Simultaneous Parameter Identification of Synchronous Generator and Excitation System Using Online Measurements

Behrooz Zaker, Gevork B. Gharehpetian, *Senior Member, IEEE*, Mehdi Karrari, and Naghi Moaddabi

***Abstract*—In this paper, a new method is presented to simultaneously identify parameters of synchronous generator and its excitation system (EXS) using measurement data. These measurements could be provided by metering devices such as data acquisition system or fault recorders of the power plant. Since a smart grid is capable of providing synchronized measurements using phasor measurement units, the desired data could also be provided by these devices. In the proposed method, the reference voltage of the EXS is considered as the input signal, while the terminal voltage and output active power of the machine are considered as output signals. The desired parameters are classified into three categories using a sensitivity analysis: 1) the parameters that affect the terminal voltage; 2) the parameters that affect the active power; and 3) the parameters that do not considerably affect either. A multistage genetic algorithm optimization is used to iteratively identify the parameters. To show the effectiveness and accuracy of the proposed method, it is applied to a single machine with a dc-type EXS connected to an infinite bus. Using the proposed method, 19 parameters of synchronous generator and its EXS are identified within four stages.**

***Index Terms*—Excitation system (EXS), multistage genetic algorithm (GA), parameter estimation, synchronous generator.**

NOMENCLATURE

ω, δ	Rotor speed and rotor angle.
ψ_d, ψ_d	Flux linkage of direct and quadratic axis.
ψ_f	Flux linkage of excitation winding.
ψ_D, ψ_Q	Flux linkage of damper windings.
M, D	Rotor inertia, damping factor.
T_m	Mechanical input torque.
T_e, T_D	Electrical output and mechanical damping torque.
ω_b	Base speed.
v_d, v_q	Voltage of direct and quadratic axis.
i_d, i_q	Current of direct and quadratic axis.
i_f	Current of excitation winding.
i_D, i_Q	Current of damping windings.
$x_{\mathrm{ld}}, x_{\mathrm{lq}}$	Leakage reactance of direct and quadratic axis.
x_{lf}	Leakage reactances of excitation winding.
$x_{\mathrm{lD}}, x_{\mathrm{lQ}}$	Leakage reactances of damper windings.
x_d, x_q	Total reactances of direct and quadratic axis.
x'_d	Transient reactance of direct axis.
x''_d, x''_q	Subtransient reactances of direct and quadratic axis.
x_f	Total reactances of excitation winding.
x_D, x_Q	Total reactances ofdamper windings.
$x_{\mathrm{md}}, x_{\mathrm{mq}}$	Mutual reactances of direct and quadratic axis.
r_a, r_F	Resistance of stator and excitation windings.
r_D, r_Q	Resistance of damper windings.
V_t, P_e	Sampled vectors of terminal voltage and output active power of simulated with typical values of parameters.
V'_t, P'_e	Sampled vectors of terminal voltage and output active power of simulated with variant values of parameters.
N	Number of samples.
V_{t_est}	Sampled vector of the estimated terminal voltage.
P_{e_est}	Sampled vector of the estimated output active power.
$X, \tilde{X}$	Pure and noisy signal.
N_{WG}	Additive white Gaussian noise (AWGN).

Manuscript received October 7, 2014; revised February 19, 2015 and August 6, 2015; accepted September 10, 2015. Date of publication October 5, 2015; date of current version April 19, 2016. Paper no. TSG-00998-2014.

The authors are with the Department of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran (e-mail: zaker.behrooz@aut.ac.ir; grptian@aut.ac.ir; karrari@aut.ac.ir; nimamoaddabi@aut.ac.ir).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSG.2015.2478971

I. INTRODUCTION

AFTER modeling of a system, the essential requirement for studying the behavior of the system, which is subjected to small or large disturbances, is a valid knowledge of parameters of system elements. These elements of a power system include synchronous generators, power transformers, transmission lines, and loads. Synchronous generators play an important role in the continuity of the operation and stability of power systems. On the other hand, most of the parameters of a synchronous generator are time varying due to aging. Therefore, identification and estimation of these parameters have been and are still a challenging issue.

Parameter identification of synchronous generator is classified into two methods: 1) offline identification and 2) online identification. In the offline methods [3]–[11], the synchronous machine is out of service, and its first and traditional one has been specified in the IEEE standards. Other offline methods include stand still frequency response [5], open circuit frequency response, least squares-based [6], and dc excitation-based methods [3]. These methods are usually time consuming, difficult to apply, and do not take into account the changes of parameters values due to aging. However, the main drawback of these methods is that the machine must be off-grid for a relatively long period of time. This kind of interruptions will lead to economic losses. To overcome the aforementioned shortcomings of offline methods, online identification methods have been proposed [11]–[21]. These methods are based on applying a small disturbance to the synchronous generator which is in service such that no interference occurs in the normal operation of the system. The online identification methods may be classified into two categories: 1) black-box; and 2) white-box modeling methods [15], [22]. The aim of the black-box modeling is mapping data sets of input and output of the system regardless of its physical structure. Different tools have been used for black-box modeling such as wavelet transform and neural networks. In white-box modeling, a known structure should be assumed for the synchronous machine.

The common structure that has been assumed in many papers is the third-order model of the synchronous machine [13]-[15], [18]–[20]. In these studies, excitation system (EXS) has not been considered and the field voltage has been perturbed as the input of the system. In [16], a fourth-order model of the synchronous machine has been studied ignoring EXS. In [17], subtransient model of synchronous generator and its parameters have been used to simulate the model but they have not been considered in the estimation of the model. In [19], a closed-loop identification method has been studied considering automatic voltage regulator (AVR) as a simplified EXS. In [23], a genetic algorithm (GA)-based method is proposed to identify the parameters of a third-order synchronous generator and a first-order AVR in the frame of Heffron–Phillips model using online measurements data. The main defect of this paper is that the subtransient parameters of the synchronous generator and other parameters of EXS have not been considered.

Along with these researches, some studies have been conducted on parameter identification of EXS using operating point data [24]–[29]. In most of these studies [25]–[27], a direct closed-loop identification procedure has been used which means that the field voltage (E_{FD}) should be accessible and measureable. In these cases, it is not necessary to model the synchronous generator with known parameters. In [29], an indirect closed-loop parameter identification of a brushless EXS has been presented, where E_{FD} has not been accessible. Therefore, the synchronous generator modeling was necessary. In these cases, the synchronous generator has been modeled as a first-order system using a known gain and time constant [29].

