Identification of Dynamic Load Model Parameters Using Particle Swarm Optimization

Young-Gon Kim[1], Hwachang Song[1*] and Byongjun Lee[2]

[1] Department of Electrical Engineering, Seoul Nat'l University of Technology, Seoul 139-743, Korea
[2] School of Electrical Engineering, Korea University, Seoul 136-701, Korea

Abstract

This paper presents a method for estimating the parameters of dynamic models for induction motor dominating loads. Using particle swarm optimization, the method finds the adequate set of parameters that best fit the sampling data from the measurement for a period of time, minimizing the error of the outputs, active and reactive power demands and satisfying the steady-state error criterion.

Key Words : dynamic load model, parameter estimation, particle swarm optimization, system identification

1. Introduction

In real system application, the component modeling critically affects the accuracy in stability analysis. This is why system identification [1] can be considered as important as the stability analysis itself. In power systems, there are several kinds of system components that need to be modeled such as generators, transmission lines, transformers, loads, etc. Of those components, loads are quite difficult to model due to the fact that they are composed of various types of equipments and have different topologies in distribution feeders. This paper mainly discusses load representation and its parameter identification in power systems for system stability studies.

In power system stability analysis, the usually used load models are static models such as ZIP and exponent based models [2-5]. These models are based on the voltage and frequency dependency of active and reactive power demands. In [6-7], first-order dynamical load models to represent the load restoration characteristic are proposed, and they are so-called aggregated load models and employed for long-term voltage stability analysis. Model parameters are the exponents for short-term and long-term voltage dependency and the time constant for dynamic load response to reduce the discrepancy between short-term and long-term loads. To identify the parameters, measurement based parameter estimation should be performed.

In recent years, there has been arisen a strong need for more accurate load modeling that can consider both static and dynamic models [8-12]. In the structure of the model, loads are represented by a ZIP model and one or two induction motors. The inclusion of induction motors is needed to check system short-term voltage stability because of their reactive power consumption behavior during comparatively low voltage level. In the load modeling, 3-rd order induction motor models are recommended with the state variables of rotor angular speed, internal voltages in the direct and quadrature axis. The induction motor model is nonlinear, so there is limitation to apply the conventional linear parameter estimation method.

This paper presents a method for estimating the parameters of an equivalent load model for induction motor dominating loads as the first step toward the improved load modeling. The method applies particle swarm optimization (PSO) [13-14] to minimize the error of the outputs using the estimated parameters, which are obtained by numerical integration with Runge-Kutta 4th order method, from the time series data with measurement. To test the feasibility of the approach, this paper includes an example applying the algorithm to 23-bus test system.

2. PSO Based Load Model Parameter Estimation

2.1 Load model structure

The structure of the equivalent load models, considered in the paper, is mainly composed of two components; they are an induction motor and a static load as shown in Fig. 1

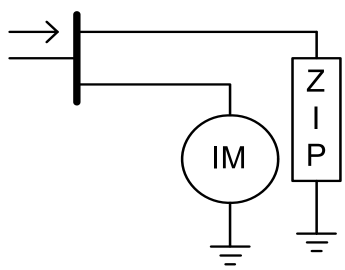

Fig. 1 Load model structure of interest

The static load model used in the paper is a ZIP model and active and reactive load demand, P_{ZIP} and Q_{ZIP}, of the model can be expressed as follows:

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* Corresponding author
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$$P_{ZIP} = P_{ZIPo}\left[a_p(V/V_o)^2 + b_p(V/V_o) + c_p\right] \quad (1)$$

$$Q_{ZIP} = Q_{ZIPo}\left[a_q(V/V_o)^2 + b_q(V/V_o) + c_q\right] \quad (2)$$

where P_{ZIPo} and Q_{ZIPo} are active and reactive load demand when voltage magnitude of the load bus is V_o as the reference. In (1) and (2), a_p, b_p and c_p are the coefficients for the ratio of constant impedance, constant current and constant power portion to the active load, respectively; a_q, b_q and c_q are those for the reactive load.

As for the dynamic load behavior, the 3rd order induction motor model [2-4] is employed. The equivalent circuit of the induction motor is shown in Fig. 2.

