Economic Dispatch of Power System Using Particle Swarm Optimization with Constriction Factor

Shi Yao Lim, Mohammad Montakhab, and Hassan Nouri
Bristol Institute of Technology, University of The West of England, Bristol, UK
E-mail: limshiyao@gmail.com, Mohammad.Montakhab@uwe.ac.uk, Hassan.Nouri@uwe.ac.uk

***Abstract*—The problem of economic dispatch (ED) has been tackled and solved by numerous methods. This paper provides an alternative method to solve the problem. In this paper, the particle swarm optimization (PSO) based on constriction factor is used to solve the problem of economic dispatch in power system. The application of a constriction factor into PSO is a useful strategy to ensure convergence of the particle swarm algorithm. The feasibility of the proposed method is demonstrated and compared with the results of other methods i.e. genetic algorithms (GA), evolutionary programming (EP), modified PSO, and in particular improved PSO (IPSO). The results indicate the applicability of the proposed method to the practical ED problem.**

***Index Terms*—Constriction factor, economic dispatch, non-smooth optimization, particle swarm optimization**

I. Introduction

The economic dispatch (ED) of power generating units has always occupied an important position in the electric power industry. ED is a computational process where the total required generation is distributed among the generation units in operation, by minimizing the selected cost criterion, subject to load and operational constraints. For any specified load condition, ED determines the power output of each plant (and each generating unit within the plant) which will minimize the overall cost of fuel needed to serve the system load [1]. ED is used in real-time energy management power system control by most programs to allocate the total generation among the available units. ED focuses upon coordinating the production cost at all power plants operating on the system.

In the traditional ED problem, the cost function for each generator has been approximately represented by a single quadratic function and is solved using mathematical programming based optimization techniques such as lambda-iteration method, gradient-based method, etc[2]. These methods require incremental fuel cost curves which are piece-wise linear and monotonically increasing to find the global optimal solution. Unfortunately, the input-output characteristics of generating units are inherently highly non-linear due to valve-point loadings. Thus, the practical ED problem with valve-point effects is represented as a non-smooth optimization problem with equality and inequality constraints. This makes the problem of finding the global optimum solution challenging. Dynamic programming (DP) method [3] is one of the approaches to solve the non-linear and discontinuous ED problem, but it suffers from the problem of "curse of dimensionality" or local optimality. In order to overcome this problem, several alternative methods have been developed such as evolutionary programming (EP) [4], genetic algorithm (GA) [5], tabu search [6], neural network [7], and particle swarm optimization [8, 9].

Particle swarm optimization (PSO), a member of the wide category of swarm intelligence methods first introduced by James Kennedy and Russel C. Eberhart in 1995 [10], is one of the most powerful methods for solving global optimization problems. It was first inspired by social behavior of organisms such as fish schooling and bird flocking resulted in the possibilities of utilizing this behavior as an optimization tool [11]. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particle. Every particle finds its personal best position and the group best position through iteration, and then modifies their progressing direction and speed to reach the optimized position quickly. Because of the rapid convergence speed of PSO, it has been successfully applied in many areas.

Since its introduction, PSO has attracted much attention from researchers around the world. Many researchers have indicated that PSO often converges significantly faster to the global optimum but has difficulties in premature convergence, performance and the diversity loss in optimization process. Clerc [12], in his study on stability and convergence of PSO has indicated that use of a constriction factor may be necessary to innsure convergence of the particle swarm algorithm. His research indicated that the inclusion of properly defined constriction coefficients increases the rate of convergence; further, these coefficients can prevent explosion and induce particles to converge on local optima.

In this paper, a novel approach is proposed to solve the non-smooth ED problem with valve-point effect using the PSO with constriction factor. The application of a constriction factor into PSO is a useful strategy to ensure convergence of the particle swarm algorithm. Unlike other evolutionary computation methods, the proposed method ensures the convergence of the search procedure based on the mathematical theory. In order to verify its feasibility, the proposed method is tested on a three-generator power system and the results are compared with those of other methods and in particular the improved PSO (IPSO) [2] to demonstrate its performance. The results indicate the applicability of the proposed method to the practical ED problem.