In recent years, phasor measurement units (PMUs) have been widely used in power systems to provide high-quality online data in order to monitor, control, and protect network's components [30]. PMUs have two basic rates: 1) sampling rate; and 2) phasor transferring rate. Todays, PMUs can provide a sampling rate of 10 kHz and phasor transferring rate of 1 sample per each cycle. These accurate measurements can be used for parameter validation, calibration, and identification purposes [31]. However, it is also possible to use a data acquisition system with a proper sampling rate instead of PMUs. Besides that, fault recorders data of a specific experiment and measurement could be used for these purposes.

Indirect closed-loop parameter identification of an EXS considering a full-order synchronous generator has been a challenging problem due to large numbers of unknown parameters. Generally, in system identification and modeling problems, the increase in number of parameters that should be estimated is one of the main challenging issues. For example, in black-box modeling using polynomial structure the number of parameters that should be estimated increases significantly with the increase in the polynomial order. To overcome this problem, some auxiliary methods such as orthogonal matching pursuit have been proposed [32]. In this paper, a new method based on parameters classification and multistage GA is presented to simultaneously identify the parameters of the synchronous generator and its EXS with low estimation error using online measurements. In the proposed method, the reference voltage of EXS is considered as the input signal which is perturbed with a pseudo random binary sequence (PRBS) [14], while the terminal voltage and output active power of the machine are considered as output signals. This method does not require additional measurements such as the rotor angle used in [14]. It is assumed that the field voltage (E_{FD}) is not accessible and measureable (e.g., in brushless EXS). The desired parameters are classified into three categories using a sensitivity analysis: 1) effective on voltage (EOV); 2) effective on active power (EOP); and 3) neutral (NEU). Thereafter, the parameters of each category are iteratively identified using the corresponding output signal in the identification procedure.

This paper is organized as follows. The synchronous generator and EXS models are outlined in Section II. The proposed identification method is explained in Section III. In Section IV, the simulation results are presented and finally, Section V concludes this paper.

II. Synchronous Generator and Excitation System Models

A. Synchronous Generator Model

The effect of stator and damper windings are considered in seventh-order nonlinear model of a synchronous machine compared to low-order linear structures such as Heffron–Phillips model [1]. In the basic model of the synchronous generator for single machine system, flux linkages are chosen as state variables. This model contains two state equations of rotor dynamics and five for stator, damper, and field windings. These equations are as follows:

$$\begin{aligned}
\dot{\omega} &= 1/M(T_m - T_e - T_D)\\
\dot{\delta} &= \omega_b(\omega - 1)\\
\dot{\psi}_d/\omega_b &= v_d + r_a i_d + \omega\psi_q\\
\dot{\psi}_q/\omega_b &= v_q + r_a i_q - \omega\psi_d\\
\dot{\psi}_f/\omega_b &= v_f - r_f i_f\\
\dot{\psi}_D/\omega_b &= -r_D i_D\\
\dot{\psi}_Q/\omega_b &= -r_Q i_Q
\end{aligned} \tag{1}$$

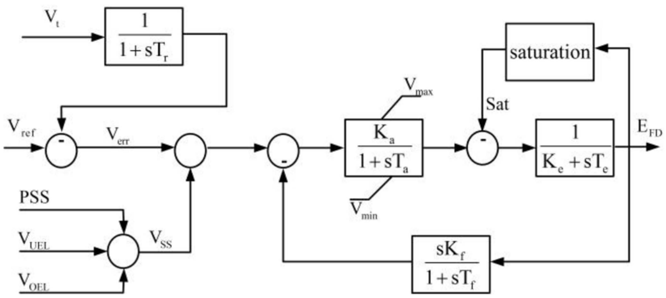

Fig. 1. IEEE-T1 EXS.

TABLE I
EXS SIGNALS AND PARAMETERS

Block	Parameters and signals
Rectifier	T_r
AVR	K_a, T_a
Exciter	K_e, T_e
EXS stabilizer	K_f, T_f
Saturation	A, B
AVR limits	V_{min}, V_{max}
Reference voltage	V_{ref}
Terminal voltage	V_t
Power system stabilizer (PSS), under excitation, and over excitation	PSS, V_{UEL}, V_{OEL}
Field voltage	E_{FD}
Saturation	Sat

where

$$\begin{bmatrix} \psi_d \\ \psi_f \\ \psi_D \end{bmatrix} = \frac{1}{\omega_b}\begin{bmatrix} X_d & X_{\text{md}} & X_{\text{md}} \\ X_{\text{md}} & X_f & X_{\text{md}} \\ X_{\text{md}} & X_{\text{md}} & X_D \end{bmatrix}\begin{bmatrix} -i_d \\ i_f \\ i_D \end{bmatrix}$$
$$\begin{bmatrix} \psi_q \\ \psi_Q \end{bmatrix} = \frac{1}{\omega_b}\begin{bmatrix} X_q & X_{\text{mq}} \\ X_{\text{mq}} & X_Q \end{bmatrix}\begin{bmatrix} -i_q \\ i_Q \end{bmatrix}. \tag{2}$$

The reactances are defined as follows:

$$\begin{aligned} X_d &= X_{\text{ld}} + X_{\text{md}} \\ X'_d &= X_{\text{ld}} + (X_{\text{md}}||X_{\text{lf}}) = X_{\text{ld}} + (X_{\text{md}} \cdot X_{\text{lf}})/X_f \\ X''_d &= X_{\text{ld}} + (X_{\text{md}}||X_{\text{lf}}||X_{\text{lD}}) \\ X_q &= X_{\text{lq}} + X_{\text{mq}} \\ X''_q &= X_{\text{lq}} + \left(X_{\text{mq}}||X_{\text{lQ}}\right). \end{aligned} \tag{3}$$

The details of the high-order nonlinear modeling have been completely discussed in [1].

B. Excitation System

The EXS, considered in this paper, is the IEEE Type 1 exciter, which is a dc EXS. The block diagram of this EXS is shown in Fig. 1. This model has five blocks of rectifier, AVR, exciter, saturation, and EXS stabilizer. The parameters of each block and signals of this model are given in Table I.

