in a 3-phase system and power system software is required to establish the Park's Model parameters. With due attention to the high capability of ANN and in an applied approach, the 3-phase measurements that are considered as the inputs of the ANNs, as well as the outputs, are the dynamic parameters in the Park's reference frame.

In this work, an ANN with one hidden layer is suitable enough to represent all nonlinear performances [42]. The number of neurons in the hidden layer would vary for different applications and could usually depend on the nature of nonlinear correlation, the size of the training set, and the number of input variables. A few heuristic rules are recommended as follows [43]:

- The number of hidden layer neurons is equal to twice the number of input layer neurons plus one, or

- The number of hidden layer neurons is equal to the number of input layer neurons plus the number of output layer neurons, or
- The number of hidden layer neurons is equal to the sum of the number of inputs, and the number of outputs divided by two.

Initially, the number of neurons in the hidden layer is specified by the optimization process for the proposed rules. The first evaluation shows that the first rule is the best fit with the network structure. Furthermore, the minimum error of estimation is obtained by performing supplementary optimization for a wide range of reasonable options. This process is developed via a database, which includes all types of defined disturbances. In order to introduce non-linearity into the network, a hyperbolic-tangent sigmoid transfer function is used in all hidden layer neurons. This is a differentiable and bounded function, as should be.

Within this work, a comparative analysis has also been performed by the authors on the contribution of training method to the performance of ANN in parameter estimation. Based on this, the Levenberg-Marquardt back-propagation algorithm, which presented the best performance, is used for training. The weight factors of the neural network are adjusted such that the sum squared error between outputs of PEANN and corresponding desired outputs is minimized.

In [25], [26], it is also confirmed that disturbance conditions are effective on the observability of the dynamic parameters in operating data. Thus, these conditions can have a contribution to the accuracy of the estimation. The current research is derived in such a way that the disturbance contributions to the performance of PEANN can be evaluated. For this purpose, the PEANN is supplied with data representing various types of disturbances, in a way, the performance of the estimator with training data can be evaluated. This approach would provide an optimal structure of the estimator considering minimum error for all disturbance conditions being considered. This structure will be used to evaluate test data for all disturbance conditions.

Furthermore, the impact of each disturbance on the accuracy of the parameters is also obtained from the actual test data. The idea is to train the proposed estimator with data representing the dynamic behaviour of a large number of different hydro generators. After sufficient training, the PEANN will be able to generalize and implement what it has learned into a function as a parameter estimator.

IV. DEVELOPMENT OF PEANN

In order to generate the necessary data, dynamic simulations are performed on a hydro generator connected to an infinite bus through a transmission line. This is required for training, testing and parameter estimation. The vector of the dynamic parameters for each generator i is defined as $\zeta(i)$.

$$\zeta(i) = \big[X_d(i) \;\; X_d'(i) \;\; X_d''(i) \; X_q(i) \;\; X_q''(i) \;\; T_{do}'(i) \;\; T_{do}''(i) \;\; T_{qo}''(i) \; X_l(i) \;\; H(i) \big]^T \tag{11}$$

Components of the above vector are the dynamic parameters defined in Table 1.

Furthermore, let $\xi_i(t)$ be the vector comprising sequences of the measurable operating data.

$$\xi_i(t) = \begin{bmatrix} P_{eo_i}(t_0) & P_{eo_i}(t_0+T) & \cdots & P_{eo_i}(t_0+nT) \\ Q_{eo_i}(t_0) & Q_{eo_i}(t_0+T) & \cdots & Q_{eo_i}(t_0+nT) \\ \omega_{m_i}(t_0) & \omega_{m_i}(t_0+T) & \cdots & \omega_{m_i}(t_0+nT) \\ \delta_i(t_0) & \delta_i(t_0+T) & \cdots & \delta_i(t_0+nT) \\ i_{S_i}(t_0) & i_{S_i}(t_0+T) & \cdots & i_{S_i}(t_0+nT) \\ V_{S_i}(t_0) & V_{S_i}(t_0+T) & \cdots & V_{S_i}(t_0+nT) \end{bmatrix} \tag{12}$$

where:

P_{eo_i} is output active power of ith generator,
Q_{eo_i} is output reactive power of ith generator,
ω_{m_i} is mechanical rotor speed of ith generator,
δ_i is load angle of i^{th} generator,
i_{S_i} is stator current of i^{th} generator,
V_{S_i} is stator voltage of i^{th} generator.

A. TRAINING DATA

In order to generate the required training database, dynamic simulations were performed on 419 different hydro generators and the calculated dynamic behaviour of generators is considered as acquired measurement data. Changes of $\pm 10\%$ in dynamic parameters of the generators, in 10 steps of 1% variation, were also simulated and included in the training database. This would cover the maximum variation that normally may occur in the generator characteristics.

All disturbances that occur during synchronous generator operation are categorized into three types, including:

- Change in Excitation voltage,
- Change in Prime mover torque,
- Fault in Connected grid.