The rest of the paper is structured as follows. The ED problem formulation is described in Section II. In Section III, the proposed PSO with constriction factor algorithm for solving the ED problem is explained. Section IV presents the simulation results and comparison with those of other methods. Finally, in Section V, conclusions are drawn, based on the results found from the simulation analyses in Section IV.

II. Economic Dispatch Formulation

A. Basic Economic Dispatch Formulation

The primary concern of an ED problem is the minimization of its objective function. The total cost generated that meets the demand and satisfies all other constraints associated is selected as the objective function. In general, the ED problem can be formulated mathematically as a constrained optimization problem with an objective function of the form:

$$F_T = \sum_{i=1}^{N} F_i(P_i) \tag{1}$$

where F_T is the total generation cost; N is the total number of generating units; F_i is the power generation cost function of the ith unit. Generally, the fuel cost of a thermal generation unit is considered as a second order polynomial function

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{2}$$

where P_i is the power of the ith generating unit; a_i, b_i, c_i are the cost coefficients of the ith generating unit. This model is subjected to the following constraints:

1) Real Power Balance Equation

For power balance, an equality constraint should be satisfied. The total generated power should be equal to total load demand plus the total losses

$$\sum_{i=1}^{N} P_i = P_{Demand} + P_{Loss} \tag{3}$$

where P_{Demand} is the total system demand and P_{Loss} is the total line loss. For simplicity, in this phase of the research, we assume that the losses are zero (i.e., $P_{Loss} = 0$).

2) Unit Operating Limits

There is a limit on the amount of power which a unit can deliver. The power output of any unit should not exceed its rating nor should it be below that necessary for stable operation. Generation output of each unit should lie between maximum and minimum limits. The corresponding inequality constraints for each generator are;

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{4}$$

where P_i is the output power of generator i; $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum power outputs of generator i, respectively.

B. Economic Dispatch with Valve-Point Effect

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions [2]. The valve opening process of multi-valve steam turbines produces a ripple-like effect in the heat rate curve of the generators. These "valve-points" are illustrated in Fig. 1.

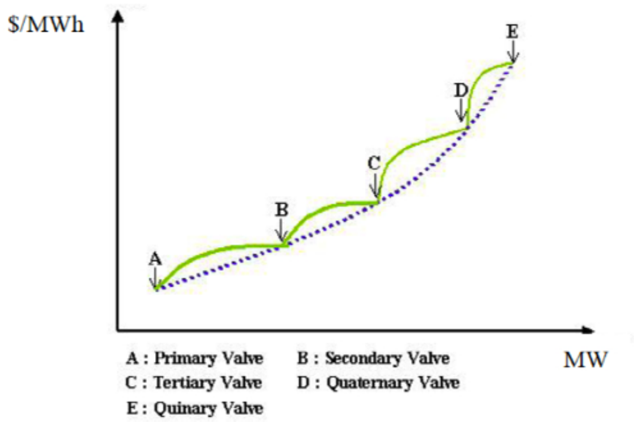

Fig. 1. Incremental fuel cost versus power output for a 5 valve steam turbine unit.

The significance of this effect is that the actual cost curve function of a large steam plant is not continuous but more important it is non-linear. The valve-point effects are taken into consideration in the ED problem by superimposing the basic quadratic fuel-cost characteristics with the rectified sinusoid component as follows:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin\left(f_i \times \left(P_{i,\min} - P_i\right)\right)\right| \tag{5}$$

where e_i and f_i are the coefficients of generator i reflecting valve-point effects.

III. Particle Swarm Optimization with Constriction Factor

A. Basic Concept of Particle Swarm Optimization

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Kennedy and Eberhart in 1995 [8,9], discovered through simplified social model simulation. It stimulates the behaviors of bird flocking involving the scenario of a group of birds randomly looking for food in an area. PSO is motivated from this scenario and is developed to solve complex optimization problems.

