

OPTIMAL PID CONTROLLER DESIGN FOR AVR SYSTEM USING NEW OPTIMIZATION ALGORITHM

A. Karimi H. Eskandari M. Sedighizadeh A. Rezazadeh A. Pirayesh

*Faculty of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran
alikaarimi1368@yahoo.com, hos.eskandari@sbu.ac.ir, mos_sedighizadeh@yahoo.com
a-rezazade@sbu.ac.ir, a_pirayesh@sbu.ac.ir*

Abstract- During the history of science of computational, many evolutionary algorithms approaches were proposed having more or less success in solving various optimization problems. The algorithm is applied for numerical simulations based on optimized proportional integral derivative (PID) control of an automatic regulator voltage system for nominal system parameters and step reference voltage input illustrate the effectiveness and efficiency of IHBMO approach. Improve Honey Bee Mating Optimization algorithm and Genetic Algorithm (GA) and Big Bang-Big Crunch Optimization are applied to parameters optimization of PID controller. Simulation results is shown that the performance of IHBMO is better than GA and BB-BC, it is provided that a preferable method to optimization parameters of PID controller and the comparison shows the IHBMO-PID algorithm has more efficiency and robustness in improving the step response of an AVR system.

Keywords: PID, Big Bang-Big Crunch Optimization (BB-BC) Improve Honey Bee Mating Optimization (IHBMO), Automatic Voltage Regulator (AVR).

I. INTRODUCTION

Optimization problems are widely encountered in various fields in science and technology. Sometimes such problems can be very complex because of the actual and practical nature of the objective function or the model constraints. A typical optimization problem minimizes or maximizes an objective function subject to complex and nonlinear characteristics with heavy equality and/or in equality constraints. Taking the valve-point effects and multiple fuels into account will increase the number of local minimum points in the fuel cost function and make the problem of finding the global optimum more difficult.

Evolutionary algorithms (EA) are search method inspired by natural selection and survival of the fittest in the biological world and behavior of social insects such as ants and bees. With development of computer science and technology, many evolutionary algorithms such as genetic algorithm (GA) [1], particle swarm optimization (PSO) [2], simulated annealing (SA) and Tabu search (TS) [3] were proposed to find PID parameters.

One of the recently proposed evolutionary algorithms that have shown great potential and good perspective for the solution of various optimization problems is honey bee mating optimization (HBMO) [4]. The HBMO algorithm has been used to solve a single reservoir optimization problem [5, 7], data mining [6, 8], state estimation in distribution networks [8], multi-objective distribution feeder reconfiguration [9, 10]. These optimization algorithms suffer from slow convergence that leads to inefficient methods with high number of iterations. To address this problem, in this paper a new algorithm is presented. The optimization algorithm that is proposed in this paper, in comparison with the algorithms mentioned in [5, 8, 11] benefits faster runtime and needs lower number of iterations to achieve optimum point than them, leading to higher performance.

Nowadays, DGs are widely used in the power systems to improve the overall conditions of the network. Less environmental impact, high electric efficiency, low variable maintenance cost, quick start up, low installation cost and many other benefits, encourage the system manager to utilize this type of generation in the network so the system needs the evolutionary algorithms to achieve optimal DG allocation [23].

Original HBMO often converges to local optima. In order to avoid this shortcoming, in this paper, we propose a new HBMO algorithm to find optimal PID parameters. In the proposed algorithm first the original HBMO is combined with a chaotic local search (CLS) and then a new method is proposed to improve the mating processing [11, 12]. The proposed approach is called the improved honey-bee mating optimization (IHBMO).

The main contributions of this paper are:

1. Presenting an improved version of the honey bee mating optimization (HBMO) algorithm.
2. Find the PID parameter of AVR.

The paper is organized as follows: Section II presents the Overview of PID Controllers. Section III GA Optimization is introduced section IV includes Big Bang-Big Crunch Optimization (BB-BC) section V contains a brief overview of the Honey Bee Mating Optimization (HBMO) algorithm and Improve Honey Bee Mating Optimization (IHBMO) algorithm.

Section VI includes the description of an AVR Model, Simulation result and comparisons are provided in section VII. Finally, section VIII outlines the conclusion.