The saturation signal is modeled as follows [2]:

$$\text{Sat} = A \cdot e^{(B.E_{\text{FD}})} \cdot E_{\text{FD}}. \tag{4}$$

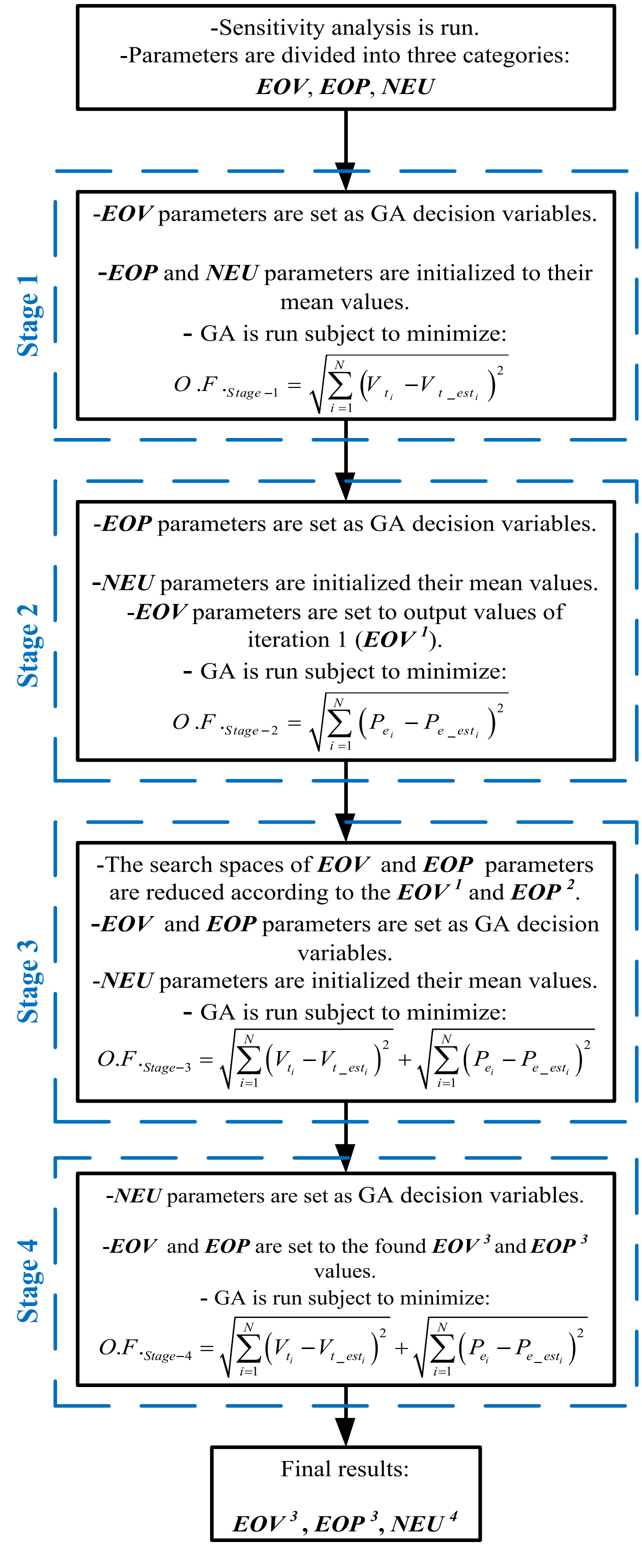

Fig. 2. Identification procedure flowchart.

III. PROPOSED IDENTIFICATION METHOD

This paper aims at the simultaneous parameter identification of the synchronous generator and EXS without measuring the E_{FD}. The solution of this paper is based on a multistage GA which is shown in Fig. 2. The fundamentals of GA are well explained in [33] and [34].

The identification procedure is explained in the following steps.

Step 1: For a specific operating point, the reference voltage of EXS is considered as the input signal that is perturbed using a PRBS with domain of 5% of the nominal value.

Step 2: The simulated input and output signals using actual parameters of the system are sampled. The terminal voltage (V_t) and output active power (P_e) are considered as output signals.

Step 3: Sensitivity analysis is run. For this purpose, a single machine connected to an infinite bus which is case study of this paper is considered. The synchronous generator and EXS parameters are set to the typical values depending on the machine and EXS type. According to the standards, each parameter can vary in a specific range between a lower and upper bounds [30]. Each time, a parameter is selected. It is initialized with the lower bound value while the other parameters are set to their typical values. The simulation is run using a PRBS as the input signal that perturbed reference voltage. The terminal voltage and output active power are sampled as output signals. Using the following equations, the errors of the voltage and active power are calculated:

$$\mathrm{Error}_V = \sqrt{\sum_{i=1}^{N}\left(V_{t_i} - V'_{t_i}\right)^2}$$
$$\mathrm{Error}_P = \sqrt{\sum_{i=1}^{N}\left(P_{e_i} - P'_{e_i}\right)^2}. \tag{5}$$

Then, the selected parameter is set to the next step of its allowed range and simulation is run again. This procedure is done for each parameter while its value reaches to the upper bound value. Thereafter, according to the calculated errors for each parameter, it will be obvious that these parameters can be divided into three categories: 1) EOV; 2) EOP; and 3) NEU.

Step 4: This step is the first stage of the identification procedure. EOV parameters are set as GA decision variables while EOP and NEU parameters are initialized with the mean value of their allowed range. Optimization is run subject to minimize the following objective function:

$$\mathrm{OF}_{\mathrm{stage1}} = \sqrt{\sum_{i=1}^{N}\left(V_{t_i} - V_{t\_\mathrm{est}_i}\right)^2}. \tag{6}$$

Estimated parameters of this stage are called EOV^1.

Step 5: EOP parameters are set as GA decision variables while EOV parameters are set to EOV^1 and NEU parameters are still initialized with the mean value of their allowed range. Optimization is run to minimize the following objective function:

$$\mathrm{OF}_{\mathrm{stage2}} = \sqrt{\sum_{i=1}^{N}\left(P_{e_i} - P_{e\_\mathrm{est}_i}\right)^2}. \tag{7}$$

Estimated parameters of the second stage are called EOP^2.

Step 6: In the third stage, the search space of EOV and EOP parameters are limited according to the estimated values of two last stages (EOV^1 and EOP^2). This will help to find desired values faster. Both EOV and EOP parameters are set as GA decision variables while NEU parameters are still initialized with the mean value of their allowed range. Optimization is run to minimize the following objective function:

$$\mathrm{OF}_{\mathrm{stage3}} = \sqrt{\sum_{i=1}^{N}\left(V_{t_i} - V_{t\_\mathrm{est}_i}\right)^2} + \sqrt{\sum_{i=1}^{N}\left(P_{e_i} - P_{e\_\mathrm{est}_i}\right)^2}. \tag{8}$$

The estimated parameters of this stage are called EOV^3 and EOP^3. It will be shown in next section that the estimated parameters are close to the desired parameters values with a very good accuracy.

Step 7: In the last stage, NEU parameters are set as GA decision variables while EOV and EOP parameters are set to the found values, i.e., EOV^3 and EOP^3. Optimization is run to minimize (8) and finally NEU parameters values are estimated which are called NEU^4. Current set of estimated parameters (i.e., EOV^3, EOP3, and NEU^4) are the final results.