In the conventional PSO, suppose that the target problem has n dimensions and a population of particles, which encode solutions to the problem, move in the search space in an attempt to uncover better solutions. Each particle has a position vector of X_i and a velocity vector V_i. The position vector X_i and the velocity vector V_i of the ith particle in the n-dimensional search space can be represented as

$X_i = (x_{i1}, x_{i2}, ..., x_{in})$ and $V_i = (v_{i1}, v_{i2}, ..., v_{in})$, respectively. Each particle has a memory of the best position in the search space that it has found so far $(Pbest_i)$, and knows the best location found to date by all the particles in the swarm $(Gbest)$. Let $Pbest = (x_{i1}^{Pbest}, x_{i2}^{Pbest}, ..., x_{in}^{Pbest})$ and $Gbest = (x_1^{Gbest}, x_2^{Gbest}, ..., x_n^{Gbest})$ be the best position of the individual i and all the individuals so far, respectively. At each step, the velocity of the ith particle will be updated according to the following equation in the PSO algorithm:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \times \left(Pbest_i^k - X_i^k\right) + c_2 r_2 \times \left(Gbest^k - X_i^k\right) \quad (6)$$

where,

V_i^k	velocity of individual i at iteration k,
ω	inertia weight parameter,
c_1, c_2	acceleration coefficients,
r_1, r_2	random numbers between 0 and 1,
X_i^k	position of individual i at iteration k,
$Pbest_i^k$	best position of individual i at iteration k,
$Gbest^k$	best position of the group until iteration k.

In this velocity updating process, the acceleration coefficients c_1, c_2 and the inertia weight ω are predefined and r_1, r_2 are uniformly generated random numbers in the range of [0, 1]. In general, the inertia weight ω is set according to the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{Iter_{\max}} \times Iter \quad (7)$$

where,

$\omega_{\max}$, $\omega_{\min}$	initial and final inertia parameter weights,
$Iter_{\max}$	maximum iteration number,
$Iter$	current iteration number.

The approach using (7) is called the "inertia weight approach (IWA)" [13]. Using the above equations, diversification characteristic is gradually decreased and a certain velocity, which gradually moves the current searching point close to *Pbest* and *Gbest* can be calculated. Each individual moves from the current position (searching point in the solution space) to the next one by the modified velocity in (6) using the following equation:

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (8)$$

B. Constriction Factor Approach (CFA)

After Kennedy and Eberhart proposed the original particle swarm, a lot of improved particle swarms were introduced. The particle swarm with constriction factor is very typical. Clerc [14], in his study on stability and convergence of PSO have introduced a constriction factor, *K*. Clerc indicates that the use of a constriction factor may be necessary to insure convergence of the particle swarm algorithm. He established some mathematical foundation to explain the behavior of a simplified PSO model in its search for an optimal solution [14].

The basic system equations of the PSO (6-8) can be considered as a kind of difference equations. Therefore, the system dynamics, namely, the search procedure, can be analyzed by the Eigen value analysis and can be controlled so that the system has the following features:

a) The system converges,
b) The system can search different regions efficiently by avoiding premature convergence.

In order to insure convergence of the PSO algorithm, the velocity of the CFA can be expressed as follows:

$$V_i^{k+1} = K\left[V_i^k + c_1 r_1 \times \left(Pbest_i^k - X_i^k\right) + c_2 r_2 \times \left(Gbest^k - X_i^k\right)\right] \quad (9)$$

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \text{ where } \varphi = c_1 + c_2, \ \varphi > 4 \quad (10)$$

The convergence characteristic of the system can be controlled by φ. In the CFA, φ must be greater than 4.0 to guarantee stability. However, as φ increases, the constriction factor K decreases and diversification is reduced, yielding slower response. Typically, when the constriction factor is used, φ is set to 4.1 (i.e. $c_1, c_2 = 2.05$) and the constant multiplier K is thus 0.729.

The CFA results in convergence of the individuals over time. Unlike other evolutionary computation methods, the CFA ensures the convergence of the search procedure based on the mathematical theory. Thus, the CFA can generate higher quality solutions than the basic PSO approach.

C. PSO with Constriction Factor for ED Problems

In this section, the PSO with constriction factor algorithm will be described in solving the ED problem. Details on how to deal with the equality and inequality constraints of the ED problem when modifying each individual's searching point are based on the improved PSO (IPSO) method proposed by J. B. Park [2]. In subsequent sections, the detailed implementation strategies of the proposed method are described.