II. OVERVIEW OF PID CONTROLLERS

A PID controller is a combination of a proportional, an integral and a derivative controller, integrating the main features of all three. Figure 1 demonstrates a simplified block diagram of a plant controlled by a PID. The output of a PID controller, which is the processed error signal, can be presented as:

$$u(t) = K_p \cdot e(t) + K_i \cdot \int e(t)dt + K_d \cdot \frac{d}{dt} e(t) \tag{1}$$

where K_p , K_i and K_d are the proportional, integral and derivative gains, respectively.

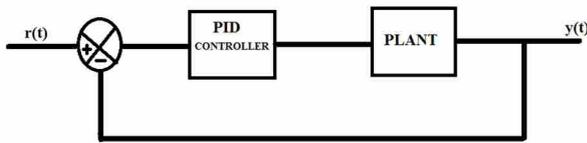


Figure 1. A plant controlled by PID controller [13]

In general, the objective of PID controllers like any other controller is to provide stability as well as reference tracking and disturbance rejection, which are all design criteria related to steady domain of response. Different indices have been suggested to evaluate the performance of a controller based on the above objectives. The most common ones are the integrated absolute error (IAE), integrated squared error (ISE), integrated time squared error (ITSE), and integrated time absolute error (ITAE). These indices are normally calculated under step testing input in the time domain as:

$$IAE = \int_0^{\infty} |r(t) - y(t)| dt = \int_0^{\infty} |e(t)| dt \tag{2}$$

$$ISE = \int_0^{\infty} e(t)^2 dt \tag{3}$$

$$ITSE = \int_0^{\infty} t \cdot e(t)^2 dt \tag{4}$$

$$ITAE = \int_0^{\infty} t \cdot |e(t)| dt \tag{5}$$

Obviously as they all represent the concept of error; minimization of these indices is desired. For the transient domain of response, maximum overshoot (OS), settling time (t_s) and rise time (t_r) are normally considered significant where the benefit of faster systems, necessitates minimum possible values for them. For tuning PID controllers that is finding the optimum gains for the best performance, one or a weighted combination of these criteria is employed. While weights and number of indices are diversely reported in the literature, it is generally accepted that time weighted indices are more appropriate as the errors occurring later in the transient response are penalized heavily.

In this paper, selection of any of these criteria has been constrained by benchmark problems, though *ITSE* index is calculated and reported independently to make comparison more sensible [13, 14].

III. BASIC GA OPTIMIZATION

The parameters tuning of PID controller is the combination and optimization of multivariables, simple genetic algorithms could solve the shortcoming of current methods of parameters tuning [15,16], which can only satisfy single requirement of system however, the normal genetic algorithm bases on simulation of genetic mechanism and theory of biological evolution, have been introduced. GA brings theory of biological evolution into the optimization of parameters through the crossover and mutation operations. It selects the best value of the fitness function and it is reserved. Then it makes up the new cluster. The genetic evolution will not stop one by one until it contents with constrain condition. Genetic Algorithm Process:

- Step 1. Initialize the parameter with a population of random solutions, such as crossover rate, mutant rate, numbers of cluster and numbers of generation. Determine the coding mode.
- Step 2. Compute and evaluate the value of the fitness function.
- Step 3. Go to the crossover and mutation operation and makeup the new cluster.
- Step 4. Go to the step 2 until get the best value. [13]

IV. BIG BANG-BIG CRUNCH OPTIMIZATION

The Big Bang-Big Crunch (BB-BC) optimization method is built on two main steps: The first step is the Big Bang phase where candidate solutions are randomly distributed over the search space and the next step is the Big Crunch where a contraction procedure calculates a center of mass for the population. The initial Big Bang population is randomly generated over the entire search space just like the other evolutionary search algorithms. All subsequent Big Bang phases are randomly distributed about the center of mass or the best fit individual in a similar fashion. In [21], the working principle of this evolutionary method is explained as to transform a convergent solution to a chaotic state which is a new set of solutions. The procedure of the BB-BC optimization is given in the table below:

- Step 1. (Big Bang phase): An initial generation of N candidates is generated randomly in the search space.
- Step 2. The cost function values of all the candidate solutions are computed.
- Step 3. (Big Crunch Phase): The center of mass is calculated. Either the best fit individual or the center of mass is chosen as the point of Big Bang Phase.
- Step 4. New candidates are calculated around the new point calculated in step 3 by adding or subtracting a random number whose value decreases as the iterations elapse.
- Step 5. Return to Step 2 until stopping criteria has been met.