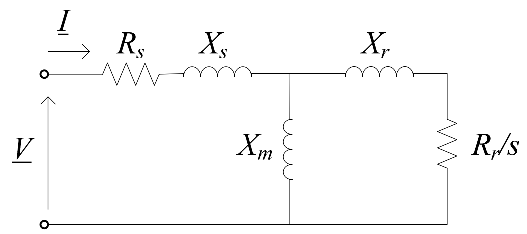

Fig. 2 Equivalent circuit of an induction motor

In Fig. 2, R_s and X_s are the stator resistance and reactance, respectively; X_m is the magnetization reactance; R_r and X_r are the rotator resistance and reactance, respectively; $\underline{V}$ and $\underline{I}$ are the vector for the motor terminal voltage and current, respectively; s denotes the slip of the motor, which can be expressed as $(\omega_m - \omega_o)/\omega_o$. ω_m and ω_o stand for the rotor angular velocity and its synchronous value.

The usually used model of induction motor in stability studies is the 3rd order model, and it can be expressed mathematically as follows:

$$\dot{E}_d' = -\frac{1}{T_o'}\left[E_d' + (X - X')I_q\right] + \omega_o s E_q' \quad (3)$$

$$\dot{E}_q' = -\frac{1}{T_o'}\left[E_q' - (X - X')I_d\right] - \omega_o s E_d' \quad (4)$$

$$\dot{s} = \frac{1}{2H}(T_m - T_e) \quad (5)$$

$$I_d = \frac{1}{R_s^2 + X'^2}\left[R_s(V_d - E_d') - X'(V_q - E_q')\right] \quad (6)$$

$$I_q = \frac{1}{R_s^2 + X'^2}\left[R_s(V_q - E_q') - X'(V_d - E_d')\right] \quad (7)$$

where E_d' and E_q' denote the direct and quadrature-axis components of the internal voltage, respectively, inside the transient rotor short-circuit reactance, X', from the terminal; X is the rotor open-circuit reactance; T_o' is the transient open-circuit time constant; H is the inertia constant; T_m and T_e are the mechanical and electrical torque, respectively.

In (5), T_m can be expressed as follows:

$$T_m = T_{Lo}\left[A(1-s)^2 + B(1-s) + C\right] \quad (8)$$

where T_{Lo} is the reference torque of the mechanical load.

2.2 PSO-based parameter estimation

For the study load bus, the input parameters are voltage magnitude and angle at the node, and the outputs are active and reactive power demand. The main interest of the paper is the voltage dependency of the load. It is assumed that from the measurement, a number of samples for the input and outputs are obtained with a certain sampling frequency.

To find the best fit for the parameters of the load model structure in Fig. 1, this paper employs a particle swarm optimization (PSO) algorithm. Fig. 2 briefly shows the load model parameter estimation procedure.

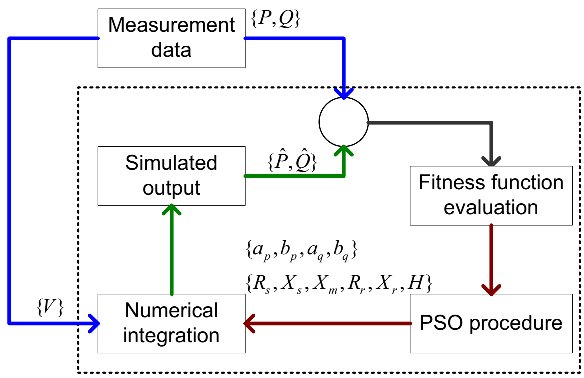

Fig. 3 Estimation procedure for load model parameters

During the estimation procedure, the estimated outputs by each particle of PSO are obtained as follows:

$$\hat{P} = \hat{P}_{ZIP} + \hat{P}_{IM} \quad (9)$$

$$\hat{Q} = \hat{Q}_{ZIP} + \hat{Q}_{IM} \quad (10)$$

where $\hat{P}_{ZIP}$ and $\hat{Q}_{ZIP}$ are the estimated active and reactive outputs from the ZIP load, and $\hat{P}_{IM}$ and $\hat{Q}_{IM}$ are those from the induction motor. In this paper, the outputs by the motor are estimated by numerical integration with Runge-Kutta 4th order method.

For parameter estimation, this paper adopts the prediction-error approach, of several procedures [1]. The fitness function in the optimization is the summed error between the measured outputs, $\{P, Q\}$, and the simulated outputs, $\{\hat{P}, \hat{Q}\}$. The fitness function can be explained mathematically as follows:

$$f(\cdot) = \frac{1}{2N_S}\sum_{i=1}^{N_S}\left[\left(P_i - \hat{P}_i\right)^2 + \left(Q_i - \hat{Q}_i\right)^2\right] \quad (9)$$

where N_S is the total number of samples for the estimation.

