Pertanika J. Sci. & Technol. 25 (S): 275 - 286 (2017)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Adaptive Particle Swarm Optimisation for Solving Non-Convex Economic Dispatch Problems

Nurhafizah Jamain[1], Ismail Musirin[1], Mohd Helmi Mansor[2]*, Muhammad Murtadha Othman[1] and Siti Aliyah Mohd Salleh[2]

[1]*Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM), Shah Alam, Selangor, Malaysia*
[2]*Department of Electrical Power Engineering, College of Engineering, UNITEN, Kajang, Selangor, Malaysia*
[3]*Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM), Pasir Gudang, Johor, Malaysia*

ABSTRACT

This paper presents adaptive particle swarm optimization for solving non-convex economic dispatch problems. In this study, a new technique was developed known as adaptive particle swarm optimization (APSO), to alleviate the problems experienced in the traditional particle swarm optimisation (PSO). The traditional PSO was reported that this technique always stuck at local minima. In APSO, economic dispatch problem are considered with valve point effects. The search efficiency was improved when a new parameter was inserted into the velocity term. This has achieved local minima. In order to show the effectiveness of the proposed technique, this study examined two case studies, with and without contingency.

Keywords: Adaptive Particle Swarm Optimization (APSO), economic dispatch, valve-point effects

INTRODUCTION

The aim to achieve secure power delivery with minimal cost is important. Thus, economic dispatch has become an important issue in power system operation and planning. Optimal results within the generators in a system need to be achieved at the lowest possible cost, operational constraints and subject to transmission (Momoh, 2001; Wood & Wollenberg, 1996). The US Energy Policy Act of 2005 defines economic dispatch as "the operation of generating facilities to produce energy at the lowest cost to reliably serve consumers, recognizing any operational limits of generation and transmission facilities"

ARTICLE INFO

Article history:
Received: 28 September 2016
Accepted: 03 February 2017

E-mail addresses:
norhafizahjamain@yahoo.com (Norhafizah Jamain),
ismailbm@salam.uitm.edu.my (Ismail Musirin),
mhelmi@uniten.edu.my (Mohd Helmi Mansor),
mamat505my@yahoo.com (Muhammad Murtadha Othman),
aliyah385@johor.uitm.edu.my (Siti Aliyah Mohd Salleh)
*Corresponding Author

ISSN: 0128-7680

(109th Congress, 2005). Economic dispatch is the short-term determination of the optimal output of a number of electricity generation facilities, to meet the system load, at the lowest possible cost, subject to transmission and operational constraints and has non-convex characteristics (Lee & EI-Sharkawi, 2002). Characteristics of the input-output of generating units are not smooth due to valve-point loadings, prohibited operating zones and multi-fuel effects. Solving this problem using mathematical methods requires presentation as a non-convex optimisation problem with constraints (Park, Jeong, Shin, & Lee, 2010). Yare et al. introduced Heuristic Algorithms for solving convex and non-convex economic dispatch. Three heuristic algorithms, namely genetic algorithm, differential evolution and modified particle swarm optimisation, have been introduced to solve economic dispatch problem. The modified particle swarm optimisation offer a better solution to solve economic dispatch problem in terms of locating optimal solution compared with genetic algorithm and differential evolution (Yare, Venayagamoorthy, & Saber, 2009). Lin, Cheng and Tsay (2001) have applied integrated artificial intelligence which is evolutionary programming, tabu search and quadratic programming methods for solving non-convex economic dispatch problem. Based on the results, the proposed methods are effective compared with the previous evolutionary computation algorithm (Lin, Cheng, & Tsay, 2001). In the past few decades, many different methods have been developed to solve economic dispatch problems, such as gradient method, Newton method, lambda iteration, linear programming and quadratic programming method. However, most of these methods cannot solve non-convex economic dispatch problem and highly nonlinear solution space due to the curse of dimensionality or local optimality (Abdullah, Bakar, Rahim, Jamian, & Aman, 2012). Modern heuristic algorithm such as evolutionary programming (Yang, Yang, & Huang, 1996), genetic algorithm (Chen & Chang, 1995), simulated annealing, Hopfield neural network, evolutionary strategy optimisation, differential evolution, bacterial foraging algorithm, ant colony optimisation, tabu search (Lin et al., 2001), artificial immune system and particle swarm optimisation show potential to solve complex economic dispatch problems. Though these methods cannot guarantee to find global optima, they often achieve a near global optimal solution (Abdullah et al., 2012). Particle swarm optimisation (PSO) is a modern heuristic algorithm that is widely implemented in the economic dispatch problem because of the less storage requirement, simple implementation and able to find a global optimum solution. The PSO was introduced by Kennedy and Eberhart in 1995, inspired by the group behaviour of animals such as bird flocks or fish schools (Harman, 1995). It is also suitable to solve large scale of non-convex optimisation problems due to its simplicity (Basu, 2015). However, PSO still has disadvantages such as insufficient capability to find nearby extreme points, lack of efficient mechanism to treat constraints and local optimal trapping due to premature convergence (Park et al., 2010).