After the Big Bang, a contraction procedure is applied during the Big Crunch. In this phase, the contraction operator takes the current positions of each candidate solution in the population and its associated cost function value and computes a center of mass. The center of mass can be computed as:

$$x_c = \frac{\sum_{i=1}^N \frac{1}{f_i} x_i}{\sum_{i=1}^N \frac{1}{f_i}} \quad (6)$$

where, x_i is position of candidate, x_c is position of the center of mass, f_i is cost function value of candidate i , and N is population size. Instead of the center of mass, the best fit individual can also be chosen as the starting point in the Big Bang phase.

The new generation for the next iteration Big Bang phase is normally distributed around x_c :

$$x_i^{new} = x_c + \sigma \quad (7)$$

where, x_i^{new} is the new candidate solution i , and σ is standard deviation of a standard normal distribution. The standard deviation decreases as the iterations elapse according to the following:

$$\sigma = \frac{r \cdot \alpha (x_{max} - x_{min})}{k} \quad (8)$$

where, r is random number, σ is a parameter limiting the size of the search space, x_{max} and x_{min} are the upper and lower limits, and k is the number of the iterations. Therefore, the new point is generated as follows:

$$x_i^{new} = x_c + \frac{r \cdot \alpha (x_{max} - x_{min})}{k} \quad (9)$$

Since normally distributed numbers can be exceeding ± 1 , it is necessary to limit population to the prescribed search space boundaries. This narrowing down restricts the candidate solutions into the search space boundaries [21].

V. IMPROVED HONEY BEE MATING OPTIMIZATION (IHBMO)

A. Original HBMO Algorithm

Actually, the optimal solution of the nonlinear scheduling problem is important and it has complex computational optimization process. This problem is a challenging undertaking to accommodate variations in the power system, especially when several generation units are employed the HBMO algorithm simulates the mating process of honeybees. This process starts when the queen flights away from the hive performing the mating flight during which the drones follow the queen and mate with her in the air. The algorithm is a swarm-based algorithm since it uses a swarm of bees where there are three kinds of bees: the queen (reproductive female), the drones (male) and the workers (non-reproductive female). There are a number of procedures that can be applied inside the swarm. In the original HBMO algorithm, the procedure of mating of the queen with the drones has been described in [8, 17, 22].

A drone mates with a queen probabilistically using an annealing function as follows [8, 17]:

$$\text{prob}(D) = \exp\left(-\frac{\Delta(f)}{S(k)}\right) \quad (10)$$

where, $\text{prob}(D)$ is the probability of adding the sperm of drone D to the spermatheca of the queen, $\Delta(f)$ is the absolute difference between the fitness of D and the fitness of the queen and $S(k)$ is the speed of the queen at iteration k . The probability of mating is high when the queen is with the high speed level, or when the fitness of the drone is as good as the queen's. After each transition in space, the queen's speed decreases equals:

$$S(k+1) = \alpha \times S(k) \quad (11)$$

where, α is a factor $\in [0,1]$ and is the amount of speed reduction after each transition and each step. The speed of the queen is initialized randomly. A number of mating flights are then realized. At the start of a mating flight drones are generated randomly and the queen selects a drone using the probabilistic rule in Equation (6). If the mating is successful (i.e. the drone passes the probabilistic decision rule), the drone's sperm is stored in the queen's spermatheca. By using the s of the drone's and the queen's genotypes, a new brood (trial solution) is generated, which can be improved later by employing workers to conduct local search.

B. Improved Honey Bee Mating Optimization (IHBMO) Algorithm

In the original HBMO, the broods are generated by mating between the queen and one drone:

$$X_{Broodj} = X_{queen} + \beta \times (X_{queen} - D_i) \quad (12)$$

$$X_{Broodj} = [x_{broodj1}, x_{broodj2}, \dots, x_{broodjN}]_{1 \times N}$$

where D_i is the its drone stored in the spermatheca and $\beta \in [0,1]$ is called mating factor. Traditional mating process combines the features of two parent structures to form two similar off springs. Its purpose is the maintenance and exchange of queen's place. But this cannot guarantee the convergence to the optimal point and sometimes causes premature convergence to local minima. In this paper, a new approach is proposed to improve the broods as described in the following:

