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Research Paper

ECONOMIC DISPATCH IN POWER SYSTEMS USING SIMULATED ANNEALING-BASED-CLONAL SELECTION OPTIMIZATION APPROACH

Mahya Aghaee[1]* and Elnaz Ghanbaryan[2]

Corresponding Author: **Mahya Aghaee, ✉ mahiaaghaee@gmail.com*

This paper presents an efficient approach for solving the Economic load Dispatch (ED) problem with valve-point effects using Simulated Annealing-based-Clonal selection as a hybrid technique. The main aim for solving economic dispatch problem is to schedule the outputs of the committed generating units in order to meet the system load at least fuel cost under various operating constraints. Since economic dispatch is a nonlinear nonconvex problem, stochastic search algorithms seem to be appropriate solutions. Hence, this study proposes a hybrid method (SA-Clonal) which combines the Clonal framework with the selection operation of Simulated Annealing (SA). The proposed method has been tested on three systems with different constraints and obtained results have been compared with the results of other stochastic search algorithms. The satisfying results acquired from the comparison ensure the efficiency of the proposed method.

Keywords: Simulated annealing, Clonal selection algorithm, Economic load dispatch, Valve point effects

INTRODUCTION

The ultimate goal of the power system is to deliver electric power reliably and economically from generators to loads. The rules are aimed to balance supply and demand without creating overloads, congestion, or any other similar problems in short-term or real-time. This problem can be managed from demand side, via methods such as Demand Response (DR) management, in which electricity usage changes by end users from their normal consumption patterns in response to changes in electricity price overtime (Arani *et al.*, 2011). From generation viewpoint, this problem can be categorized as generation dispatch, in specific, Economic generation Dispatch (ED).

The main goal of the Economic load Dispatch (ED) as an optimization problem is allocating generation among the committed units such that the constraints (e.g., matching load demand) imposed are satisfied at

[1] Electrical Engineering Department, Southern Illinois University, 1263 Lincoln Drive, Carbondale, IL 62901-6899.

[2] Electrical and Computer Engineering, Imam Khomeini International University, Postal Code: 34149-16818, Qazvin Islamic Republic of Iran.

minimal possible cost. So far, several models are presented in the literature to solve this problem as an optimization problem. Some conventional solutions include linear programming (Nanda *et al.*, 1994), nonlinear programming (Lowery, 1996) and dynamic programming (Dodu *et al.*, 1972). Moreover, different heuristic methods have been presented during the last few years such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Pattern Search (PS), Harmony Search (HS), Evolutionary Programming (EP), Simulated Annealing (SA), Clonal Selection Algorithm (CSA) etc. Although such heuristic methods suffer from some disadvantages and setbacks, they still can provide a reasonable solution and are widely employed in solving power system problems (Yousefian and Monsef, 2011; Naziri and Karrari, 2011; Rahimi and Famouri, 2013; Morsali *et al.*, 2014; Rahimi and Famouri, 2014; Davoudi *et al.*, 2015; and Davoudi *et al.*, 2016). To mention some of the advantages of heuristic methods, for instance, GA can scan a vast area of solution space very fast and it has this capability that is not affected by bad proposals because such proposals can be simply discarded during the process. However, while GA guarantees to provide the best solution (closest to global optimum), it is very time-consuming and cannot claim the exact solution. Another popular heuristic method is PSO which is an efficient global search algorithm and has this advantage which is not sensitive to the scaling of design variables. PSO unlike many other classic methods can be simply implemented and can be easily parallelized for concurrent processing; however, it suffers from the slow convergence rate in the refined search and it also might get stuck into the local optimums (Kirkpatrick *et al.*, 1983; and Selvakumar and Thanushkodi, 2007). Another well-established heuristic method is SA which is known as a robust search tool for finding the global optimum. It has this advantage that can be utilized to implement various combined optimization problems. However, SA has this issue that cannot be utilized to tune the control parameters of the annealing schedule easily (Vasileios Karakasis and Andreas Stafylopati, 2008). Another popular method which vastly is employed by literature to solve optimization problems is Clonal selection algorithm. This method is a population based stochastic approach. This method has significant flexibilities and can be employed in combination with other stochastic search algorithms to find the best optimum solution regardless of the initial parameter values and with a very fast convergence rate (Elyas *et al.*, 2014).