This paper presents adaptive particle swarm optimization (APSO) to solve non-convex economic dispatch problem. In this study, a new parameter on velocity has been added to enhance search efficiency. In addition, local minimum has been achieved without exacerbating the speed of convergence and the quality of the structure of the particle swarm optimisation. To show effectiveness of the proposed algorithm, two case studies, namely with and without contingency, are examined in this study. Classical particle swarm optimization methods were also compared.

METHOD

Problem Formulation

This section describes the objective function for the optimisation process and relevant mathematical equation of economic dispatch.

Objective Function

Cost minimisation of thermal generator is the main objective in economic dispatch. Various constraints need to be satisfied for this reason. Determination of optimal combination of power output to meet the demand at minimum cost while satisfying the constraints are also considered. The fuel cost production is given in (2):

$$\text{Minimize } Ft = \sum_{i=1}^{N} Fi\ (Pi) \quad i = 1,2, \ldots, N \qquad [1]$$

$$\text{Min} \sum_{i=1}^{N} Fi(Pi) = \sum_{i=1}^{N} ai + biPi + ciPi^2 \qquad [2]$$

where:

Ft	:	total generation cost;	N	:	number of committed generators;
Fi	:	fuel cost for generator i;	Pi	:	power output of ith generating unit.
aj, bj, cj	:	cost coefficients of ith generating unit;			

The APSO is proposed to address economic dispatch problems considering valve point effects. Ripple in the heat rate function due to valve-point effects can result in the fuel cost function have multiple local optima, discontinuous and highly non-linear. Therefore, the cost function (2) considering valve-point effects can be described as follows:

$$\text{Min} \sum_{i=1}^{N} Fi(Pi) = \sum_{i=1}^{N} ai + biPi + ciPi^2 + |ei \text{ x } \sin(fi \text{ x } (Pi, min - Pi)| \qquad [3]$$

where di and ei are the fuel cost coefficients of generator i with valve-point effects.

Equality and Inequality Constraints

Power balance equation. Power balance equation represents the relationship between the total generated power, load power and total transmission loss. The total generated power must be equal to total load demand and total transmission loss.

$$\sum_{i=1}^{N} Pi = Pload + Ploss \qquad [4]$$

Where Pload is the total load demand and Ploss is total transmission loss. The transmission loss can be represented using B coefficients as follows:

$$Ploss=\sum_{i=1}^{N}\sum_{j=1}^{N} Pi\ Bij\ Pj + \sum_{i=1}^{N} Boi\ Pi + Boo \quad [5]$$

where Bij, Boj and Boi are B coefficients.

Minimum and maximum power limits. Corresponding inequality constraint for each generator power output should be within its minimum and maximum limits such as

$$Pi,min \leq Pi \leq Pi,max \quad [6]$$

where Pi,min and Pi,max are minimum and maximum limit output of generator i.

Optimisation Techniques

In this section, algorithms for optimisation techniques, namely the particle swarm optimization (PSO) and the proposed adaptive particle swarm optimization (APSO), are explained.