At first four drones ($X_{s,z1}, X_{s,z2}, X_{s,z3}, X_{s,z4}$) among the sorted drones (in spermatheca) are selected randomly such that $z_1 \neq z_2 \neq z_3 \neq z_4$. Then a changing drone position vector is calculated as:

$$X_{change} = [X_{change}^1, X_{change}^2, \dots, X_{change}^N] = X_{s,z1} + \text{rand}(1) \cdot (X_{s,z2} - X_{s,z1}) + \text{rand}(2) \cdot (X_{queen}^t - X_{s,z4}) \quad (13)$$

$$X_{brood}^{t+1} = \begin{cases} X_{change}^j & \text{if } \text{rand}(3) \leq \text{rand}(4) \\ & \text{or } j = \text{randperm}(\cdot) \\ X_{queen}^{t,j} & \text{Otherwise} \end{cases} \quad (14)$$

where, $\text{randperm}(\cdot)$ is a randomly chosen index from $1, 2, \dots, N$ and $\text{rand}(1), \text{rand}(2), \text{rand}(3)$ and $\text{rand}(4)$ are random numbers between zero and one. The utilization of improvements in the breeding process can be useful to escape more easily from local minima compared to the traditional mating. In this way problems can be solved.

VI. AVR MODEL

The problem of dynamic stability of power system has challenged power system engineers since over three decades now. In a synchronous generator, the electromechanical coupling between the rotor and the rest of the system causes it to behave in a manner similar to a spring mass damper system, which exhibits an oscillatory behavior around the equilibrium state, following any disturbance, such as sudden change in loads, change in transmission line parameters, fluctuations in loads, change in transmission line parameters, fluctuations in the output of turbine and faults and others.

Synchronous generator excitation control is one of the most important measures to enhance power system stability and to guarantee the quality of electrical power it provides. Essentially, an AVR is to hold the terminal voltage magnitude, $V_t(s)$, of a synchronous generator at a specified level [18]. In the linearized model, the transfer function relating the generator terminal voltage to its field voltage can be represented by a gain K_g and a time constant τ_g . In Gaining [19] and Mukherjee and Ghoshal [20] has taken the generator transfer function as $K_g/(\tau_g \cdot s + 1)$, where K_g depends on load (0.7-1.0) and $1 \leq \tau_g \leq 2$ s. The same model has been taken in this work.

A simplified AVR system comprises four main components, namely amplifier, exciter, generator, and sensor [18]. In this work, the transfer functions of AVR model are compensated with a PID controller. The block diagram representation of AVR system using PID control and HBMO procedure is shown in Figure 2.

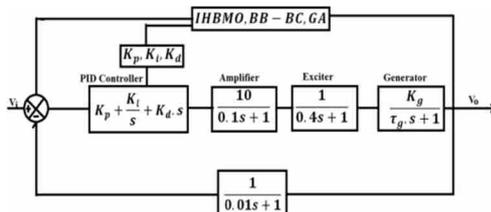


Figure 2. Representation of an AVR system using a PID controller with IHBMO and GA and BB-BC tuning [18]

In Figure 3, the step response of the AVR system in open loop is shown (terminal voltage). In this case, the transfer function of system is given by:

$$G(s) = \frac{0.07s + 7}{0.004s^4 + 0.0454s^3 + 0.555s^2 + 1.51s + 8} \quad (15)$$

where the transfer function has two real poles (-99.9798, -11.9284) and two complex poles (-0.7959±4.017i). In this case, the transfer function without controller is stable, but it presents oscillatory behavior.

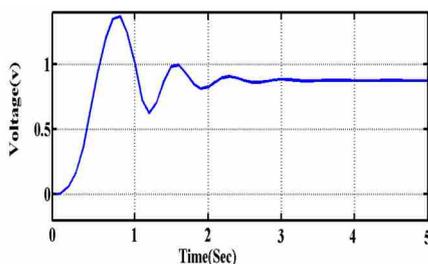


Figure 3. Response in open loop of AVR system with $K_g=0.7$ and $\tau_g=1.0$

VII. SIMULATION RESULTS

Each optimization method was implemented in Matlab. In this paper, the IHBMO approaches are adopted using 300 cost function evaluations in each run on tuning of PID controller for the AVR. In the tested cases to AVR system two operating conditions: (i) $K_g = 0.7$, $\tau_g = 1.0$ and (ii) $K_g = 1.0$, $\tau_g = 2.0$, the maximum number of generations was 90 and population size was 300. The searching ranges are set as $0 \leq k_p, k_i, k_d \leq 1.5$.