In this paper, a novel hybrid optimization algorithm is presented to solve the economic load dispatch problem. This method is Simulated Annealing-Clonal selection and it is the combination of Clonal selection algorithm and SA. The intention is to benefit from all the positive characteristics of these two methods and compensate the disadvantages of each method with the advantages of the other method.

PROBLEM DEFINITION

The main objective of solving an economic dispatch problem in a power system is to find an optimum way of allocation of the loads between generating units. This optimization typically means providing the minimum cost while maintaining all the system constraints including meeting the total load demand. In this paper, the objective function is minimizing the cost. This economic load dispatch problem can be summarized as shown in (1).

$$\min F_t(P) = \sum_{i=1}^{n} F_i(P_i) \qquad ...(1)$$

In the classical economic dispatch problem, $F_i(P_i)$ is considered as a quadratic and polynomial function which is formulated as (2).

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \qquad ...(2)$$

where $F_i(P_i)$ and P_i are the cost function and the power output of unit *i*, respectively and a_i, b_i and c_i are cost coefficients of this unit.

However, in generation units with valve loading effects, the input-output curve has remarkable differences compared with smooth cost function. In this paper, in order to consider valve-point effects, sinusoidal functions are added to the polynomial cost function. Hence, the cost function of generation units with valve-point loading are formulated as follows:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin(f_i(P_i^{\min} - P_i)) \right| \qquad ...(3)$$

where e_i and f_i are the constants of the valve point effect of i[th] unit. In this paper, the cost function of each unit is considered with effects of multi-fuel type on polynomial term. Therefore, the fuel cost function for i[th] unit is formulized as:

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1} P_i + c_{i1} P_i^2 + \left| e_{i1} \sin(f_{i1}(P_{i1}^{\min} - P_{i1})) \right| \xrightarrow{fuel1} P_i^{\min} \le P_i \le P_{i1}^{\max} \\ a_{i2} + b_{i2} P_i + c_{i2} P_i^2 + \left| e_{i2} \sin(f_{i2}(P_{i2}^{\min} - P_{i2})) \right| \xrightarrow{fuel2} P_{i2}^{\min} \le P_i \le P_{i2}^{\max} \\ . \\ . \\ . \\ a_{im} + b_{im} P_i + c_{im} P_i^2 + \left| e_{im} \sin(f_{im}(P_{im}^{\min} - P_{im})) \right| \xrightarrow{fuelm} P_{im}^{\min} \le P_i \le P_i^{\max} \end{cases} \qquad ...(4)$$

This objective function is subjected to active power balance of system's aggregated generation, load demand, P_D, and active power loss, P_L, as shown in (5).

$$\sum_{i=1}^{K} P_i = P_D + P_L \qquad ...(5)$$

It worth noting that in this economic dispatch problem, P_L is neglected. Moreover, a second set of constraints is applied to generation limits for each unit as in (6).

$$P_{i,\min} \le P_i \le P_{i\max} \qquad ...(6)$$

where, $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum generation limits of unit *i*, respectively. Finally, generation unit ramp rate limits could be considered as another set of constraints applied on economic load dispatch, which are defined as follows:

$$P_{i,t} - P_{i,(t-1)} < UR_i \text{ for } i = 1, \ldots, n \qquad ...(7)$$

$$P_{i,(t-1)} - P_{i,t} < DU_i \text{ for } i = 1, \ldots, n \qquad ...(8)$$

where, UR_i and DU_i are limits on the speed of ramping output of generating unit *i* up and down, respectively.

SA-CLONAL ALGORITHM

Clonal Selection Algorithm

The Artificial Immune System (AIS) is a powerful computational intelligence technique, which mimics the biological immune system and human body natural defense mechanism. Clonal Selection Algorithms (CSA) as a class of algorithms in AIS are inspired by clonal selection theory and has been widely applied in power system analysis (Elyas *et al.*, 2014) and power system modeling (Nejad *et al.*, 2012).