Data for training PEANNs are obtained by a step change of 10% in excitation, a step change of 10% in prime-mover torque and a three-phase short circuit of 10 mSec in the connected grid. The vectors $\xi_i(t)$ and $\varsigma(i)$ are formed at each time instant t, 50 six-dimensional patterns are presented in the fixed step selection, and variable step selection were used to set weighting connections of PEANN (W_i). The dynamic behaviour of the generators is recorded during each kind of disturbance separately. By this method, the contribution of disturbance on PEANN training was also analysed, and the operators had a very clear view of the performance of PEANN in each operational condition.

B. TRAINING PEANN

There is no precise rule indicating the number of training data required to train a particular ANN. However, according to [44] a good recommendation is to use 10 times as much data as there are connections in the neural network. Training data representing a large variety of different generator's dynamic performances are generated with MATPOWER.

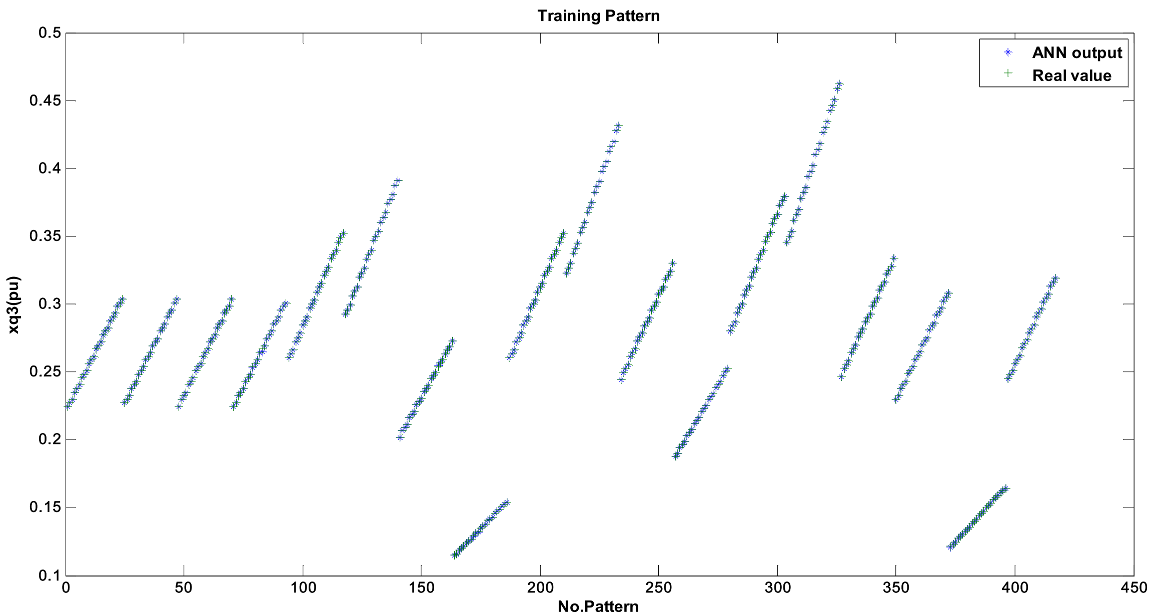


FIGURE 6. **PEANN training pattern of X''_q.**

A total of 558 sets of data were generated corresponding to the number of generators as well as the variations of their parameters simulated for each kind of disturbance. Each data set was comprised of sampling data obtained at 1000 different time instants. 50-time instants of them were selected by fixed step or variable step. Thus, a total of 27900 input/output patterns were used for presentation to each set of the estimators for training.

Using the above datasets, vector $\xi_i(t)$ was formed at every time instant t. Each PEANN was employed to estimate a dynamic parameter. Therefore, each estimator had 6 elements in the input layer and 1 element in the output layer. One hidden layer was used for each PEANN. The number of neurons in the hidden layer was specified based on the rule mentioned in section 3 and the optimization studies. A collection of 10 PEANNs were trained to identify 10 dynamic parameters of the generator.

The Mean Squared Error (MSE) is a well-known indicator of ANN performance [23], [45]. Eq. 13 evaluates MSE from the actual values (target) and the estimated values (PEANN outputs) of the dynamic parameters during the training course:

$$MSE = \frac{1}{N}\sum\nolimits_{t=1}^{N}\left(X(t) - \hat{X}(t)\right)^2 \tag{13}$$

where X and $\hat{X}$ correspond to the actual and estimated values for parameters, respectively.

Moreover, the Levenberg-Marquardt training algorithm was executed to provide second-order training speed. This algorithm was selected based on an optimization study that has been carried out between 12 well-known algorithms for the training of ANN. When the performance function has the form of a sum of squares, as is in this research, the gradient (g) can be computed using the Jacobian matrix (J) where J contains the first derivatives of the ANN errors with respect to changes in the weights and biases.

In each iteration, during the course of training, the update was computed as a function of the gradient which was used as an indicator of weights and biases convergence. The graph of training error amplitude and the histogram of training error were also used to analyse the ANN behaviour. Samples of the training patterns and the related behaviour of ANN are presented in Figure 6.

Table 2 shows the performance of PEANNs during training term which are categorized and sorted based on the relative disturbances in three grades, where "Grade 1", "Grade 2" and "Grade 3" are corresponding to the best (minimum error), intermediate and weak (maximum error) convergence performance, respectively.