IV. Simulation Results and Discussion

The case study is a single machine infinite bus system as shown in Fig. 3. The EXS is dc IEEE Type 1. The specifications of the salient pole synchronous machine, power transformer, transmission lines, and EXS are given in Tables II and III. It should be noted that because the machine is salient pole type, the transient reactance of quadratic axis (X'_q) does not exist. A PRBS with a domain of 5% of the nominal value as shown in Fig. 4 is added to the reference voltage as the input signal. The output signals, terminal voltage, and output active power are shown in Fig. 5. AWGN is added to the output signals using MATLAB command to make the identification procedure more practical as follows:

$$\tilde{X} = X + N_{\mathrm{WG}}. \tag{9}$$

The signal-to-noise ratio has been set to ten in the simulations, which is higher than the actual noises added to either output.

The sensitivity analysis is applied as explained in Section III. The results of this analysis are shown in Figs. 6–9, where the vertical axes of these figures represent the calculated

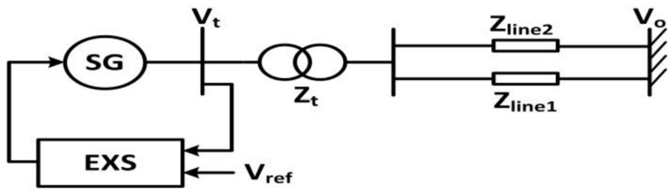

Fig. 3. Single machine infinite bus system.

TABLE II
SYSTEM PARAMETERS

Parameter	Value	Parameter	Value
Nominal Power	50MVA	T''_{do}	0.0241 s
Nominal Freq.	50Hz	T''_{qo}	0.0464 s
Nominal Vol.	10.5 kV	H	5.0000s
X_d	2.6420p.u.	D	0.0100p.u.
X_q	2.3460 p.u.	Z_t	0.1200p.u.
X'_d	0.3370 p.u.	R_{L1}=R_{L2}	0.0750 Ω/km
X''_d	0.2100 p.u.	X_{L1}=X_{L2}	0.4530 Ω/km
X''_q	0.1800 p.u.	Line length	101 km
T'_{do}	6.5000 (s)	-	-

TABLE III
EXS PARAMETERS

Parameter	Value	Parameter	Value
K_a	290.0000	T_e	0.3000s
T_a	0.00095 s	A	0.2874
K_f	0.0001	B	0.3632
T_f	1.2000 s	T_r	0.0020s
K_e	1.0000	-	-

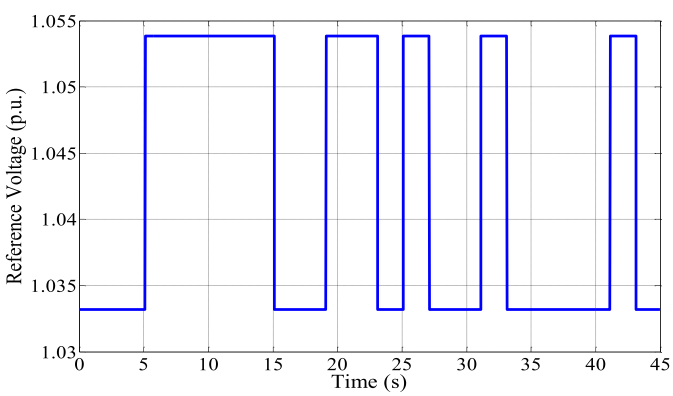

Fig. 4. Input signal (PRBS).

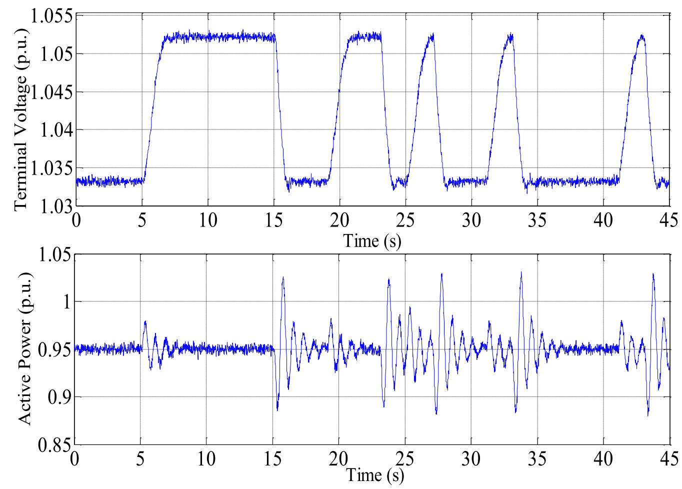

Fig. 5. Sampled output signals.

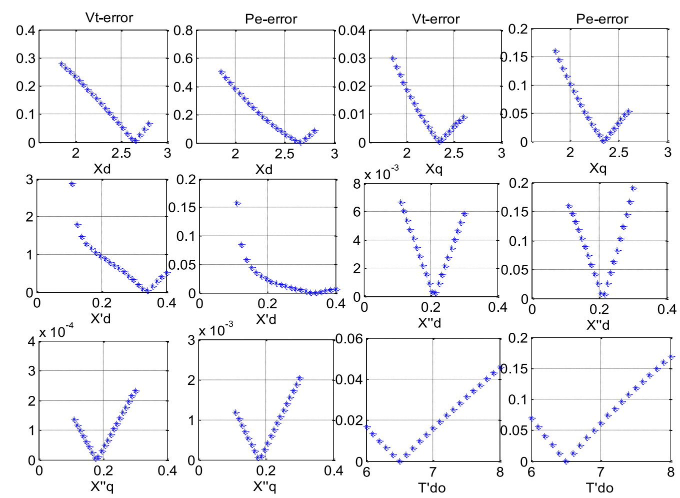

Fig. 6. Sensitivity analysis for parameters $X_d - T'_{\mathrm{do}}$.