2.3 PSO algorithm

In PSO architecture a problem is given, and some way to evaluate a proposed solution to it exists in the form of fitness function. A communication structure or social network is also defined, assigning neighbors for each individual to interact with. Then a population of individuals defined as random guesses at the problem solutions are initialized. These individuals are candidate solutions which are also known as particles. A single particle by itself is unable to accomplish anything. The power is in interactive collaboration. An iterative process to improve these candidate solutions is set in motion. The particles iteratively evaluate the fitness of the candidate solutions and remember the location where they had their best success. The individual's best position corresponding to their best solution is called the particle best or local best. Each particle makes this information available to their neighbors. Each particle has memory and remembers the following information; the particle's best position, *pbest*, where the particle itself attained its best success and the global best position, *gbest*, where its neighborhood or any particle in the swarm attained the global best success.

The first procedure of PSO is to initialization of all the particles in the solution space. Then, in each PSO iteration, each particle moves from the current position to next one by adjusting its own position and velocity based on two best positions, the personal and group best position. The particle position and velocity update equations in the simplest form that govern the PSO is given below:

$$V_i^{k+1} = w \cdot V_i^k + C_1 \cdot r_1 (p_{pbest}^k - X_i^k) + C_2 \cdot r_2 \cdot (p_{gbest} - X_i^k) \tag{12}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{13}$$

$$w = w_2 + (w_2 - w_1) \cdot (k_{\max} - k) / (k_{\max}) \tag{14}$$

where X_i^{k+1} represents the current position of the particle, X_i^k is the previous particle's position, V_i^{k+1} is the current velocity of the particle, V_i^k is the previous velocity of the particle. C_1 and C_2, are the acceleration coefficients while r_1, and r_2 are random numbers uniformly distributed in the interval [0, 1]. P_{pbest}^k is the personal best position of the particle, p_{gbest} is the global best position of the swarm. w_1 and w_2 stands for the initial and final value of inertia weight respectively. k_{max} is the maximum number of iterations and k as the current iteration number. The PSO represented by (12)~(14) is called PSO with linearly decreasing inertia weight (PSO-LDIW).

Basically, PSO can provide solutions to unconstrained optimization problems. The movements of main variables, in the PSO procedure, are confined within the feasible solution space, but inadequately selected induction parameters might cause divergence in numerical integration even though the input time series shows a stable trajectory. Thus, the paper adopts an extension of the fitness function as follows:

$$\tilde{f}(\cdot) = f(\cdot) + K_1 b_{div} + K_2 b_{inf} \tag{15}$$

where b_{div} and b_{inf} are binary variables for the numerical divergence and infeasibility, which can be 0 or 1, respectively. K_1 and K_2 are the penalty constants for divergent and infeasible cases. K_1 and K_2 need to be set to very high values. In (15), infeasibility term needs to be added for those cases where the sum of a_p and b_p (or a_q and b_q) is greater than 1 in the ZIP load.

2.4 Overall procedure

The overall procedure of the PSO load model parameter identification is as follows:

Step 1	Input sampling data and set the PSO independent run number, *i*, to 1.
Step 2	Initialize all the particles within the feasible region in the parameter space, and set the PSO iteration number, *k*, to 1.
Step 3	If *k* is greater than $k_{\max}$, then go to Step 7.
Step 4	Perform numerical integration with the parameter set for each particle and calculate the extended fitness function value.
Step 5	Determine the particle's velocity with (12) and move each particle's using (13).
Step 6	Increase *k* by 1 and change the inertia weight depending on *k* with (14). Go to Step 3.
Step 7	Print out the parameter set of the group best position and verify the steady state output with the generated parameter set.
Step 8	Increase *i* by 1, and if *i* is greater than $i_{\max}$, then go to the next step.
Step 9	Do the time domain simulation with adequate parameter sets and then select one that best fits the measured trajectory.

PSO is a metaheuristic approach to search the solution space within the given feasible region, so it only uses the information of fitness function values for each particle's position. In the authors' experience, several parameter sets, provided by an independent run of PSO, may cause the induction motor's steady state active and reactive outputs that are quite far from the reasonable range. Thus, it is recognized that there is a need to consider the steady state outputs calculated with each parameter set for the verification process. The steady state outputs of an induction motor can be calculated as follows:

$$P(V,s) = \frac{(R_s + R_{eq})V^2}{(R_s + R_{eq})^2 + (X_s + X_{eq})^2} \tag{16}$$

$$Q(V,s) = \frac{(X_s + X_{eq})V^2}{(R_s + R_{eq})^2 + (X_s + X_{eq})^2} \tag{17}$$

$$R_{eq} + jX_{eq} = \frac{jX_m\left(R_r / s + jX_r\right)}{R_r / s + j(X_m + X_r)}$$

3. Numerical Examples

The proposed estimation algorithm for the dynamic load model parameters was applied to 23-bus test system [15]. The one-line diagram of the systems was shown in Fig. 4.