However, the training database, which is used in the next steps, e.g., the optimization of ANN structure includes all types of faults.

V. PERFORMANCE VALIDATION OF THE DEVELOPED PEANN

Using a record of experimentally measured input-output data obtained during a transient disturbance event; it is possible to identify the generator dynamic parameters. To test the capabilities of the trained PEANN in estimating the parameters under online conditions, simulated measurements were generated by the machine operating in a one machine-infinite bus environment. It should be noted that under practical operating conditions, measurement data acquired experimentally will be used by the PEANN instead of the above simulated data.

The test database was obtained by initiating three specified types of disturbances. The simulations have been performed

TABLE 2. Salient pole synchronous generator model performance during training term.

Parameters	Grade 1			Grade 2			Grade 3		
	Dis.	*Performance*	*Gradient*	*Dis.*	*Performance*	*Gradient*	*Dis.*	*Performance*	*Gradient*
X_d	S	7.61e-07	0.00063	P	7.61e-07	0.000630	E	9.56e-07	0.000229
X_q	P	8.99e-07	0.04740	S	9.74e-07	0.00245	E	0.0270	5.30e-05
X'_d	S	5.83e-07	0.00389	P	8.28e-07	0.00269	E	1.482	0.0312
X''_d	P	8.70e-08	0.00157	S	9.39e-07	0.00157	E	0.0619	3.67e-05
X''_q	P	2.32e-07	0.00485	S	9.77e-07	3.14e-05	E	9.79e-06	0.000304
T'_{do}	P	9.83e-07	2.50e-05	S	9.87e-07	1.29e-05	E	3.05e-05	0.000612
T''_{do}	P	3.86e-07	0.0309	S	5.56e-07	0.00738	E	7.18e-06	0.00588
T''_{qo}	P	6.75e-07	0.0036	E	9.70e-07	0.0215	S	0.00889	0.00136
X_l	P	7.83e-08	0.0134	S	6.69e-07	0.000819	E	9.17e-06	9.37e-05
H	S	4.40e-07	0.0007	E	6.64e-07	0.000473	P	9.87e-07	0.000528

E: Excitation Disturbance P: Prime-Mover Torque Disturbance

S: Short Circuit (Connected Grid Disturbance)

during the dynamic performance of 132 hydro generators for all disturbances. The simulation also involved the changes of the parameters from their initial values. The recent database was not considered in the training process. It was presented to the networks as 39600 test patterns of six-dimensional input vectors.

As a measure of performance, the Sum Squared Error (SSE) between the actual amounts of the dynamic parameters and the estimated values (PEANN outputs) were compared for the above test cases. This statistical criterion measures the total deviation of the response values from the fit to the target values. With respect to individual dynamic parameter i, the corresponding Sum of Squared Error is denoted as SSE_i and defined as [23], [46]:

$$SSE_i = \sum_{j=1}^{N} w_i \left(y_{ij} - \hat{y}_{ij}\right)^2 \tag{14}$$

where y_{ij} and $\hat{y}_{ij}$ represent the corresponding actual and estimated values for dynamic parameter $\#i$ respectively. w_i defines which of the weight function amount is applied for the above parameter estimation.

To evaluate the performance of the PEANN, Absolute Percentage Error (APE) and Mean Absolute Percentage Error (MAPE), as two well-known criteria [47], were also employed. These are defined as:

$$APE = \frac{|P_{estimate} - P_{actual}|}{P_{actual}} \times 100\% \tag{15}$$

where P is the value of the dynamic parameter of hydro generator which is under estimation.

$$MAPE = \frac{1}{N_i} \sum_{N_i} APE_i \tag{16}$$

where N_i is the number of test patterns.

Mode (most frequent values), range, amplitude and histogram of the test error are also utilized to analyse the PEANN performance in tracking the dynamic parameters.

As an example, the values estimated by the PEANN, and the corresponding actual amount of a parameter are shown in Figure 7. This figure reveals a high accuracy matching of the real and PEANN estimated values.

Table 3 shows the results of the PEANN model for the dynamic parameters' tracking. As mentioned earlier, MAPE was used to measure the estimation accuracy in the above operating conditions. In this application, solid structure PEANNs are used to estimate generator dynamic parameters. In this structure, the number of neurons in the hidden layer are determined using the rules mentioned in section III.

As another development stage, an extra optimisation has been performed for each PEANN structure, indeed on the number of neurons in the hidden layer. The results illustrate that the optimal number of neurons in this layer can be very different for estimating a dynamic parameter comparing to others. It can be resulted due to various correlations existing between dynamic parameters and the generator output measurements. By this approach, estimators' performances are improved dramatically as given in Table 4.

This strategy provides information on the contribution of disturbance type to the parameter identification, say the maximum and minimum error of estimation in different operational scenarios. "Grade 1" is related to the tests providing the best result with the minimum error of estimation and "Grade 3" is related to the tests leading to the weakest estimation with the maximum error.

It is also beneficial for the scheduled tests that which kind of disturbance provides the best results; especially considering the fact that in most cases harmless tests provide more accurate estimations compared with the harmful tests.