Particle Swarm Optimization (PSO). Particle Swarm Optimization (PSO) is an optimisation technique based on swarm algorithm. It emulates the behaviour of animals such as bird flocks or fish schools (Harman, 1995). Additionally, it is an optimisation tool that provides a population-based search algorithm. It also searches in parallel style using a group of particles and each particle represents a solution to the problem. Particles change their states or positions with time and fly in multidimensional search space. Each particle approaches the optimum point through present velocity, previous experience and experience of its neighbours. The position and velocity of particle i in n-dimensional search space are represented as vectors $X_i = (x_{i1},..., x_{in})$ and $V_i = (v_{i1},\ldots,v_{in})$ respectively. The updated velocity and position of each particle are calculated as follows:

$$V_i^{(k+1)} = w.V_i^k + c_1.rn_1.\left(Pbest_i^k - X_i^k\right) \quad + c_2.rn_2.\left(Gbest^k - X_i^k\right) \quad [7]$$

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

where:

V_i^k : velocity of particle i at iteration k; rn_1, rn_2 : random numbers between 0 and 1
W : inertia weight factor; X_i^k : position of particle i at iteration k
c_1, c_2 : acceleration coefficients;

Rate of convergence for PSO algorithm depends on the inertia weight factor, w. This parameter is used based on descending linear function. The mathematical relationship for w is expressed by the following equation: -

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \text{ x } iter \qquad [9]$$

Where iter is the current iteration, $iter_{max}$ is the maximum iteration number and wmax and wmin are maximum and minimum value of weighting factor respectively.

Proposed Adaptive Particle Swarm Optimization (APSO). The PSO performance is affected by variation of its parameters, in particular the inertia weight and two acceleration coefficients. Modification of equation (7) is done by incorporating momentum for particles to search for broader space. The proposed updated velocity of APSO is given by the following relationship: -

$$V_i^{(k+1)} = w.V_i^k + rand(1).rn_1.\left(Pbest_i^k - X_i^k\right) + rand(1).rn_2.\left(Gbest^k - X_i^k\right) \qquad [10]$$

Acceleration coefficients of c_1 and c_2 are random in nature ranging from 0 to 1.

$$0 \leq c_1 \leq 1 \qquad i.e: \quad c_1 = rand(1) \qquad [11]$$

$$0 \leq c_2 \leq 1 \qquad i.e: \quad c_2 = rand(1) \qquad [12]$$

Algorithm of APSO for Economic Dispatch Problem with Valve-Point Effects

Figure 1 is, the flowchart of the proposed APSO algorithm and the mechanics describe how to solve economic dispatch problem with valve-point effects.

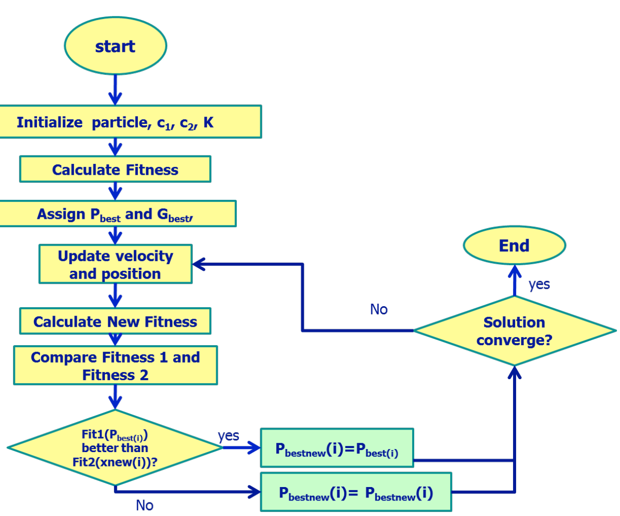

Figure 1. Flowchart of Adaptive Particle Swarm Optimization (APSO)

The steps are as follows: -

Step 1: Initialise the particle's parameters randomly, such as position, velocity, iteration number and counter. The number of generating units in economic dispatch problem is the dimension in APSO. The initial velocity is set to zero. The ith particle for n-dimension is represented as:

$$P_i = (P_{i1}, P_{i2}, \dots, P_{in}) \quad [13]$$

The particles of each dimension are generated randomly within the minimum and maximum bound as given in equation (14): -

$$P_i = r \times (P_{max} - P_{min}) + P_{min}) \quad [14]$$

Step 2: Objective function evaluation: In this step, computation of fitness for each particle is performed in order to determine whether the fitness needs to be minimised or vice versa. Minimisation of the fitness value is the objective function of the study which correlates with cost minimisation. In short, the objective function is minimisation of the fitness values in the problem formulations. The fitness equation is expressed below:-

$$f(P_i) = \sum_{i=1}^{N} Fi(Pi) + k|\sum_{i=1}^{N} Pi - P_D - P_L| \quad [15]$$

Where k is penalty parameter, P_i is input power of generator at bus i, P_D is load demand at bus i and P_L is loss at bus i.