1) Initialization of Individuals

In the initialization process, a set of individuals (i.e. a group) is created at random within the system constraints. In this paper, an individual for the ED problem is composed of a set of elements (i.e., generator outputs). Thus, individual i at iteration 0 can be represented as the vector $P_i^0 = (P_{i1}, ..., P_{in})$ where n is the number of generators. The velocity of individual i at iteration 0 can be represented as the vector $V_i^0 = (V_{i0}, ..., V_{in})$ and this corresponds to the generation update quantity covering all generators. The elements of position and velocity have the same unit (i.e., MW) in this case. Note that individuals initialized must satisfy the equality constraint (3) and inequality constraints (4) defined in Section II. That is, the sum of all elements of individual i (i.e.,

$\sum_{j=1}^{n} P_{ij}$) should be equal to the total system demand (i.e., P_{Demand}) neglecting transmission losses (i.e., $P_{Loss}=0$) and the created element j of individual i at random (i.e., P_{ij}) should be located within its boundary. Unfortunately, the created position of an individual is not always guaranteed to satisfy the inequality constraints (4). Provided that any element of an individual violates the inequality constraints then the position of the individual is fixed to its maximum/minimum operating point as follows:

$$P_{ij}^{k+1}\begin{cases} P_{ij}^{k}+V_{ij}^{k+1} & if \quad P_{ij,\min} \le P_{ij}^{k}+V_{ij}^{k+1} \le P_{ij,\max} \\ P_{ij,\min} & if \quad P_{ij}^{k}+V_{ij}^{k+1} < P_{ij,\min} \\ P_{ij,\max} & if \quad P_{ij}^{k}+V_{ij}^{k+1} > P_{ij,\max} \end{cases} \tag{11}$$

Although the previously mentioned method always produces the position of each individual satisfying the required inequality constraints (4), the problem of satisfying the equality constraint (3) still remains to be solved. Thus, it is necessary to employ a strategy suggested in the IPSO paper such that the summation of all elements in an individual is equal to the total system demand [2]. The following procedure is employed for any individual in a group:

Step 1) Set $j=1$.

Step 2) Select an element (i.e., generator) of individual i at random and store in an index array $A(n)$.

Step 3) Create the value of the element (i.e., generation output) at random satisfying its inequality constraints.

Step 4) If $j=n-1$ then go to Step 5, otherwise $j=j+1$ and go to Step 2.

Step 5) The value of the last element of individual i is determined by subtracting $\sum_{j=1}^{n-1} P_{ij}$ from the $Demand$. If the value is within its boundary then go to Step 8, otherwise adjust the value using (11).

Step 6) Set $l=1$.

Step 7) Readjust the value of element l in the index array $A(n)$ to the value satisfying the equality constraint (i.e., $Demand-\sum_{\substack{j=1\\ j\ne l}}^{n} P_{ij}$). If the value is within its boundary then go to Step 8; otherwise, change the value of element l using (11). Set $l=l+1$, and go to Step 7. If $l=n+1$, go to Step 6.

Step 8) Stop the initialization process.

After creating the initial position of each individual, the velocity of each individual is also created at random. The following strategy is used in creating the initial velocity:

$$P_{ij,\min}-P_{ij}^{0} \le V_{ij} \le P_{ij,\max}-P_{ij}^{0} \tag{12}$$

The velocity element j of individual i is generated at random within the boundary.

The initial $Pbest$ of individual i is set as the initial position of individual i and the initial $Gbest$ is determined as the position of the individual with minimum payoff of equation (1).

2) *Updating The Velocity and Position of Individuals*

In order to modify the position of each individual, it is necessary to calculate the velocity of each individual in the next stage (i.e., generation). This can be calculated using equations (9) and (10). When the search algorithm in the proposed method looks for an optimal solution in a solution space, it has a velocity multiplied by the constriction factor K of equation (10) instead of ω in the basic PSO. Then velocity of each individual is restricted in the range of [-Vmax, Vmax] where Vmax is the maximum velocity. This prevents excessively large steps during the initial phases of the search.