Furthermore, it is worth mentioning that in this approach estimation error for all parameters has declined below acceptable standards of the conventional methods in this area. This impressive achievement has been performed using the following strategies:

- Assigning the ANN estimator to hydro generators
- Developing an estimator for each parameter separately
- Advanced optimization of ANN architecture
- Performing special studies in determining the network input parameters or generator measurement types.

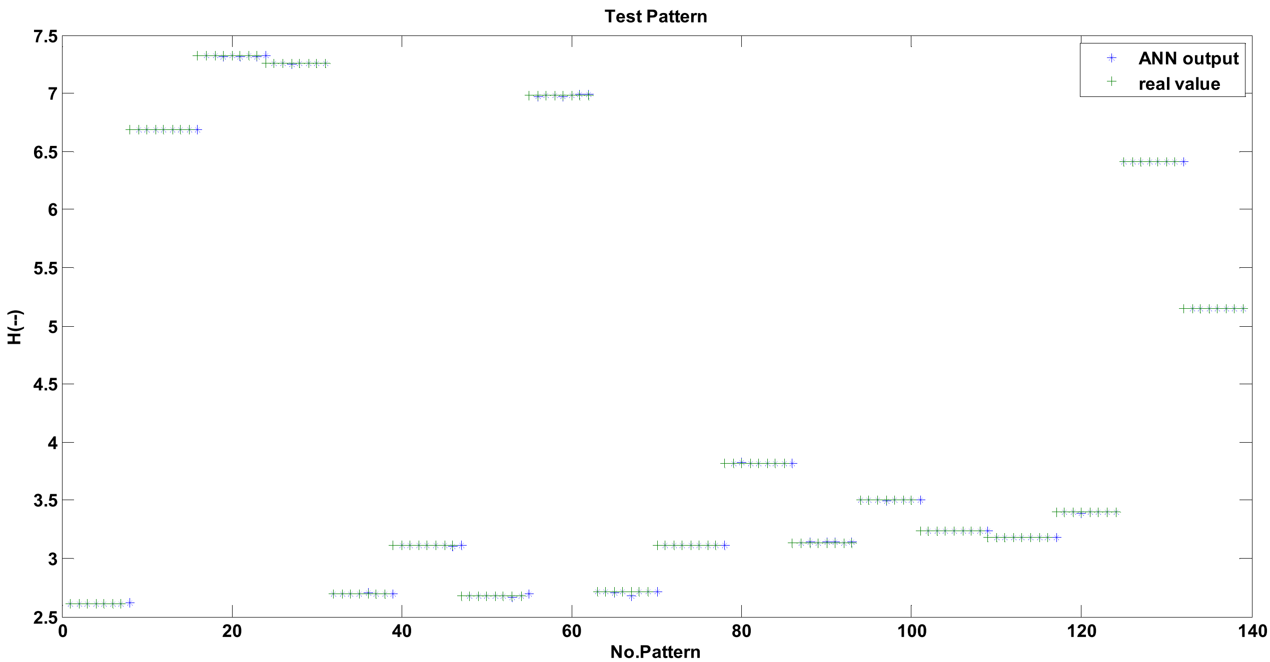


FIGURE 7. PEANN test pattern for parameter H.

TABLE 3. Salient pole synchronous generator model performance.

Parameters	Grade 1			Grade 2			Grade 3		
	Dis.	MAPE (%)	Mode	Dis.	MAPE (%)	Mode	Dis.	MAPE (%)	Mode
X_d	E	2.898	0.3157	S	2.909	0.984	S	3.298	1.473
X_q	E	0.0799	0.2521	P	0.0934	0.5893	S	0.1150	0.8222
X'_d	S	0.9618	0.5178	P	1.197	0.518	E	1.482	0.0312
X''_d	S	1.022	0.4055	P	1.023	0.4184	E	1.341	0.0329
X''_q	E	1.02	0.0440	S	1.081	0.2734	P	1.095	0.4033
T'_{do}	E	2.4000	0.0224	S	2.5500	0.0917	P	3.7540	0.0351
T''_{do}	S	3.125	0.2894	P	3.235	2.525	E	3.286	1.821
T''_{qo}	S	4.206	0.1505	E	2.508	0.0030	P	4.545	2.601
X_l	P	0.0969	0.9547	S	0.0991	0.9334	E	0.1014	0.9574
H	S	0.6867	0.0001	P	0.6913	0.0171	E	0.7056	0.0002

TABLE 4. Performance of optimised model of salient pole synchronous generator.