Step 3: Assign pbest and gbest are identified. From the whole population, pbest will be identified which is in matrix form. Pbest is identified after the population undergoes selection.

Step 4: Update the velocity and position of each particle by using equation (10).

Step 5: Fitness evaluation (Fitness 2). Second fitness calculation is performed in order to evaluate their values once they have undergone updating process.

Step 6: Compare Fitness 1 and Fitness 2 values. In this phase, new values for pbest and gbest will be deduced.

Step 7: Stopping criterion test. After number of iteration is reached, APSO algorithm will be terminated. If otherwise, otherwise goes to step 4.

RESULTS AND DISCUSSION

Two case studies with contingency and without contingency were examined to show effectiveness of the proposed APSO technique. For each test system, 10 runs were conducted to minimise total fuel cost subjected to various constraints in a power system. The generator's real power limits are:

Table 1
Generator real power limits

Gen.	Min. MW	Max. MW
1	100	500
2	50	200
3	80	300
4	50	150
5	50	200
26	50	120

Case Study 1: Normal condition

In this case, 26 generator bus with valve-point effects was examined. The values for c_1 and c_2 were set to 2 for PSO technique, while in APSO c_1 and c_2 were set to random value from 0 to 1. The idea is to use the best value of acceleration coefficients which is 2. It is used to avoid premature convergence using the full range of the search space with low social coefficient. The iteration was set to 300 in both methods. 10 runs have been done to get the best cost and to calculate the average cost of the system. Table 2 and Table 3 tabulate the results of the PSO and APSO for 10 runs respectively.

Table 2
Results of the PSO for 10 runs in normal condition

No. of runs	*e*	*f*	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P26 (MW)	Gbest ($)
1	0.9364	0.6326	441.74	169.95	278.05	134.47	177.47	74.21	15447
2	0.5976	0.7745	440.82	165.48	261.41	127.66	200.00	80.49	15453
3	0.8866	0.4188	428.72	165.06	300.00	134.57	161.94	85.76	15447
4	0.4342	0.3691	488.91	127.17	256.37	116.29	167.54	120.00	15461
5	0.6244	0.547	423.89	179.28	256.75	126.88	169.31	120.00	15461
6	0.211	0.7667	449.70	200.00	257.93	129.41	168.19	70.72	15456
7	0.6323	0.0517	463.92	169.52	237.66	134.69	200.00	69.95	15453
8	0.3667	0.6112	432.82	165.73	257.93	150.00	187.92	81.17	15449
9	0.9565	0.0426	441.77	176.38	257.08	150.00	169.94	80.46	15449
10	0.8408	0.3715	445.03	143.86	252.92	150.00	164.02	120.00	15467

It consists of the coefficient of c_1, c_2, e and f, output generator which is P1, P2, P3, P4, P5 and P26 and the value of Gbest. The coefficients of c_1, c_2, e and f are in the ranges.

All of the output generators are in the generator real power limits. Table 4 shows a comparison of performance for PSO and APSO after 10 runs. From the results, PSO and APSO have the same value of best cost which is $15447. However, APSO shows lower average cost compared with PSO, which is $15447.3. It means APSO have achieved the global optimum solution as compared to PSO. The new acceleration coefficients in the APSO method can enhance search ability and minimise the fuel cost subjected to the various constraints of a power system.

Table 3
The result of the APSO for 10 runs in normal condition

No. of runs	*c1*	*c2*	*e*	*f*	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P26 (MW)	Gbest ($)
1	0.7725	0.411	0.9871	0.8752	445.48	170.57	262.05	133.65	175.73	88.36	15447
2	0.8322	0.1784	0.2839	0.0093	445.85	171.19	263.65	132.15	177.19	85.82	15447
3	0.6701	0.3788	0.0233	0.9787	446.11	170.94	263.57	134.13	175.59	85.49	15447
4	0.8935	0.8668	0.7143	0.3494	448.76	167.69	258.36	139.37	176.91	84.65	15447
5	0.1992	0.6033	0.8737	0.6297	481.11	166.94	253.02	150.00	174.73	50.00	15449
6	0.2472	0.6309	0.3465	0.5762	445.11	174.40	264.28	132.66	173.31	86.11	15447
7	0.6135	0.7282	0.8803	0.9149	448.09	169.83	264.40	131.56	176.75	85.22	15447
8	0.9994	0.9554	0.7175	0.9087	447.69	170.43	260.02	134.29	179.14	84.23	15447
9	0.7408	0.7437	0.0905	0.9543	446.87	171.09	261.97	135.61	176.97	83.29	15447
10	0.9189	0.5654	0.9147	0.5171	443.42	172.10	257.85	143.16	176.10	83.07	15448