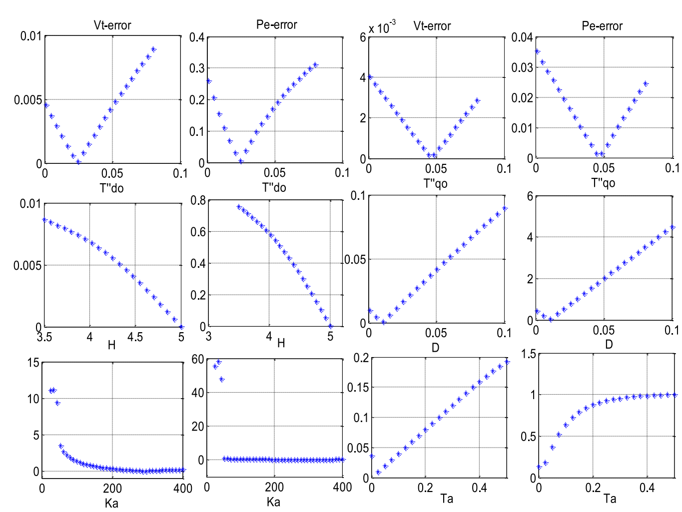

Fig. 7. Sensitivity analysis for parameters $T''_{\mathrm{do}} - T_a$.

errors using (5). The specific range of each parameter variation is given in Table IV [2], [35]. These ranges are used to carry out the sensitivity analysis and identification procedure.

Considering Figs. 6–9, it is obvious that some parameters have more considerable impact on Error_V or Error_P than others. According to results, 19 parameters of the synchronous machine and EXS are classified to EOV, EOP, and NEU groups. It is noticeable that some of these parameters such as X_d and X_q are effective on both V_t and P_e but some of them such as H, D, T'_{do}, T''_{do}, and X''_d are clearly effective on P_e. Therefore, these last five parameters are selected as EOP. Four parameters T''_{qo}, X''_q, T_f, and T_r are explicitly NEU. Among the remaining ten parameters, almost all of them are both EOP and EOV but, it should be noted that the

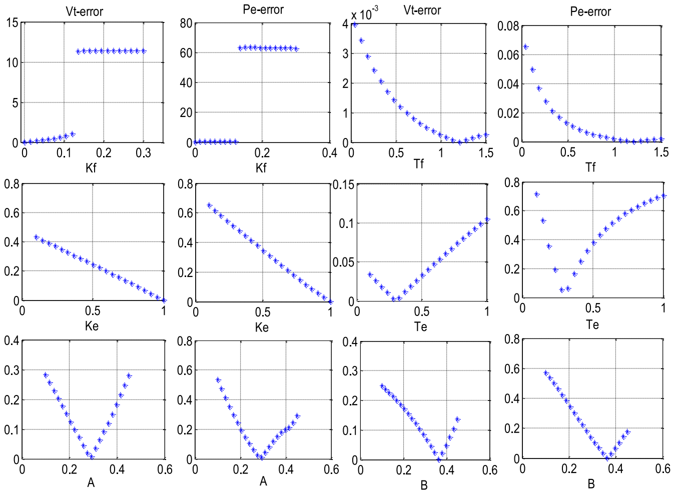

Fig. 8. Sensitivity analysis for parameters $K_f - B$.

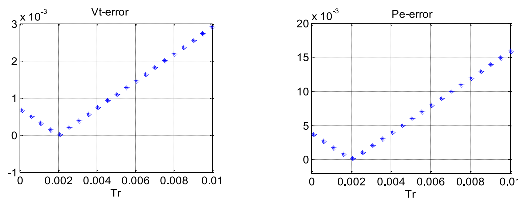

Fig. 9. Sensitivity analysis for parameter T_r.

TABLE IV
SEARCH SPACE OF PARAMETERS

Parameter	Range	Parameter	Range
X_d	[1.5~2.8]	K_a	[25~400]
X_q	[1.5~2.6]	T_a	[0.0005~0.5]
X'_d	[0.11~0.4]	K_f	[0.0005~0.3]
X''_d	[0.11~0.3]	T_f	[0.04~1.5]
X''_q	[0.11~0.3]	K_e	[0.1~1]
T'_{do}	[6~8]	T_e	[0.04~0.5]
T''_{do}	[0.001~0.08]	A	[0.1~0.5]
T''_{qo}	[0.001~0.08]	B	[0.1~0.5]
H	[3.5~5.5]	T_r	[0.001~0.05]
D	[0.001~0.1]	-	-

TABLE V
PARAMETERS CLASSIFICATION

Parameter	Class	Parameter	Class
X_d	EOV	K_a	EOV
X_q	EOV	T_a	EOV
X'_d	EOV	K_f	EOV
X''_d	EOP	T_f	NEU
X''_q	NEU	K_e	EOV
T'_{do}	EOP	T_e	EOV
T''_{do}	EOP	A	EOV
T''_{qo}	NEU	B	EOV
H	EOP	T_r	NEU
D	EOP	-	-

TABLE VI
GA OPTIMIZATION PARAMETERS

Parameter	Value	Function	Type
Initial Population	20	Selection	Stochastic uniform
Crossover fraction	0.8	Mutation	Adaptive feasible
Number of generations	150	Crossover	Scattered

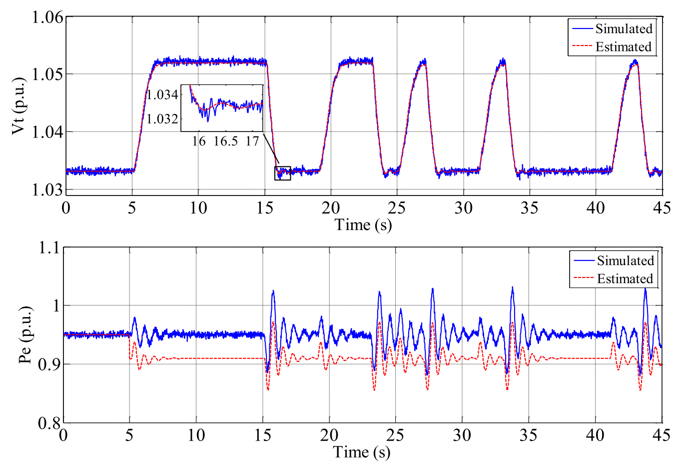

Fig. 10. Comparison of simulated and estimated output signals using stage 1 set of parameters.

main purpose of parameters classification is to identify them using a multistage procedure which makes it easier to handle the identification of a large number of parameters. Therefore, when a parameter is effective on both voltage and power it could be considered either in EOV or in EOP category as required. Therefore, the remaining ten parameters that have impact on V_t are selected as EOV in spite of their considerable impact on P_e. The classification of these parameters is given in Table V.

After sensitivity analysis and classification, the identification procedure is started according to Fig. 2. The implementation parameters of the GA optimization are given in Table VI. The results of the identification procedure are shown in Figs. 10–13 and Table VII. The simulated signals using actual parameters and estimated ones are compared in these figures.