Parameters	NNH	Grade 1			Grade 2			Grade 3		
		Dis.	MAPE (%)	Std	Dis.	MAPE (%)	Std	Dis.	MAPE (%)	Std
X_d	15	E	0.1027	0.0688	S	0.1085	0.0895	P	0.1272	0.0899
X_q	13	E	0.0799	0.0731	P	0.0934	0.1351	S	0.1150	0.1623
X'_d	10	E	0.0127	0.0151	S	0.0136	0.0100	P	0.0559	0.0274
X''_d	11	S	0.0175	0.0481	E	0.0440	0.0826	P	0.0859	0.0905
X''_q	10	P	0.0379	0.0370	E	0.0439	0.0330	S	0.0771	0.0623
T'_{do}	13	E	2.4000	2.4470	S	2.5500	2.5890	P	3.7540	2.9990
T''_{do}	7	E	0.0001	0.0001	P	0.0005	0.0015	S	0.0036	0.0029
T''_{qo}	6	P	0.0002	0.0002	E	0.0003	0.0002	S	0.0017	0.0014
X_l	13	P	0.0958	0.1678	S	0.0991	0.1695	E	0.1014	0.1731
H	13	S	0.6867	2.1700	P	0.6913	8.1720	E	0.7056	2.1630

NNH: Number of Neurons in Hidden layer S_{td}: Standard Deviation
P: Prime-Mover Torque Disturbance E: Excitation Disturbance,
S: Short Circuit (Connected Grid Disturbance)

In this work, the measured data can be affected by noise. Thus, Standard deviation (Std) was applied as a criterion for evaluation of noise corrupted data. In this approach, any deviation in the parameter value more than two times the

TABLE 5. Comparative analysis of identification error.

	Method 1	Method 2	Method 3	Proposed Method
Max. Error%	5.3571	4.71	13.3	3.7540
Min. Error%	0.0365	1.07	0.09	0.0001

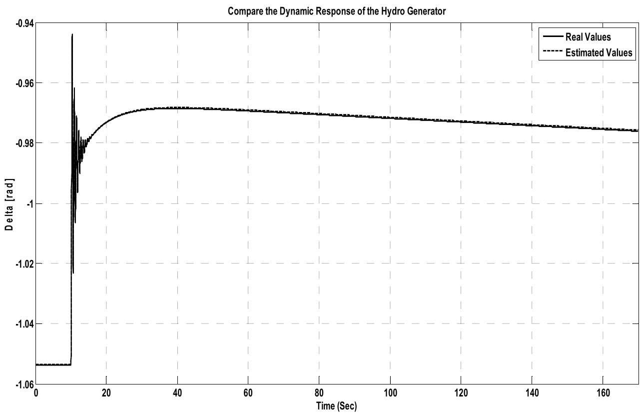


FIGURE 8. Delta variation test of a sample generator.

Std was used as an alarm of unsafe estimation or incipient fault. In the above condition, further analysis using a scheduled test would be required.

In Table 4, this indicator is also employed in the analysis of the test results, and the values obtained can be a good reference for future work related to this case.

Although in this approach estimation error in all parameters declined below the acceptable margins, making an extra comparative analysis between the other methods or different applications of ANN and the proposed strategy can present a clearer view of the robustness of the proposed approach. This comparison is developed in Table 5 and confirms the high ability of this method against others.
where:

Method 1: Rotor Body Parameters Estimation by ANN [16].

Method 2: Synchronous Generator Model Identification by Computational Method [48]

Method 3: Synchronous Generator Parameters Estimation by Least Squared Method [9]

In order to evaluate the capabilities of the proposed method in another approach, simulations are performed to compare the dynamic response of a hydro generator to an actual system event against the results from the simulations using the estimated parameters obtained by this method. Sample of results for the rotor angle variations against +10% change in prime-mover torque of an 86 MW hydro generator is presented in Figure 8. The findings of this process also illustrate the great similarity between the dynamic performance of the actual generators and the simulations that used the parameters estimated by this approach.

VI. CONCLUSION

In this work, neural network-based estimators have been developed to identify the full set of dynamic parameters of hydro generators by processing sequences of measurements obtained during common transient disturbance events. Robustness considerations indicate that the estimators are not only able to estimates all machine dynamic parameters (including q-axis parameters) with acceptable accuracy degree, but also keep the estimation error below the promising value of 2.4%. This performance represents an improvement over conventional approaches which are recommended for this application.

The above robustness along with the availability of generator measurements (V_s, I_s, P_e, Q_e, ω_m and δ) used as PEANN inputs, and the user-friendly structure of the proposed artificial intelligence-based estimators confirm the practicality of this approach.

The comparative procedure is used in this work and the separate optimisation has performed for each case have provided a clear view of the dynamic parameters' observability in hydro generators' dynamic performances. Based on this, d-axis sub-transient time constant and d-axis transient time constant have respectively maximum and minimum observability in hydro units operating data.

As the intent of this paper is to propose a methodology wherein PEANN estimators can be used to estimate and track salient pole hydro synchronous generator parameters from time-domain disturbance data, the effect of disturbance type on parameter identification has been analysed too. The findings show for 80% of the dynamic parameters of hydro generators, harmless disturbances including excitation disturbance and prime-mover disturbance have led to the best results.

The results also confirm the volubility of the earlier finding of this research group [23] in the application. Based on this, considering different dynamic parameter sets are used to simulate hydro and steam generators, which employ salient-pole and solid rotor machines respectively, developing a separate PEANN set is required for each case. Comparing the finding of this research with [40] illustrates that due to the differences existing between the response of hydro and steam generators to the common disturbances, developing special estimators for hydro units can improve the identification accuracy degree dramatically. It has reduced the maximum error of estimation from 12.92% to 2.4% for the current application. Developing an extra optimisation for each PEANN, instead of using a general optimal structure for all parameters, has declined the maximum prediction error from 3.125% to 2.4% too.