The clonal selection theory has become a widespread accepted model for how the immune system responds to infections. When an antigen such as a bacterium or a virus invades the body, the biological immune system will select the antibodies, which can effectively recognize and destroy the antigen. In the CSA a candidate solution for a specific problem is considered as an antigen, which is recognized by the antibody. Each antibody represents a possible solution to the problem with a population of a restricted number of antibodies. In this algorithm, an antigen is identified and recognized after the reproduction of immune system antibodies. Accordingly, every antibody is selected by the evaluation mechanism to obtain its affinity. Additionally, mutation procedure is performed on the regenerated antibodies generating partial differences between them. These partial differences make the antibodies population being able to recognize antigens that were not recognizable for initial antibodies.

With aforementioned introduction, steps of the Clonal selection algorithm (CLONALG) is described as follows:

1. First, the initial antibodies population, N, is generated randomly in the problem space.
2. The affinity of each antibodies is evaluated by the objective function.
3. n antibodies with the highest affinity are selected.
4. New population which has n antibodies is improved in respect to each antibody's affinity, meaning, an antibody with higher affinity are copied more than other antibodies with lower affinity.

$$n_c = round(\frac{\beta.N}{i}), i = 1,..., n \quad ...(9)$$

where, n_c is the number of offspring antibodies from i^{th} antibody and β is a constant coefficient, which indicates the rate of copy. Furthermore, the number of antibodies in the updated population, N_c, is derived by,

$$N_c = \sum_{i=1}^{n} round(\frac{\beta.N}{i}) \quad ...(10)$$

Mutate N_c antibodies of the population in respect to their affinities. In other words, antibodies with higher affinity should be mutated less than those with lower affinity.

5. The affinity of each mutated antibody is calculated and m antibodies with higher affinity are selected. Hence, the population consists of m antibodies that will enter the next generation directly.
6. p new antibodies are produced randomly and added to the existing population. These new antibodies leads to diversifying the solution which as result helps the optimization process being able to escape from its local optima. This process increases the number of antibodies in the final population to $m + p$.
7. Finally, procedure is repeated from step 2 until the termination criteria are met.

Simulated Annealing (SA)

Simulated Annealing (SA) is inspired by the process of cooling a material gradually to reach its lowest energy state, after being heated to the melting point. Two basic loops form the fundamentals of this method: One that is named the internal loop, contains a series of evaluates and moves. The other loop, named external loop, terminates the iteration when the stopping criteria is met. The algorithm initiates with an initial random guess. Then iterates through several generations while replacing existing points with the new ones to converge the solution asymptotically to the global point.

Therefore, Simulating Annealing can be performed following these steps:

1. Initiate with the starting point with a starting temperature (T0)
2. Move to a new point using the generation process (X*)
3. Update the best current solution: If the new point is closer to the global solution, replace the initial point with it. Otherwise, X* is close enough with a probability provided by the Boltzmann distribution.
4. Check the stopping criterion after reducing the temperature.
5. Stop if the criteria is met, or go to step 2 otherwise.

Note that the objective function is used to quantize the advantage of each point and hence is the measure for the energy changes (ΔF).

$$\Delta F = F(X^*) - F(X_0) \quad ...(11)$$

If $\Delta F < 0$ different point is substituted for the previous point; otherwise, the new point is validated with probability based on the Boltzmann probability distribution as follows:

$$P(\Delta F) = \exp(-\frac{\Delta F}{T}) \quad ...(12)$$

where T denotes the temperature.

It is worth mentioning that the initial temperature can significantly influence the performance of SA, as it affects the acceptance possibility of a worse point; i.e., decreasing temperature in each iteration makes it less probable for the worse point to be accepted, as (12) verifies. SA is capable of escaping from local minima, as it accepts worse points. Decreasing temperature accomplished at the end of each iteration can be achieved using different approaches including linear or nonlinear forms. Note that temperature reduction process should not be too fast or slow because it may cause the algorithm to be stuck in local optima and/or reduce its speed.