The objective function is first defined based on our desired specifications and constraints under input testing signal. The design of objective function to develop PID controller tuning is based on a performance index that considers the entire closed loop response. Typical output specifications in the time domain are peak overshooting, rise time, settling time, and steady-state error. Four kinds of performance criteria usually considered in the control design have been identified. In this work, a linear combination of ITAE criterion and a criterion based on absence of overshoot and rate of damping are employed as objective function to be minimized. This objective function is given by the ITAE.

Optimization algorithms termination is set by defining a relative fitness function error. In addition to better ability in finding best solution, IHBMO run time is less than GA. The statistical results and the best solutions obtained for two case studies are given in Tables I and II, which shows that the IHBMO is quickly damped than GA and overshoot of IHBMO is less than GA resulting better transient response of AVR to system disturbances, so algorithm IHBMO succeeded in finding the best solution for two case studies.

Figures 2 and 3 display the graphs of the closed loop with best tuning of PID controller for the AVR system. A step function is applied to generator terminal voltage. Figures 4 and 5, represents dynamic response of AVR to disturbance by optimized PID parameters. As it can be seen in Figures 4 and 5, the optimized PID controllers produce the good settling time with small or little overshoot and steady state error. For this simulation we have two states for generator that mentioned:

- a) The AVR system with $K_g=0.7$ and $\tau_g=1.0$.

In this case Figure 4 shows Terminal voltage step response of an AVR system ($K_g=0.7$, $\tau_g=1.0$) using PID with IHBMO and GA tuning. In this case IHBMO has the minimum overshoot that means it can follow step response faster.

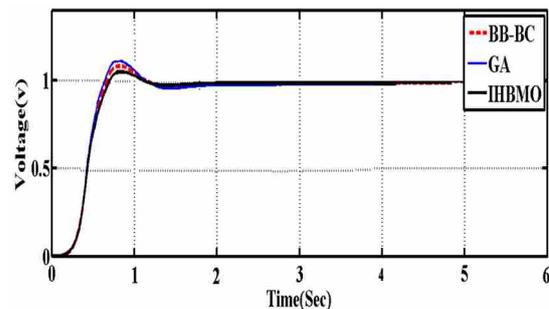


Figure 4. Terminal voltage step response of an AVR system ($K_g = 0.7$, $\tau_g = 1.0$) using PID with IHBMO and GA tuning

b) The AVR system with $K_g = 1.0$ and $\tau_g = 2.0$.

In this case Figure 5 shows Terminal voltage step response of an AVR system ($K_g = 1.0, \tau_g = 2.0$) using PID with IHBMO and GA tuning. In this case IHBMO has the minimum overshoot so it tracks step response quickly.

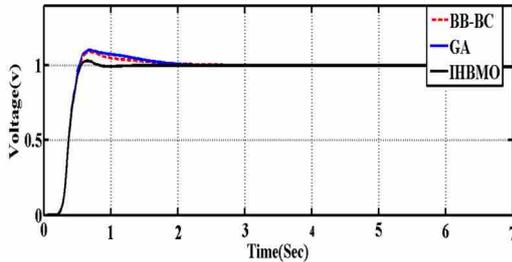


Figure 5. Terminal voltage step response of an AVR system ($K_g = 1.0, \tau_g = 2.0$) using PID with IHBMO and GA and BB-BC tuning

Table 1. Optimized PID gains and output results using IHBMO and GA and BB-BC with $K_g = 0.7$ and $\tau_g = 1$

Optimization methods	IHBMO	GA	BB-BC
K_p	1	1.2234	1.1124
K_d	0.3004	0.3057	0.7022
K_i	0.7034	0.7003	0.3022
$t_r(s)$	0.266	0.238	0.251
$t_s(s)$	0.756	1.32	1.16
$O_s(\%)$	6.33	12.6	9.58

Table 2. Optimized PID gains and output results using IHBMO and GA and BB-BC with $K_g = 1.0$ and $\tau_g = 2$

Optimization methods	IHBMO	GA	BB-BC
K_p	1	1.0242	1.0234
K_d	0.3471	0.3487	0.7028
K_i	0.4139	0.9134	0.3242
$t_r(s)$	0.333	0.306	0.32
$t_s(s)$	2.34	2.5	2.37
$O_s(\%)$	9.13	10.5	10.3

The obtained results are shown in the Tables 1 and 2 and we compare the IHBMO and GA algorithms in the tables. As we can see in Tables 1 and 2, IHBMO in term of t_r and t_s gets better result. Also, Overshoot finds lower value through IHBMO that means the algorithm reach so faster to the steady state. In order to verify it being superior to the other methods, many performance estimation schemes are performed: 1) It can obtain higher quality solution with better computation efficiency, 2) High speed convergence to steady state point.