The main objective of this research is to develop an ANN estimator as a predictive tool to update the amounts of dynamic parameters of each type of generator from data acquired during their transient performance. It can be helpful for power system operators to speed up the power system simulation process with enough accuracy. It can also be useful for them to have a reliable prediction of the generator behaviour in various terms of operation.

ACKNOWLEDGMENT

The authors would like to thank Prof. Mahmoud Mirheydar of Worcester Polytechnic Institute (WPI), Worcester, MA, USA, for his valuable comments and expert advice, Prof. Abdullah Asuhaimi Mohd Zin as the emeritus staff of Universiti Teknologi Malaysia (UTM), Johor, Malaysia, for his valuable comments and expert advice, and all the personnel of this university who have collaborated on the project. They would also like to thank for the support of the late Prof. Azhar Kheyroddin in forming this article. This publication was supported by the University of Reading.

REFERENCES

[1] A. Oonsivilai and K. A. Greyson, "Effect of electric power shedding on economic dispatch: Case study Tanzania," in *Proc. 4th IEEE Conf. Ind. Electron. Appl.*, May 2009, pp. 3252–3255.

[2] Z. Ding, S. K. Srivastava, D. A. Cartes, and S. Suryanarayanan, "Dynamic simulation-based analysis of a new load shedding scheme for a notional destroyer-class shipboard power system," *IEEE Trans. Ind. Appl.*, vol. 45, no. 3, pp. 1166–1174, May 2009.

[3] X. Han, X. Yang, J. Song, and X. Du, "Impact of dynamic loads on stability of Shanxi power grid," in *Proc. Int. Power Eng. Conf. (IPEC)*, Dec. 2007, pp. 559–563.

[4] B. Singh, E. Kyriakides, and A. M. Michaelides, "Efficient identification of synchronous machine parameters through the finite elements method," in *Proc. 7th Medit. Conf. Exhib. Power Gener., Transmiss., Distrib. Energy Convers. (MedPower)*, Nov. 2010, pp. 1–8.

[5] M. Anghel, K. A. Werley, and A. E. Motter, "Stochastic model for power grid dynamics," in *Proc. 40th Annu. Hawaii Int. Conf. Syst. Sci. (HICSS)*, Jan. 2007, p. 113.

[6] B. M. Nomikos, M. A. Kotlida, and C. D. Vournas, "Interarea oscillations and tie-line transients in the hellenic interconnected system," in *Proc. IEEE Lausanne Power Tech*, Jul. 2007, pp. 68–73.

[7] C. T. Hsu, M. S. Kang, and C. S. Chen, "Design of adaptive load shedding by artificial neural networks," *IEE Proc. Gener., Transmiss. Distrib.*, vol. 152, no. 3, pp. 415–421, May 2005.

[8] R. Wamkeue, C. Jolette, A. B. M. Mabwe, and I. Kamwa, "Cross-identification of synchronous generator parameters from RTDR test time-domain analytical responses," *IEEE Trans. Energy Convers.*, vol. 26, no. 3, pp. 776–786, Sep. 2011.

[9] A. R. Malekpour, A. R. Seifi, M. R. Hesamzadeh, and N. Hosseinzadeh, "An optimal load shedding approach for distribution networks with DGs considering capacity deficiency modelling of bulked power supply," in *Proc. Australas. Univ. Power Eng. Conf.*, Dec. 2008, pp. 1–7.

[10] M. Gupta, S. Srivastava, and J. R. P. Gupta, "Power system frequency estimation using neural network and genetic algorithm," in *Proc. Joint Int. Conf. Power Syst. Technol. IEEE Power India Conf.*, Oct. 2008.

[11] L. O. S. Grillo, A. S. E. Silva, and F. L. Freitas, "A method for online identification of a subset of synchronous generator fundamental parameters from monitoring systems data," *J. Control, Autom. Electr. Syst.*, vol. 32, no. 3, pp. 672–681, Jun. 2021.

[12] C. Lai, G. Feng, K. Mukherjee, V. Loukanov, and N. C. Kar, "Torque ripple minimization for interior PMSM with consideration of magnetic saturation incorporating online parameter identification," *IEEE Trans. Magn.*, vol. 53, no. 6, pp. 1–4, Jun. 2017.

[13] A. H. F. Silva, A. S. Magalhaes, J. S. Bulhoes, G. A. Wainer, G. P. Furriel, and W. P. Calixto, "Parametric regression applied for determination of electrical parameters of synchronous and induction generators operating in parallel on the electrical energy repowering system," *Energies*, vol. 14, no. 13, p. 3875, Jun. 2021.

[14] S. Yang, D. Ding, X. Li, Z. Xie, X. Zhang, and L. Chang, "A novel online parameter estimation method for indirect field oriented induction motor drives," *IEEE Trans. Energy Convers.*, vol. 32, no. 4, pp. 1562–1573, Dec. 2017.

[15] S. A. Odhano, P. Pescetto, H. A. A. Awan, M. Hinkkanen, G. Pellegrino, and R. Bojoi, "Parameter identification and self-commissioning in AC motor drives: A technology status review," *IEEE Trans. Power Electron.*, vol. 34, no. 4, pp. 3603–3614, Apr. 2019.