The position of each individual is modified by equation (8). Since the resulting position of an individual is not always guaranteed to satisfy the equality and inequality constraints, the modified position of an individual is adjusted by (11). Additionally, it is necessary for the position of an individual to satisfy the equality constraint (3) at the same time. To resolve the equality constraint problem without intervening the dynamic process inherent in the PSO algorithm, the following heuristic procedures are employed:

Step 1) Set $j=1$.

Step 2) Select an element (i.e., generator) of individual i at random and store in an index array $A(n)$.

Step 3) Modify the value of element j using (8), (9), and (11).

Step 4) If $j=n-1$ then go to Step 5, otherwise $j=j+1$ and go to Step 2.

Step 5) The value of the last element of individual i is determined by subtracting $\sum_{j=1}^{n-1} P_{ij}$ from the $Demand$. If the value is not within its boundary then adjust the value using (11) and go to Step 6, otherwise go to Step 8.

Step 6) Set $l=1$.

Step 7) Readjust the value of element l in the index array $A(n)$ to the value satisfying the equality constraint (i.e., $Demand-\sum_{\substack{j=1\\ j\ne l}}^{n} P_{ij}$). If the value is within its boundary then go to Step 8; otherwise, change the value of element l using (11). Set $l=l+1$, and go to Step 7. If $l=n+1$, go to Step 6.

Step 8) Stop the modification procedure.

The fuel cost for each individual considering the valve-point effect is calculated based on (5). The objective function of individual i is obtained by summing the fuel cost for each generator in the system as shown in (1).

3) *Updating Pbest and Gbest of Individuals.*

The *Pbest* of each individual at iteration $k+1$ is updated as follows:

$$Pbest_{ij}^{k+1} = X_{ij}^{k+1} \quad if \quad F_i^{k+1} < F_i^k \tag{13}$$

$$Pbest_{ij}^{k+1} = Pbest_i^k \quad if \quad F_i^{k+1} > F_i^k \tag{14}$$

where,

F_i^k the objective function evaluated at the position of individual i at iteration k,

X_{ij}^{k+1} position of individual i at iteration $k+1$,

$Pbest_{ij}^{k+1}$ best position of individual i until iteration $k+1$.

(13) and (14) compares the *Pbest* of every individual with its current fitness value. If the new position of an individual has better performance than the current *Pbest*, the *Pbest* is replaced by the new position. In contrast, if the new position of an individual has lower performance than the current *Pbest*, the *Pbest* value remains unchanged. Additionally, the $Gbest_{ij}^{k+1}$ global best position at iteration $k+1$ is set as the best evaluated position among $Pbest_{ij}^{k+1}s$.

4) *The Stopping Criteria*

The proposed method is terminated if the iteration approaches a predefined criteria, usually a sufficiently good fitness or in this case, a predefined maximum number of iterations (generations).

IV. Case Studies

In order to verify the feasibility of the proposed method, and make a comparison with the improved PSO (IPSO) method researched by J. B. Park [2], a three-generator power system was tested. In both cases, the test system is composed of three generating units and the input data of the 3-generator system are as given in Table I. The valve-point effects are considered and the transmission loss is omitted. The total demand for the system is set to 850MW.

TABLE I
DATA FOR TEST CASE (3-UNIT SYSTEM)

Unit	a_i	b_i	c_i	e_i	f_i	Pi,min	Pi,max
1	561	7.92	0.001562	300	0.0315	100	600
2	310	7.85	0.001940	200	0.0420	100	400
3	78	7.97	0.004820	150	0.0630	50	200

A. *Case I*

In order to simulate the proposed method, some parameters must be assigned and are as follows:

- Number of particles = 50;
- Maximum generation number = 10000;
- The convergence rate of the system is controlled by φ. In this case, φ is set to 4.1 (i.e. c_1, $c_2 = 2.05$) and the constriction factor K is thus 0.729.

The obtained results for the three-generator system using the proposed method are given in Table II and the results are compared with those from GA [5], EP [4], MPSO [15], and IPSO [2]. As shown in Table II, the proposed method has outperformed GA and has provided the same optimal solution as obtained by EP, MPSO and IPSO.