As it is shown in Fig. 10, in stage 1, the estimated and simulated signals of V_t have a good agreement with each other while these signals of P_e show a considerable mismatch. This is because of using (6) as objective function in which only V_t has been considered to estimate EOV parameters. In stage 2, a vice versa phenomenon has been occurred. As shown in Fig. 11, estimated and simulated signals of P_e match with a good accuracy, while these signals of V_t show mismatches. This is the result of using (7) as objective function in which only P_e has been considered to estimate EOP parameters. Since both of V_t and P_e have been considered in the objective function of (8), to estimate EOV and EOP parameters, both of estimated output signals match to their corresponding simulated signals with a very good accuracy as shown in Fig. 12.

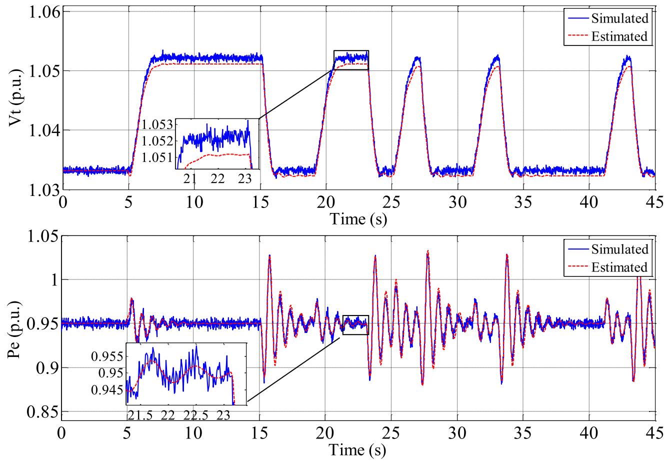

Fig. 11. Comparison of simulated and estimated output signals using stage 2 set of parameters.

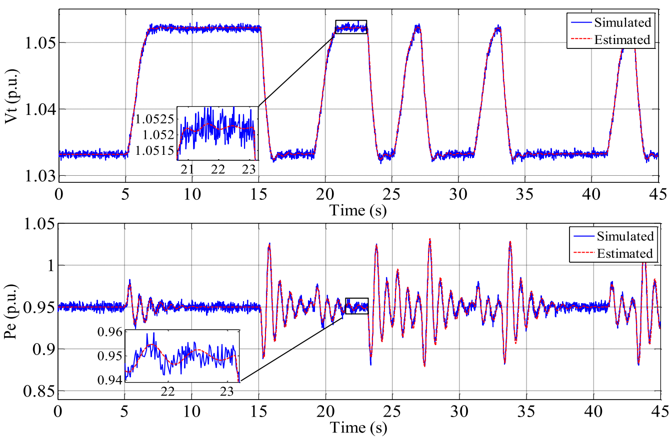

Fig. 12. Comparison of simulated and estimated output signals using stage 3 set of parameters.

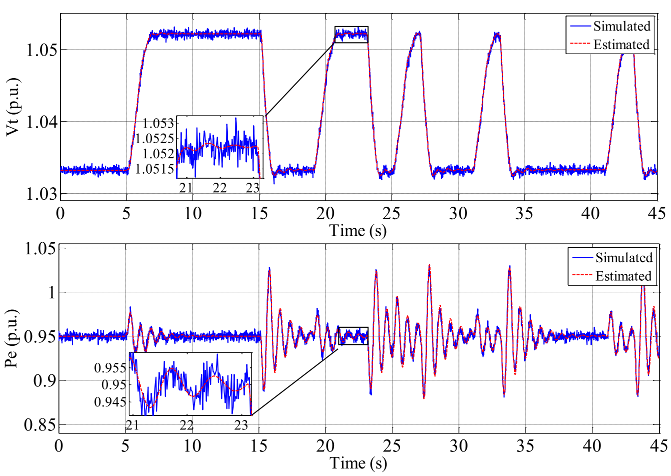

Fig. 13. Comparison of simulated and estimated output signals using stage 4 set of parameters.

The results of the identification given in Table VI show the improvement of accuracy through stages 1–3. Finally, in stage 4, NEU parameters are identified using (8). Since these parameters have not a considerable impact on neither V_t nor P_e, the estimated output signals of this stage are similar to the last stage. Final results of the parameter identification are given in "stage 4" column of Table VII.

TABLE VII
IDENTIFICATION RESULTS

Parameter	Stage1	Stage2	Stage3	Stage4	Actual Value
X_d	**2.8000**	2.8000	**2.6490**	2.6490	2.6420
X_q	**2.4000**	2.4000	**2.310**	2.3100	2.3460
X'_d	**0.3790**	0.3790	**0.3510**	0.3510	0.3370
X''_d	0.2050	**0.3000**	**0.2940**	0.2940	0.2100
X''_q	0.2050	0.2050	0.2050	**0.1110**	0.1800
T'_{do}	7.000	**6.9400**	**6.5270**	6.5270	6.5000
T''_{do}	0.0405	**0.0305**	**0.0300**	0.0300	0.0241
T''_{qo}	0.0405	0.0405	0.0405	**0.0440**	0.0464
H	4.2500	**4.7940**	**4.9830**	4.9830	5.0000
D	0.0505	**0.0100**	**0.0100**	0.0100	0.0100
K_a	**260.906**	260.906	**291.3760**	291.3760	290.0000
T_a	**0.0220**	0.0220	**0.0070**	0.0070	0.00095
K_f	**0.00005**	0.00005	**0.00005**	0.00005	0.0001
T_f	0.7700	0.7700	0.7700	**1.2320**	1.2000
K_e	**0.9440**	0.9440	**0.8980**	0.8980	1.000
T_e	**0.2150**	0.2150	**0.3240**	0.3240	0.3000
A	**0.1850**	0.1850	**0.4470**	0.4470	0.2874
B	**0.4500**	0.4500	**0.2880**	0.2880	0.3632
T_r	0.0050	0.0050	0.0050	**0.0050**	0.0020

Bold values indicate estimated parameters in each stage.