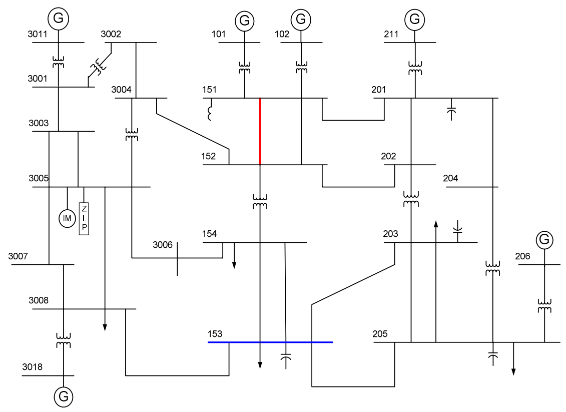

Fig. 4 One-line diagram of 23-bus test system

To obtain the time series data from a load bus of the system, a time simulation package of TSAT [16] is applied. In this simulation, the main issues of modeling can be described as follows:

- Bus 3005 is the bus of interest to obtain load model parameters. It has two types of loads, ZIP and induction motor loads. The mechanical load assumed to be represented with the quadratic term only in (8).
- All the loads except bus 3005 are represented as ZIP loads. The portions of constant impedance and current load are 30% for both of them.
- The contingency is a three-phase short-circuit fault to line 151-152, and the line is tripped 3 cycles after the fault.
- The time series data for 2 seconds with 0.5 cycle sampling frequency during the period of load restoration.

In this simulation, a standard PSO, developed in [17], was adopted. The PSO parameters used are shown in Table 1, and the range of each model parameter for the induction motor load is illustrated in Table 2. In Table 2, s_o stands for the initial slip for the numerical simulation.

Table 1. PSO parameters used in the simulation

c_1	2.0	w_1	0.9
c_2	2.0	w_2	0.4
r_1	(0,1]	# of particles	40
r_2	(0,1]	k_{max}	500

Table 2. Ranges of model parameters for induction motor

Param.	Min.	Max.	Param.	Min.	Max.
R_s	0.001	0.5	X_r	0.001	1.0
X_s	0.001	1.0	H	1.0	10.0
X_m	0.010	5.0	s_o	0.10	0.15
R_r	0.001	0.5			

In this simulation, we assumed that the active power portion of the induction motor load and the power factor of it are known. Thus, the steady state error of the given parameter set can be checked with (16) and (17). The algorithm performs fifty independent runs of PSO, and then it provides fifty sets of load model parameters for the structure in Fig. 1. Of those sets, five of them only satisfy the criterion of 5% steady state error criterion.

Fig. 5 shows the objective function value variation with respect to PSO iteration for the case providing an adequate set of parameters.

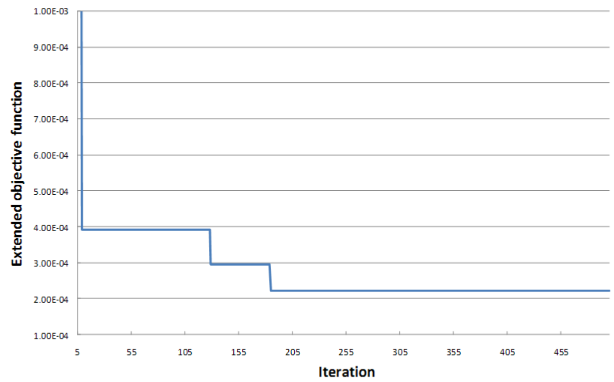

Fig. 5 Variation of the extended objective function during PSO simulation

During the initial part of the iteration, the sets of parameters cause trajectories of divergence in numerical integration, so the corresponding utility function values by (15) are very large because of K_1. After some PSO iteration, the trajectories become stable and then the procedure finds a parameter set resulting in a minimum of the utility function. Table 3 shows the parameter set, obtained in the simulation.