[16] S. Pillutla and A. Keyhani, "Neural network based modeling of round rotor synchronous generator rotor body parameters from operating data," *IEEE Trans. Energy Convers.*, vol. 14, no. 3, pp. 321–327, Sep. 1999.

[17] B. F. Rad and M. Abedi, "An optimal load-shedding scheme during contingency situations using meta-heuristics algorithms with application of AHP method," in *Proc. 11th Int. Conf. Optim. Electr. Electron. Equip.*, May 2008, pp. 167–173.

[18] M. T. Bishop and R. P. Jozwowski, *Frequency Sensing and Load Shedding Schemes*. The Line, 1999, pp. 7–8.

[19] A. J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control*. New York, NY, USA: Wiley, 1996.

[20] J. G. Thompson and B. Fox, "Adaptive load shedding for isolated power systems," *IEE Proc.-Gener., Transmiss. Distrib.*, vol. 141, no. 5, pp. 491–496, Sep. 1994.

[21] C. Concordia, L. H. Fink, and G. Poullikkas, "Load shedding on an isolated system," *IEEE Trans. Power Syst.*, vol. 10, no. 3, pp. 1467–1472, Aug. 1995.

[22] B. Delfino, S. Massucco, A. Morini, P. Scalera, and F. Silvestro, "Implementation and comparison of different under frequency load-shedding schemes," in *Proc. Power Eng. Soc. Summer Meeting. Conf.*, Jul. 2001, pp. 307–312.

[23] Y. Cao, Y. Liu, J. Li, X. Liu, and C. Hou, "Nozzle optimization of SF6 circuit breaker based on artificial neural network and genetic algorithm," in *Proc. Int. Conf. Elect. Mach. Syst.*, Oct. 2008, pp. 222–225.

[24] A. U. Khan, T. K. Bandopadhyaya, and S. Sharma, "Comparisons of stock rates prediction accuracy using different technical indicators with backpropagation neural network and genetic algorithm based backpropagation neural network," in *Proc. 1st Int. Conf. Emerg. Trends Eng. Technol.*, Jul. 2008, pp. 575–580.

[25] S. Wang and X. Dong, "Predicting China's energy consumption using artificial neural networks and genetic algorithms," in *Proc. Int. Conf. Bus. Intell. Financial Eng.*, Jul. 2009, pp. 8–11.

[26] A. A. A. E. Ela, A. Z. El-Din, and S. R. Spea, "Optimal corrective actions for power systems using multiobjective genetic algorithms," in *Proc. 42nd Int. Universities Power Eng. Conf.*, Sep. 2007, pp. 722–733.

[27] S. J. Huang and C. C. Huang, "An adaptive load shedding method with time-based design for isolated power systems," *Int. J. Elect. Power Energy Syst.*, vol. 22, no. 1, pp. 51–58, 2000.

[28] R. Maliszewski, R. Dunlop, and G. Wilson, "Frequency actuated load shedding and restoration part I—Philosophy," *IEEE Trans. Power App. Syst.*, vol. PAS-90, no. 4, pp. 1452–1459, Jul. 1971.

[29] K.-I. Kawabe and A. Yokoyama, "Minimization of interrupted power using coordinated control of multiple unified power flow controllers, generators and load shedding," in *Proc. IEEE Bucharest PowerTech*, Jun. 2009, pp. 1–7.

[30] S. J. Huang and C. C. Huang, "Adaptive approach to load shedding including pumped-storage units during underfrequency conditions," *IEE Proc. Gener., Transmiss. Distrib.*, vol. 148, no. 2, pp. 165–171, Mar. 2001.

[31] Y. Halevi and D. Kottick, "Optimization of load shedding system," *IEEE Trans. Energy Convers.*, vol. 8, no. 2, pp. 207–213, Jun. 1993.

[32] C. Ellis, H. Nouri, R. Ciric, and B. Miedzinsky, "Overview of the development, simplification and numerical analysis of synchronous machine models for stability studies," in *Proc. 42nd Int. Univ. Power Eng. Conf.*, Sep. 2007, pp. 1019–1023.

[33] B.-K. Choi, H.-D. Chiang, H. Wu, H. Li, and D. C. Yu, "Exciter model reduction and validation for large-scale power system dynamic security assessment," in *Proc. IEEE Power Energy Soc. Gen. Meeting Convers. Del. Electr. Energy 21st Century*, Jul. 2008, pp. 1–7.

[34] Y. Tan, Y. He, C. Cui, and G. Qiu, "A novel method for analog fault diagnosis based on neural networks and genetic algorithms," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 11, pp. 2631–2639, Nov. 2008.

[35] D. Craciun, S. Ichim, and Y. Besanger, "A new soft load shedding: Power system stability with contribution from consumers," in *Proc. IEEE Bucharest PowerTech*, Jun. 2009, pp. 1–6.

[36] M. Karrari and O. P. Malik, "Identification of physical parameters of a synchronous Generator from online measurements," *IEEE Trans. Energy Convers.*, vol. 19, no. 2, pp. 407–415, Jun. 2004.