SA-Clonal Combined Algorithm

In order to combine the two aforementioned approaches, the selection step of Clonal algorithm can be helped by the SA algorithm, i.e., SA algorithm can be used to pick the best population in the next iteration. Selection step can be split into two levels:

1. Selection based on Clonal algorithm
2. Selection based on SA algorithm (ultimate selection)

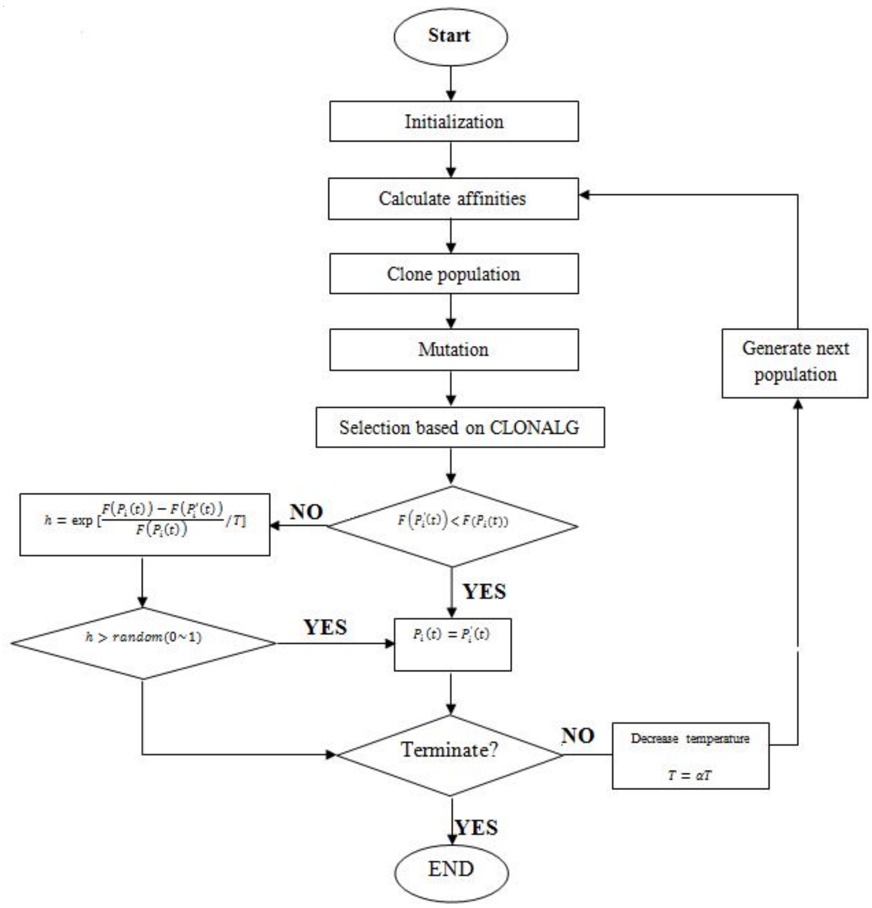
At first, the common selection method of Clonal algorithm is applied. Amounts of affinities identify the selected antibodies. Then, the selected antibodies of the earlier level are compared with the initial population, and next population can be selected based on SA algorithm as follows:

$$P(t+1) = \begin{cases} P_i'(t), F(P_i'(t)) < F(P_i(t)) \\ P_i'(t), F(P_i'(t)) > F(P_i(t)) \;\&\; h(P_i(t), P_i'(t)) > rand \\ P_i(t), otherwise \end{cases} \quad ...(13)$$

where

$$h(p_i(t), P_i'(t)) = \exp\left[\frac{F(P_i(t)) - F(P_i'(t))}{F(P_i(t))} / T\right] \quad ...(14)$$

Figure 1: Flowchart of Algorithm



$$T(iter+1) = \alpha T(iter) \text{ while } T(0) = T_0 \quad ...(15)$$

In (14), error between the parent and offspring objective functions () has been studied to remove the impact of various ranges of objective function is the rate of temperature reduction (Elyas *et al.*, 2013). The proposed combined algorithm is demonstrated in Figure 1.

The proposed algorithm has superior performance in terms of both accuracy and speed according to some existing case studies. Using a local search engine (SA), the initial selection algorithm has been improved, and a powerful selection technique (CLONAL selection algorithm) has been used to attain the best global optimum point among all local optima.