Table 3. Estimated load model parameters

R_s	0.473	R_r	0.237	a_p	0.545	a_q	0.580
X_s	0.030	X_r	0.667	b_p	0.333	b_q	0.322
X_m	2.009	H	2.483	c_p	0.122	c_q	0.097
s_o	0.1433	-	-				

For the verification of the obtained parameters, time domain simulation is performed with the estimated parameters. Fig 6 and 7 show the estimated active and reactive power outputs of the load model with the actual time trajectories with the original parameter set. In this example, the original set of parameter of the model could not be obtained. The reason might be that the range of the solution space is rather wide.

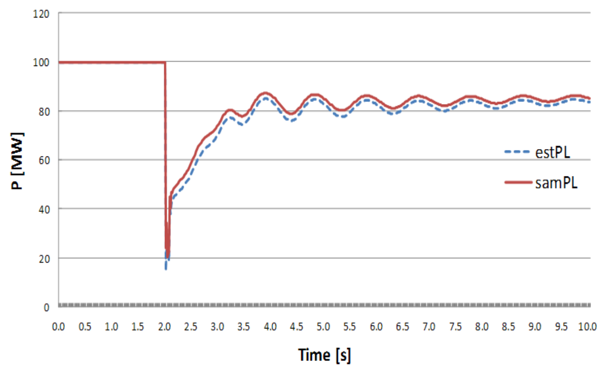

Fig. 6 P trajectories with the actual and estimated parameters

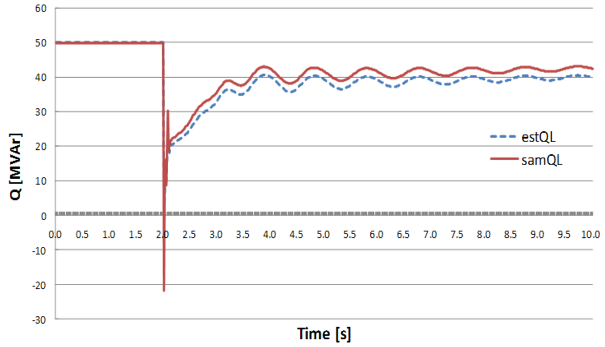

Fig. 7 Q trajectories with the actual and estimated parameters

Next, the proposed algorithm is applied for the estimation of the load model parameters including ZIP and motor load portion. The portion of them for active power is defined by α_{ZIP} and α_{IM} , and that for reactive power is done by β_{ZIP} and β_{IM}. Table 4 shows the set of parameters for the case.

Table 4. Estimated load model parameters including ZIP and motor load portion

R_s	0.424	R_r	0.139	a_p	0.386	a_q	0.221
X_s	0.159	X_r	0.188	b_p	0.354	b_q	0.744
X_m	4.819	H	4.722	c_p	0.260	c_q	0.035
α_{IM}	0.537	β_{IM}	0.444	α_{ZIP}	0.463	β_{ZIP}	0.556
s_o	0.1209	-	-				

Also for verification of the parameter set, seen in Table 4, time domain simulation is performed and the simulation output and the sampled data are compared. Fig. 8 and 9 illustrate the comparison results for active and reactive power output with the simulation result and the sampled data.

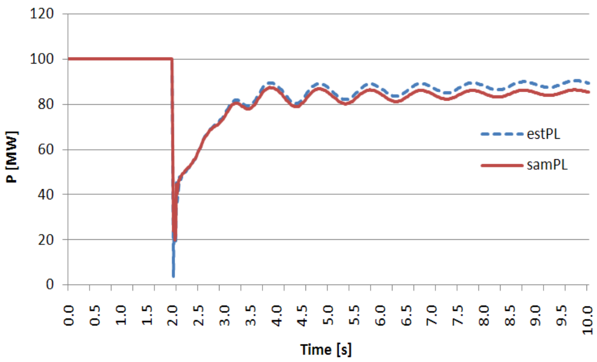

Fig. 8 P trajectories with the actual and estimated parameters

The difference between the 1st and 2nd case is whether to include the portion parameters for ZIP and motor load in the estimation procedure using PSO. In the 1st case, the active power portion of ZIP is around the half of the pre-fault condition, but in the 2nd case, α_{ZIP} and β_{ZIP} are free to change in the given range of 0 to 1.