TABLE VIII
ERRORS OF ESTIMATIONS

Parameter	Error	Parameter	Error	Parameter	Error
X_d	0.0063	T''_{qo}	0.0020	K_e	0.1173
X_q	0.0105	H	0.0119	T_e	0.0656
X'_d	0.1234	D	0.0000	A	0.2512
X''_d	0.1815	K_a	0.0089	B	0.2512
X''_q	0.0013	T_a	0.0475	T_r	0.0070
T'_{do}	0.0045	K_f	0.0058	**ALL**	**0.1910**
T''_{do}	0.0496	T_f	0.0003	-	-

To show the accuracy of the estimated parameters, the error index is defined as follows:

$$\mathrm{Error}(p_k) = \sqrt{\sum_i \left(V_{t_i} - \hat{V}_{t_i}\right)^2} + \sqrt{\sum_i \left(P_{e_i} - \hat{P}_{e_i}\right)^2} \quad k = 1, \ldots, 19 \quad (10)$$

where, p_k is the kth parameter of Table VII, V_t and P_e are sampled vectors of the simulated system when all parameters have their actual values, and $\hat{V}_t$ and $\hat{P}_e$ are sampled vectors of the simulated system when all parameters have their actual values (from the sixth column of Table VII) except kth parameter which has its estimated value (from the fifth column of Table VII). Indeed, this index shows the effect of kth parameter on the estimated signals. The results are given in Table VIII. The last row of Table VIII shows the error when all the parameters have their estimated values. The results show that most of

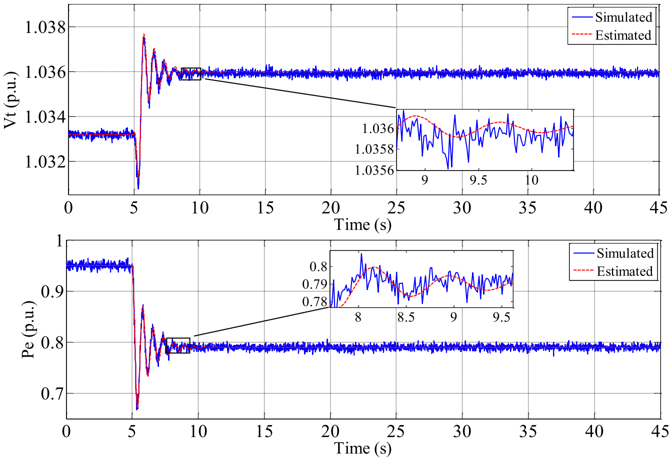

Fig. 14. Comparison of simulated and estimated output signals (validation test).

the parameters have been accurately estimated. Although estimations of some parameters such as X''_d , X''_q, T''_{do}, A, and T_r seem not very accurate according to the results of Table VII, the errors of Table VIII prove that these estimations have acceptable accuracy.

For validation purpose, a step change is applied to the input mechanical power to change the operating point. The simulation has been carried out using both actual values of the parameters and estimated ones. The results show the good accuracy of the estimated parameters for new operating point as shown in Fig. 14.

It should be noted that since the proposed method uses local measurements of the synchronous generator terminals (V_t and P_e), the identification procedure will be the same when the generator is not connected to a multimachine power system. Indeed, the type of network that generator is connected to is important in such identification methodologies that are based on the white-box model of the system such as [13], [14], and [20], where the main idea is identifying the parameters of the state space model of the system which depends on the network configuration. But the proposed approach of this paper just tries to estimate the desired parameters in order to fit the simulated outputs (V_t and P_e) to the measured ones regardless of the system configuration.

V. Conclusion

A new multistage GA-based method has been presented to simultaneously identify the parameters of the synchronous generator and its EXS using online measurements which could be provided by PMUs in a smart grid. Due to large number of parameters (19, in this paper), the simultaneous closed-loop parameter identification was a challenging problem which has been solved using the proposed method. This method has been applied to a single machine infinite bus system and the simulation results show its effectiveness. In addition, a validation test has been done using a step change in operating point which shows that the estimated parameters are valid for different operating points.

References

[1] Y. N. Yu, *Electric Power System Dynamic.* New York, NY, USA: Academic, 1983.
[2] P. Kundor, *Power System Stability and Control.* New York, NY, USA: McGraw-Hill, 1994.
[3] M. Hasni, O. Touhami, R. Ibtiouen, M. Fadel, and S. Caux, "Estimation of synchronous machine parameters by standstill tests," *Math. Comput. Simulat.*, vol. 81, no. 2, pp. 277–289, 2010.
[4] R. Wamkeue, C. Jolette, A. B. M. Mabwe, and I. Kamwa, "Cross-identification of synchronous generator parameters from RTDT test time-domain analytical responses," *IEEE Trans. Energy Convers.*, vol. 26, no. 3, pp. 776–786, Sep. 2011.
[5] T. L. Vandoorn, F. M. De Belie, T. J. Vyncke, J. A. Melkebeek, and P. Lataire, "Generation of multisinusoidal test signals for the identification of synchronous-machine parameters by using a voltage-source inverter," *IEEE Trans. Ind. Electron.*, vol. 57, no. 1, pp. 430–439, Jan. 2010.
[6] E. Mouni, S. Tnani, and G. Champenois, "Synchronous generator modeling and parameter estimation using least square method," *J. Simulat. Model. Pract. Theory*, vol. 16, no. 6, pp. 678–689, 2008.
[7] M. A. Arjona, M. Cisneros-Gonzales, and C. Hernandez, "Parameter estimation of a synchronous generator using a sine cardinal perturbation and mixed stochastic-deterministics algorithms," *IEEE Trans. Ind. Electron.*, vol. 58, no. 2, pp. 486–493, Feb. 2011.
[8] M. A. Arjona, C. Hernandez, M. Cisneros-Gonzales, and R. Escarela-Perez, "Estimation of synchronous generator parameters using the standstill step-voltage test and a hybrid genetic algorithm," *Int. J. Elect. Power Energy Syst.*, vol. 35, no. 1, pp. 105–111, 2012.
[9] J. Lidenholm and U. Lundin, "Estimation of hydropower generator parameters through field simulations of standard tests," *IEEE Trans. Energy Convers.*, vol. 25, no. 4, pp. 931–939, Dec. 2010.
[10] F. P. de Mello and J. R. Ribeiro, "Derivation of synchronous machine parameters from tests," *IEEE Trans. Power App. Syst.*, vol. 96, no. 4, pp. 1211–1218, Jul. 1977.
[11] *Test Procedures for Synchronous Machines, Part I—Acceptance and Performance Testing, Part II—Test Procedures and Parameter Determination for Dynamic Analysis*, IEEE Standard 115, 2010.
[12] M. Huang, W. Li, and W. Yan, "Estimation parameters of synchronous generators using square-root unscented Kalman filter," *Elect. Power Syst. Res.*, vol. 80, no. 9, pp. 1137–1144, 2010.
[13] M. Dehghani and S. K. Y. Nikravesh, "Nonlinear state space model identification of synchronous generators," *Elect. Power Syst. Res.*, vol. 78, no. 5, pp. 926–940, 2008.
[14] 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.
[15] E. Ghahremani, M. Karrari, and O. P. Malik, "Synchronous generator third-order model parameter estimation using on-line experimental data," *IET Gener. Transm. Distrib.*, vol. 2, no. 5, pp. 708–719, Sep. 2008.
[16] E. Ghahremani and I. Kamwa, "Online estimation of a synchronous generator using unscented Kalman filter from phasor measurements units," *IEEE Trans. Energy Convers.*, vol. 26, no. 4, pp. 1099–1108, Dec. 2011.
[17] L. Fan and Y. Wehbe, "Extended Kalman filtering-based real-time dynamic state and parameter estimation using PMU data," *Elect. Power Syst. Res.*, vol. 103, pp. 168–177, Oct. 2013.
[18] P. Kou *et al.*, "Parameters identification of nonlinear state space model of synchronous generator," *Eng. Appl. Artif. Intell.*, vol. 24, no. 7, pp. 1227–1237, 2011.
[19] M. Soliman, D. Westwik, and O. P. Malik, "Identification of Heffron–Phillips model parameters for synchronous generators operating in closed loop," *IET Gener. Transm. Distrib.*, vol. 2, no. 4, pp. 530–541, Jul. 2008.
[20] M. Dehghani and S. K. Y. Nikravesh, "State-space model parameter identification in large-scale power systems," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1449–1457, Aug. 2008.
[21] 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.
[22] B. Zaker, G. B. Gharehpetian, M. Mirsalim, and N. Moaddabi, "PMU-based linear and nonlinear black-box modeling of power systems," in *Proc. ICEE*, Mashhad, Iran, 2013, pp. 1–6.
[23] B. Zaker, G. B. Gharehpetian, and N. Moaddabi, "Parameter identification of Heffron–Phillips model considering AVR using on-line measurements data," presented at the Int. Conf. Renew. Energies Power Qual. (ICREPQ), Cordoba, Spain, Apr. 2014, pp. 1–6.