We also performed 100 trials for three methods proposed controllers with different random number to observe the variation in their evaluation values. In addition, the maximum, minimum, and average evaluation values were obtained by the two methods. The results were shown in Table 3. As can be seen, the evaluation values of the IHBMO-PID controller generated fluctuation in a small range ($\Delta E = 0.0025$), thus verifying that the IHBMO-PID controller has better convergence characteristic.

Table 3. Comparison of computation efficiency of all methods

Methods	IHBMO	BB-BC	GA
Max.	1.2230	1.2250	1.2300
Min.	1.0013	1.1232	1.2275
$\Delta E=(Max.-Min.)$	0.2217	0.1018	0.0025
Average	1.11215	1.1742	1.22875

VIII. CONCLUSIONS

Although the control technology has been developing rapidly during recent years, PID control algorithm has been widely used in the industrial control with its simple, high reliability and robustness. According to the results of IHBMO, GA, BB-BC, it is obvious that IHBMO rapidly converge to the minimum point of fitness function. Consequently, in term of performance the proposed method overcomes to GA, BB-BC. In the present paper, a systematic way for tuning PID type controllers in AVR system has been analyzed. This tuning method uses closed loop data to determine the controller settings for a PID type controller using classical GA and BB-BC and IHBMO approaches. Through the simulation of a AVR system, the results show that the proposed controller can perform an efficient search for the optimal PID controller parameters. The IHBMO methodologies were successfully validated for tuning of PID controller for the AVR system about two different operational conditions of generator.

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BIOGRAPHIES



Ali Karimi received the B.Sc. degree in Electrical Engineering from Shiraz University, Shiraz, Iran in 2011 and is pursuing the M.Sc. in Electric Power Engineering from Shahid Beheshti University, Tehran, Iran in 2013. His main research interests are DC microgrid and renewable energy, dynamic modeling and analysis in power system.



Hossein Eskandari received the B.Sc. degree in Electrical Engineering from Jundi Shapour University of Technology, Ahvaz, Iran in 2010 and and the M.Sc. degree in Electric Power Engineering from Shahid Beheshti University, Tehran, Iran, in 2013. His main research interests are in the Optimization, control system and instrument.



Mostafa Sedighzadeh received the B.Sc. degree in Electrical Engineering from Shahid Chamran University, Ahvaz, Iran in 1996 and M.Sc. and Ph.D. degrees in Electrical Engineering from Iran University of Science and Technology, Tehran, Iran, in 1998 and 2004, respectively. From 2000 to 2007, he was with power system studies group of Moshanir Company, Tehran, Iran. Currently, he is an Assistant Professor in Faculty of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran. His research interests are power system control and modeling, FACTS devices, artificial intelligence, application of optimization in power systems and distributed generation.



Alireza Rezazadeh received the B.Sc. degree in Electrical Engineering and M.Sc. in Electric Power Engineering from University of Tehran, Tehran, Iran, in 1990, 1993, respectively. He received his Ph.D. degree in Electric Power Engineering from University of Tehran with the collaboration of the Electrical Engineering Laboratory of the Institute National Polytechnic of Grenoble, France, in 1999. Currently he is an Associated Professor with the Shahid Beheshti University, Tehran, Iran. His main research interests are in the control and optimization power system.



Abolfazl Pirayesh received the B.Sc. degree in Electrical Engineering and M.Sc. degree in Electric Power Engineering from Sharif University of Technology, Tehran, Iran, in 1998 and 2000, respectively. He received his Ph.D. in Electric Power Engineering from Sharif University in 2006 with the collaboration of the Electrical Engineering Laboratory of the Institute National Polytechnic of Grenoble, France. Currently he is an Assistant Professor with Shahid Beheshti University, Tehran. His main research interests are in the areas of power system operations and planning and deregulation issues.