In this paper, the error between the sampled and simulation data by the estimated parameter set is evaluated using the following indices [10]:

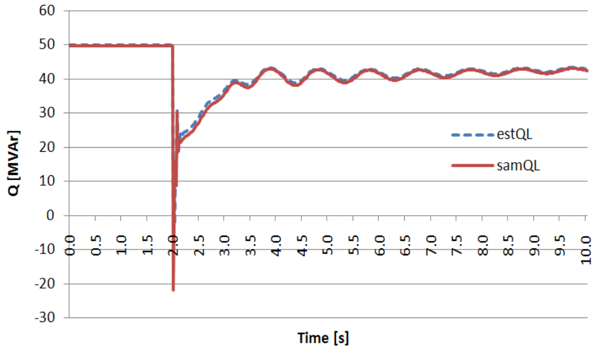

Fig. 9 Q trajectories with the actual and estimated parameters

In this paper, the error between the sampled and simulation data by the estimated parameter set is evaluated using the following indices [10]:

$$\varepsilon = 100 \times \frac{\left(\frac{1}{N_S} \sum_{i=1}^{N_S} (y_i - \hat{y}_i)^2 \right)^{1/2}}{\left(\frac{1}{N_S} \sum_{i=1}^{N_S} (y_i)^2 \right)^{1/2}} \% \tag{18}$$

$$SNR = -20 \log_{10}(\varepsilon) dB \tag{19}$$

where y_i and $\hat{y}_i$ are the i-th sampled data and simulated output with the estimated parameters. In (19), SNR is short for signal-to-noise ratios.

Table 5 shows the values of the two indices, calculated for the two cases. As in Table 5, the parameter sets obtained in the 2nd case can provide better simulation results from the viewpoint of deviation. Compared to the result described in [10], the error terms for active and reactive power for case 2 are slightly more than those. In [10], the stochastic approximation technique is employed.

In the authors' experience, the algorithm, proposed in this paper, is adequate for the situation where the system operators are not that well informed of the load model parameters during a period of time. In other words, it can be applied for load model parameter estimation in the long-term period. As one of current research trends, the researchers are very interested in on-line load modeling using the information from the rather fast monitoring devices such as PMU (phasor measurement units) [18]. For the purpose of on-line load modeling, a deterministic algorithm, one of steepest descent algorithms, needs to be combined with PSO into a kind of hybrid technique.

Table 5. Error indices for the two cases

Case 1		Case 2	
ε_P	3.82 [%]	ε_P	2.97 [%]
SNR_P	28.36 [dB]	SNR_P	30.53 [dB]
ε_Q	5.83 [%]	ε_Q	2.92 [%]
SNR_P	24.69 [dB]	SNR_P	30.70 [dB]

4. Conclusions

This paper presents a PSO based load modeling method to estimate the parameters for the load model structure including static and dynamic parts. The method can provide adequate sets of the load model parameters that minimize the error between the actual measurement and simulated data and satisfy the steady state error criterion.

As a future work in this topic, such a hybrid algorithm with PSO and a deterministic optimization technique needs to be employed to speed up the estimation time and to apply the deterministic local optimization algorithm when the system operating point is slightly moved and hence the parameters may be also slightly changed in the short-term period.

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Young-Gon Kim

He received B.S degree in the School of Electronic Engineering and Information Engineering from Kunsan National University, in 2008. Currently he is a graduate student for his Master Degree in the Department of Electrical Engineering, Seoul Nat'l University of Technology. His research interests are system modeling and power system stability and control.

Phone : +82-2-970-6402

E-mail : kimyg@snut.ac.kr

Hwachang Song

He received B.S., M.S. and Ph.D. in Electrical Engineering from Korea University in 1997, 1999 and 2003, respectively. He was a Post-doctoral Visiting Scholar at Iowa State University from 2003 to 2004. He was working as a faculty member in the School of Electronic and Information Engineering, Kunsan National University, from 2005 to 2008. Currently, he is an Assistant Professor in the Department of Electrical Engineering, Seoul Nat'l University of Technology. His research areas of interest are nonlinear optimization, power system stability and control, and system modeling.

Phone : +82-2-970-6402

E-mail : hcsong@snut.ac.kr

Byongjun Lee

He received his B.S. degree from Korea University, Seoul, Korea in 1987, M.S. and Ph.D. degrees in Electrical Engineering from Iowa State University in 1991 and 1994. From 1994 to 1995, he was a Postdoctoral Research Associate at the same university. From 1995 to 1996, he worked as a Senior Research Engineer at the Mitsubishi Electric Corp. in Kobe, Japan. Currently, he is the chairman of the advanced power systems research center (APSRC), supported by the Ministry of Knowledge Economy, and a professor in the Department of Electrical Engineering at Korea University.

Phone : +82-2-3290-3242

E-mail : leeb@korea.ac.kr