Table 4
Comparison of performance for PSO and APSO in normal condition

Method	Worst cost ($)	Best cost ($)	Average cost ($)
PSO	15467	15447	15454.3
APSO	15449	15447	15447.3

Table 5
The results of the PSO for 10 runs with contingency

No. of runs	*e*	*f*	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P26 (MW)	Gbest ($)
1	0.7142	0.7477	449.45	171.73	259.57	138.17	175.97	81.24	15452
2	0.7411	0.2215	453.29	200.00	243.12	131.72	169.67	78.51	15461
3	0.2309	0.6416	444.95	167.58	256.40	150.00	172.64	84.39	15454
4	0.7507	0.0538	447.13	170.89	263.28	134.53	175.21	85.14	15452
5	0.1714	0.5278	421.56	184.21	260.10	150.00	171.03	89.08	15454
6	0.2324	0.5619	446.16	171.25	258.88	137.33	177.02	85.47	15452
7	0.5014	0.6109	437.31	200.00	242.44	116.63	160.37	####	15481
8	0.1589	0.7631	440.72	142.41	300.00	124.40	200.00	68.93	15479
9	0.4725	0.8258	451.07	176.84	267.56	150.00	180.68	50.00	15465
10	0.5417	0.3579	476.67	145.33	257.58	133.05	176.68	86.96	15452

Case Study 2: Contingency condition

In this case, 26 generator bus with valve-point effects was examined. For PSO method, c_1 and c_2 values were set to 2 while in APSO c_1 and c_2 were set to random value which is from 0 to 1. The idea is to use the best value of acceleration coefficients which is 2. It is used to avoid premature convergence using the full range of the search space with low social coefficient. The iteration was set to 300 in both methods. Ten runs were done to get the best cost and to calculate the average cost of the system. Table 5 and Table 6 show the results of PSO and APSO for 10 runs respectively. It consists of the coefficient of c_1, c_2, e and f, output generator which is P1, P2, P3, P4, P5 and P26 and the value of Gbest. The coefficients of c_1, c_2, e and f are between the ranges. All of the output generators are in the range of the generator real power limits.

Table 6
The results of the PSO for 10 runs with contingency

No. of runs	*c1*	*c2*	*e*	*f*	P1 (MW)	P2 (MW)	P3 (MW)	P4 (MW)	P5 (MW)	P26 (MW)	Gbest ($)
1	0.7873	0.1716	0.4236	0.784	446.53	174.59	260.30	135.67	177.89	81.17	15452
2	0.1153	0.5452	0.4553	0.118	444.56	169.53	266.22	134.77	186.11	74.98	15452
3	0.5141	0.9474	0.0921	0.732	447.97	172.30	262.27	136.10	174.42	83.10	15451
4	0.6126	0.582	0.1081	0.793	446.23	170.58	263.11	139.19	176.38	80.63	15452
5	0.9747	0.6514	0.9751	0.981	447.00	171.18	260.41	136.93	175.66	84.96	15451
6	0.2291	0.7643	0.4568	0.132	431.61	164.91	265.19	137.46	200.00	76.93	15458
7	0.0619	0.9838	0.98	0.624	444.51	152.32	246.22	145.99	200.00	86.98	15459
8	0.0245	0.9388	0.8024	0.329	446.92	176.69	248.26	150.00	173.59	80.57	15455
9	0.3766	0.5573	0.3791	0.258	439.52	167.62	261.43	129.62	200.00	78.00	15458
10	0.9042	0.6085	0.8656	0.785	438.49	166.31	259.13	135.52	200.00	76.66	15458

Table 7 compares performance for PSO and APSO after 10 runs with contingency. From the results, APSO methods displayed minimal cost compared with PSO which is $15451. This means APSO achieved global optimum solution compared to PSO. The new acceleration coefficients in the APSO method can enhance search ability and minimise fuel cost subjected to various constraints of a power system.