TABLE II
COMPARISON OF SIMULATION RESULTS OF EACH METHOD CONSIDERING VALVE-POINT EFFECT (3-UNIT SYSTEM)

Unit	GA	EP	MPSO	IPSO	CFPSO
1	300.00	300.26	300.27	300.27	300.27
2	400.00	400.00	400.00	400.00	400.00
3	150.00	149.74	149.73	149.73	149.73
TP	850.00	850.00	850.00	850.00	850.00
TC	8237.60	8234.07	8234.07	8234.07	8234.07

TP: TOTAL POWER [MW], TC: TOTAL GENERATION COST [$],
CFPSO: CONSTRICTION FACTOR BASED PSO

B. *Case II*

In this case, the maximum number of generations is set to 100 and the number of particles limited to 5. In order to further test the performance of the proposed method when compared to the IPSO in solving the non-smooth ED problem with valve-point effect, both methods were applied on a three-generator system where the fitness of the best particle for each method was being investigated.

The criterion for the comparison is the achievement of the best cost of 8234.07 [$] in the shortest generation. In addition to that, observations were made on the best, mean, and worst costs, and standard deviation. Fig. 2 shows the fitness value of the best particle for both methods and Table III summarizes the results of both simulations.

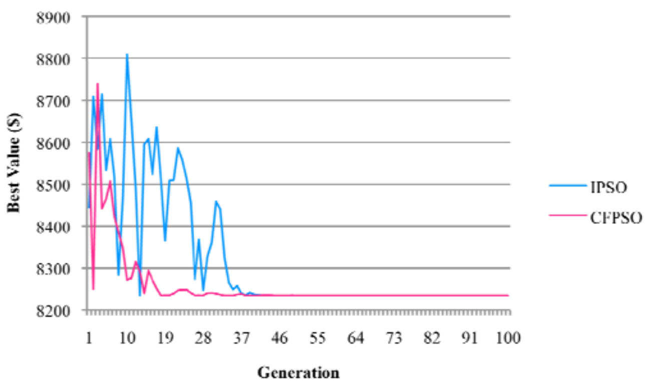

Fig. 2. Fitness of the best particles for the IPSO and CFPSO.

TABLE III
DETAILED COMPARISON OF THE IPSO AND CFPSO
(3-UNIT SYSTEM, 5 PARTICLES, AND 100 GENERATIONS)

	Cost [$]			STD	BCG
	Best	**Mean**	**Worst**		
IPSO	8234.07	8319.90	8810.15	145.42	47
CFPSO	8234.07	8258.45	8739.77	76.12	45

STD: STANDARD DEVIATION, BCG: BEST COST GENERATION NO.

The simulation results indicate that the proposed method exhibits good performance. As seen in Table III, the proposed method finds the cheapest cost faster than the IPSO. From Fig.

2, it can be observed that the IPSO suffers from a lot of fluctuations in reaching the optimal result in different generations. In this respect the superiority of the proposed method is quite evident.

V. CONCLUSION

This paper presents a novel approach for solving the non-smooth ED problem with valve-point effects based on the PSO with constriction factor. The proposed method includes a constriction factor K into the velocity updating equation, which has an effect of reducing the velocity of the particles as the search progresses thereby ensures convergence of the particle swarm algorithm. The appropriate parameter values for the ED by the constriction factor approach are the same as those recommended by other PSO papers. The robust convergence characteristic of the proposed method is also ensured in solving the ED problem.

Simulation results on the three-generator system demonstrate the feasibility and effectiveness of the proposed method in minimizing cost of the generation. The results also show that improvements were made to solve the ED problem more effectively. Finally, it has been demonstrated that the proposed algorithm improves the convergence and performs better when compared with the improved PSO (IPSO).

VI. REFERENCES

[1] A. J. Wood and B. F. Wollenberg, *Power Generation, Operation and Control, 2nd Edition*, New York: John Wiley & Sons, 1996.

[2] J. B. Park, K. S. Lee, J. R. Shin and K. Y. Lee, "A particle swarm optimization for economic dispatch with nonsmooth cost functions", *IEEE Trans. on Power Systems*, Vol. 8, No. 3, pp. 1325-1332, Aug. 1993.