[37] J.-C. Wang, N. D. Chiang, C.-T. Huang, and Y. T. Chen, "Identification of synchronous generator saturation models based on on-line digital measurements," *IEE Proc. Gener., Transmiss. Distrib.*, vol. 142, no. 3, pp. 225–232, May 1995.
[38] O. Shariati, P. Esmaili, M. R. Aghamohammadi, and A. A. B. M. Zin, "Observability of synchronous generators' parameters in its dynamic performance," in *Proc. IEEE 17th Int. Conf. Smart Technol. (EUROCON)*, Jul. 2017, pp. 387–392.
[39] H. B. Karayaka, A. Keyhani, G. T. Heydt, B. L. Agrawal, and D. A. Selin, "Neural network based modeling of a large steam turbine-generator rotor body parameters from on-line disturbance data," *IEEE Trans. Energy Convers.*, vol. 16, no. 4, pp. 305–311, Dec. 2001.
[40] O. Shariati, A. A. M. Zin, A. Khairuddin, and M. R. Aghamohammadi, "Development and implementation of neural network observers to estimate synchronous generators' dynamic parameters using on-line operating data," *Electr. Eng.*, vol. 96, no. 1, pp. 45–54, Mar. 2014.
[41] L. T. Bui and S. Alam, *Multi-Objective Optimization in Computational Intelligence: Theory and Practice: Theory and Practice*. New York, NY, USA: Hershey, 2008.
[42] H. You, V. Vittal, J. Jung, C.-C. Liu, and M. Amin, "An intelligent adaptive load shedding scheme," in *Proc. PSCC*, Seville, Spain, 2002, pp. 24–28.
[43] M. Shahidehpour, H. Yamin, and Z. Li, *Market Operation in Electric Power Systems*. New York, NY, USA: IEEE, 2002.
[44] V. V. Terzija, "Adaptive underfrequency load shedding based on the magnitude of the disturbance estimation," *IEEE Trans. Power Syst.*, vol. 21, no. 3, pp. 1260–1266, Aug. 2006.
[45] P. M. Anderson and M. Mirheydar, "A low-order system frequency response model," *IEEE Trans. Power Syst.*, vol. 5, no. 3, pp. 720–729, Aug. 1990.
[46] M. Zima, M. Larsson, P. Korba, C. Rehtanz, and G. Andersson, "Design aspects for wide-area monitoring and control systems," *Proc. IEEE*, vol. 93, no. 5, pp. 980–996, May 2005.
[47] A. Saffarian, M. Sanaye-pasand, and H. Asadi, "Performance investigation of new combinational load shedding schemes," in *Proc. Joint Int. Conf. Power Syst. Technol. IEEE Power India Conf.*, Oct. 2008, pp. 1–8.
[48] H. B. Karayaka, A. Keyhani, G. T. Heydt, B. L. Agrawal, and D. A. Selin, "Synchronous generator model identification and parameter estimation from operating data," *IEEE Trans. Energy Convers.*, vol. 18, no. 1, pp. 121–126, Mar. 2003.

O. SHARIATI (Member, IEEE) was born in Birjand, Iran, in 1977. He received the B.Sc. degree in applied electrical (power) engineering-transmission and distribution networks from Shahid Abbaspour Technical and Engineering Campus, Shahid Beheshti University, Iran, in 2002, the M.Sc. degree in electrical power engineering from Islamic Azad University, South Tehran Branch, and the Ph.D. degree in electrical power engineering from University Technology Malaysia (UTM), Malaysia, in 2015. He is currently a Postdoctoral Researcher at the University of Reading, U.K. He is also an Assistant Professor of electrical power engineering with the Department of Electrical Engineering, Islamic Azad University, Birjand Branch. His research interests include complex power system modeling, dynamics and protection, and artificial intelligence application in electrical power systems.

M. R. AGHAMOHAMMADI (Member, IEEE) was born in Iran, in 1955. He received the B.Sc. degree from Sharif University of Technology, in 1985, the M.Sc. degree from Manchester University, in 1989, and the Ph.D. degree from Tohoku University, Japan, in 1994. He is currently an Associate Professor with the Electrical Engineering Department, Abbaspour Campus, Shahid Beheshti University, and the Head of Iran Dynamic Research Centre. His research interests include application of intelligent techniques and non-model-based approaches for dynamic security assessment, and enhancement of power systems.

B. POTTER (Member, IEEE) received the M.Eng. degree in engineering science from the University of Oxford, in 2001, and the Ph.D. degree in modeling of induction machines from the University of Reading, in 2005. He subsequently managed research and development activity for several years in industry, including development work on wireless power transfer systems, before joining the University of Reading as a Lecturer, in 2009, and then as an Associate Professor of energy systems with the School of the Built Environment. He is currently a Senior Research Fellow at the University and within industry. His academic research has been largely focused on energy systems of various flavors, for over 20 years, with applications including energy storage, network planning and modeling, and the integration of electric vehicles in the grid. His current research interests include development of control methods and business models for the new generation of energy networks-the smart grid-to ensure that the integration of active elements, such as renewable energy resources, electric vehicles, and energy storage devices will have positive impacts for both network operators and end users.