Table 7
Comparison of performance for PSO and APSO with contingency

Method	Worst cost ($)	Best cost ($)	Average cost ($)
PSO	15481	15452	15460.2
APSO	15459	15451	15454.6

CONCLUSION

This paper had discussed adaptive particle swarm optimization (APSO) method for solving non-convex economic dispatch problem considering valve-point effects. A random value of acceleration coefficients or social parameter is assigned to enhance search ability and escape from a local minimum for two case studies which is in normal condition and contingency condition. Both cases show that APSO have lower average cost in the system. This means that APSO achieved global optimum solution compared with particle swarm optimization (PSO). The entire coefficients are in the range. The new acceleration coefficients in the APSO method can enhance search ability and minimise fuel cost subjected to the various constraints of a power system. Output of the generator shows that it is in the limit which means the power output meets the demand at minimum cost. Thus, it can be concluded that the objectives of this system are achievable which is able to minimise the fuel cost subjected to the various constraints of a power system and determine an optimal combination of power output to meet the demand at minimum cost. When classical particle swarm optimisation methods were compared, the proposed adaptive particle swarm optimization was able to provide better solution. Thus, APSO can be applied for solution of complex power system optimisation problems.

ACKNOWLEDGEMENTS

The authors acknowledge cooperation rendered by Institute of Research Management and Innovation (IRMI) UiTM, Shah Alam, Selangor, Malaysia and Ministry of Higher Education (MOHE) to undertake this research. This research was supported by MOHE under the Research Acculturation Grant Scheme (RAGS) with project code: 600-RMI/RAGS 5/3 (187/2014).

REFERENCES

109th Congress. Energy Policy Act of 2005, 8 Public Law 109-58 594–1143 (2005).

Abdullah, M. N., Bakar, A. H. A., Rahim, N. A., Jamian, J. J., & Aman, M. M. (2012). Economic dispatch with valve point effect using iteration particle swarm optimization. In *2012 47th International Universities Power Engineering Conference (UPEC*) (pp. 1–6). IEEE. http://doi.org/10.1109/UPEC.2012.6398693

Basu, M. (2015). Modified particle swarm optimization for nonconvex economic dispatch problems. *International Journal of Electrical Power & Energy Systems, 69*, 304–312. http://doi.org/10.1016/j.ijepes.2015.01.015

Chen, P. -H., & Chang, H. -C. (1995). Large-scale economic dispatch by genetic algorithm. *IEEE Transactions on Power Systems, 10*(4), 1919–1926. http://doi.org/10.1109/59.476058

Harman, R. (1995). A very brief introduction to particle swarm optimization.

Lee, K. Y., & EI-Sharkawi, M. A. (2002). Tutorial on Modern Heuristic Optimization Techniques with Applications to Power Systems. *IEEE Power Engineering Society (02TP160)*. Retrieved from http://sites.ieee.org/pes-resource-center/files/2013/10/TP160_Full_Content.pdf

Lin, W. M., Cheng, F. S., & Tsay, M. T. (2001). Nonconvex economic dispatch by integrated artificial intelligence. *IEEE Transactions on Power Systems, 16*(2), 307-311.

Momoh, J. A. (2001). *Electric power system applications of optimization*. Marcel Dekker, Inc., New York.

Park, J. B., Jeong, Y. W., Shin, J. R., & Lee, K. Y. (2010). An improved particle swarm optimization for nonconvex economic dispatch problems. *IEEE Transactions on Power Systems, 25*(1), 156-166.

Wood, A. J., & Wollenberg, B. F. (1996). *Power generation, operation and control. 2nd edition.* Wiley and Sons, New York.

Yang, H. T., Yang, P. C., & Huang, C. L. (1996). Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions. *IEEE transactions on Power Systems, 11*(1), 112-118.

Yare, Y., Venayagamoorthy, G. K., & Saber, A. Y. (2009). Heuristic Algorithms for Solving Convex and Nonconvex Economic Dispatch. In *2009 15th International Conference on Intelligent System Applications to Power Systems* (pp. 1–8). IEEE. http://doi.org/10.1109/ISAP.2009.5352852