[24] D. C. Aliprantis, S. D. Sudhoff, and B. T. Kuhn, "Genetic algorithm-based parameter identification of a hysteretic brushless exciter model," *IEEE Trans. Energy Convers.*, vol. 21, no. 1, pp. 148–154, Mar. 2006.

[25] R. Bhaskar, M. L. Crow, E. Ludwig, K. T. Erickson, and K. S. Shah, "Nonlinear parameter estimation of excitation systems," *IEEE Trans. Power Syst.*, vol. 15, no. 4, pp. 1225–1231, Nov. 2000.

[26] J. Q. Puma and D. G. Colome, "Parameters identification of excitation system models using genetic algorithms," *IET Gener. Transm. Distrib.,* vol. 2, no. 3, pp. 456–467, May 2008.

[27] A. J. Saavedra-Montes, J. M. Ramirez-Scarpetta, C. A. Ramos-Paja, and O. P. Malik, "Identification of excitation systems with the generator online," *Elect. Power Syst. Res.*, vol. 87, pp. 1–9, Jun. 2012.

[28] A. J. Saavedra-Montes, J. M. Ramirez-Scarpetta, and O. P. Malik, "Methodology to estimate parameters of an excitation system based on experimental conditions," *Elect. Power Syst. Res.*, vol. 81, no. 1, pp. 170–176, 2011.

[29] M. Rasouli and M. Karrari, "Nonlinear identification of a brushless excitation system via field tests," *IEEE Trans. Energy Convers.*, vol. 19, no. 4, pp. 733–740, Dec. 2004.

[30] *IEEE Standard for Synchrophasors for Power Systems*, IEEE Standard PC37.118, 2005.

[31] Z. Huang, P. Du, D. Kosterev, and S. Yang, "Generator dynamic model validation and parameter calibration using phasor measurements at the point of connection," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1939–1949, May 2013.

[32] Z. Zhang and S. G. Mallat, "Matching pursuits with time-frequency dictionaries," *IEEE Trans. Signals Process.*, vol. 41, no. 12, pp. 3397–3415, Dec. 1993.

[33] J. H. Holland, *Adaptation in Natural and Artificial Systems*. Ann Arbor, MI, USA: Univ. Michigan, 1975.

[34] A. E. Eiben and J. E. Smith*, Introduction to Evolutionary Computing*. Berlin, Germany: Springer-Verlag, 2003.

[35] (Mar. 13, 2008). *BOSL Controllers Standard 1*. [Online]. Available: www.siemens.com/power-technologies/software

Behrooz Zaker was born in Shiraz, Iran, in 1989. He received the B.Sc. degree from Shiraz University, Shiraz, Iran, and the M.Sc. degree from the Amirkabir University of Technology, Tehran, Iran, in 2011 and 2013, respectively, where he is currently pursuing the Ph.D. degree, all in electrical power engineering.

His current research interests include system identification, power system dynamics, distributed generation systems, and microgrids.

Gevork B. Gharehpetian (M'00–SM'08) received the B.S., M.S., and Ph.D. degrees in electrical engineering from Tabriz University, Tabriz, Iran; the Amirkabir University of Technology (AUT), Tehran, Iran; and Tehran University, Tehran, respectively, graduating all with First Class Honors, in 1987, 1989, and 1996, respectively.

He was with the High Voltage Institute of RWTH, Aachen, Germany. He was an Assistant Professor from 1997 to 2003, an Associate Professor from 2004 to 2007, and has been a Professor since 2007 with AUT. He was a Distinguished Professor of the Ministry of Higher Education, Tehran, Iran, and a Distinguished Researcher of the Iranian Association of Electrical and Electronics Engineers (IAEEE), Tehran, Iran. He is a member of the Center of Excellence in Power Systems. His current research interests include smart grid, microgrids, flexible ac transmission systems and high-voltage dc systems, and monitoring of power transformers and its transients. He has authored over 850 journal and conference papers.

Dr. Gharehpetian was a recipient of a scholarship from the German Academic Exchange Service for his Ph.D. degree, from 1993 to 1996, and the National Prize in 2008 and 2010. Since 2004, he has been the Editor-in-Chief of the *Journal of IAEEE*. He is a Distinguished Member and Central Board Member of IAEEE.

Mehdi Karrari received the Ph.D. degree in control engineering from Sheffield University, Sheffield, U.K., in 1991.

Since 1991, he has been with the Amirkabir University of Technology, Tehran, Iran. He has authored or co-authored over 100 technical papers and one book entitled *Power System Dynamics and Control* in Persian, (Tehran Polytechnic Press, 2004). His current research interests include power system modeling, modeling and identification of dynamic systems, and large-scale and distributed systems.

Naghi Moaddabi was born in Rasht, Iran, in 1984. He received the B.Sc., M.Sc., and Ph.D. degrees in electrical power engineering from the Amirkabir University of Technology, Tehran, Iran, in 2006, 2008, and 2014, respectively.

He has a lot of practical experience in protection and control design of high-voltage substations in Iran. His current research interests include power system protection, power system stability, power electronics, and distributed generation systems.