[3] Z. X. Liang and J. D. Glover, "A zoom feature for a dynamic programming solution to economic dispatch including transmission losses", *IEEE Trans. on Power Systems*, Vol. 7, No. 2, pp. 544-550, May 1992.

[4] H. T. Yang, P. C. Yang and C. L. Huang, "Evolutionary programming based economic dispatch with the valve point loading", *IEEE Trans. on Power Systems*, Vol. 11, No. 1, pp. 112-118, Feb. 1996.

[5] D. C. Walters and G. B. Sheble, "Genetic algorithm solution of economic dispatch with the valve-point loading", *IEEE Trans. on Power Systems*, Vol. 8, No. 3, pp. 1325-1332, Aug. 1993.

[6] W. M. Lin, F. S. Cheng and M. T. Tsay, "An improved Tabu search for economic dispatch with multiple minima", *IEEE Trans. on Power Systems*, Vol. 17, No. 1, pp.108-112, Feb. 2002.

[7] K. Y. Lee, A. Sode-Yome and J. H. Park, "Adaptive Hopfield neural network for economic load dispatch", *IEEE Trans. on Power Systems*, Vol. 13, No. 2, pp. 519-526, May 1998.

[8] R. C. Eberhart and Y. Shi, "Comparing inertia weights and constriction factors in particle swarm optimization", *Proceedings of the 2000 Congress on Evolutionary Computation*, Vol. 1, pp. 84-88, 2000.

[9] Y. Shi and R. C. Eberhart, "Particle swarm optimization: developments, applications, and resources", *Proceedings of the 2001 Congress on Evolutionary Computation*, Vol. 1, pp. 81-86, 2001.

[10] J. Kennedy and R. C. Eberhart, "Particle swarm optimization", *Proceedings of IEEE International Conference on Neural Networks (ICNN'95)*, Vol. IV, pp. 1942-1948, Perth, Australia, 1995.

[11] Z. L. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints", *IEEE Trans. on Power Systems*, Vol. 18, No. 3, pp. 1187-1195, Aug. 2003.

[12] M. Clerc, "The swarm and the queen: towards a deterministic and adaptive particle swarm optimization," *Proceedings of the 1999 Congress on Evolutionary Computation*, Vol. 3, pp. 1951-1957, 1999.

[13] J. Kennedy and R. C. Eberhart, *Swarm Intelligence*. San Francisco, CA: Morgan Kaufmann, 2001.

[14] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE Trans. on Evolutionary Computation*, Vol. 6, No. 1, pp. 58-73, Feb. 2002.

[15] Y. H. Hou, L. J. Lu, X. Y. Xiong, and Y. W. Wu, "Economic dispatch of power systems based on the modified particle swarm optimization algorithm", *Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005 IEEE/PES*, pp. 1-6, 2005.

BIOGRAPHIES

Shi Yao Lim received BEng (Hons) degree in electrical and electronic engineering in 2009 from University of the West of England, Bristol, United Kingdom. His main research interests include power system optimization, artificial intelligence in power system, loss minimization and power system reliability.

Dr Mohammad Montakhab is a member of the Power Systems and Electronics Research Group (PSERG) at the University of the West of England, Bristol, UK. After receiving his Master degree in electrical engineering in Iran he worked for eight years as the Chief Dispatcher of power systems control centre in Iran In 1984 he came to the United Kingdom and after receiving his PhD he worked for several years in the universities of London and Exter before joining the University of West of England. As part of his international activities he was general chair of the AIESP06 Conference which was held in 2006 in Portugal and currently he is Chief Editor of the International Journal of Innovations in Energy Systems and Power. His main research interests is application of artificial intelligence in power systems.

Dr Hassan Nouri is currently a Reader in electrical power and energy and Director of the Power Systems and Electronics Research Group at the University of the West of England, Bristol, UK. He is Chairman of the European Electromagnetic User Group EEUG and also a Senior Member of IEEE. His research interests include the analysis of power systems, electric arc phenomena, power electronics, neural networks, fuzzy logic and application of finite elements in Power Engineering.