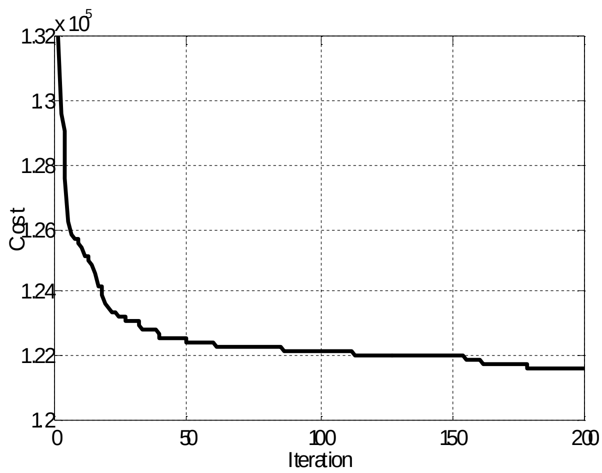
NUMERICAL RESULTS

Capability of proposed method for solving the ED problem has been tested with 3 benchmark functions, for validation purposes. Power operation limits, power balance and valve loading effects is assigned for limitations in a 40 generation unit ED for the first scenario. The second and third scenarios consist of 10 generation units with the same constraints as described in the first scenario in addition to generating unit ramp rate limits and multi-fuel options as new constraints. α and $T(0) = 1$ are selected for the new method.

Test Case A: 40 Thermal Units

As it is mentioned earlier, in the scenario power system consists of 40 thermal units with valve loading effects. Moreover, power operation and power balance constraints are considered. In this test case, the load demand is assumed to be P_D = 10500 MW. The best, average and the worst results of different methods tested on this system are assessed in the following table, which demonstrates that the proposed method has better solution rather than other methods. Figure 2 delivers the convergence process for 40 units scenario.

Figure 2: Convergance Process of the Total Cost for Case A



Test Case B: 10 Thermal Units with Ramp Rate Limits

In the second test system with 10 units, the load demand is assumed to be P_D = 1800 MW and generating unit ramp rate limits are added to previous constraints, while the simulation is executed for 24 hours. The best, average and the worst results of different methods tested on this test case are compared in Table VI. According to Figure 3, It is expected that due the inclusion of ramp rate limits and hence decreasing in flexibility of ED problem, the total

Table 1: Average, Worst and Best Results Comparison with Different Methods for Test Case A

Methods	Total Generation Cost ($)		
	Best	Average	Worst
MPSO (Elyas *et al.*, 2013)	122252.26	---	---
ESO (Chen *et al.*, 1996)	122122.16	122558.45	123143.07
PSO-LRS (Manoharan *et al.*, 2008)	122035.79	122558.45	123461.67
Improved GA (Park *et al*., 2005)	121915.93	122811.41	123334
HPSOWN (Manoharan *et al.*, 2008)	121915.3	122844.4	---
IGAMU (Park *et al.*, 2005)	121819.25	---	---
NPSO (Manoharan et al., 2008)	121704.73	122221.36	122995.09
NPSO-LRS (Manoharan *et al.*, 2008)	121664.43	122209.31	122981.59
CBPSO-RVM (Elyas *et al*., 2013)	121555.32	122281.14	123094.98
SA-CLONAL	121486.12	121507.33	121591.7
Mean time (t)	11.3		

Figure 3: Results of Economic Dispatch for Case B (MW)

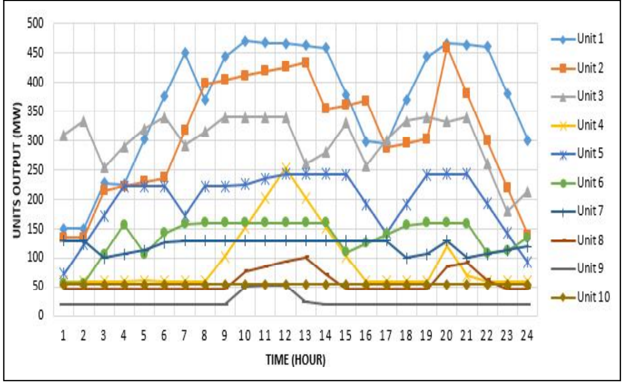


Table 2: Average, Worst and Best Results Comparison with Different Methods for Case B

Methods	Total Generation Cost ($)		
	Best	Average	Worst
EP	1054685	1057323	---
EP-SQP	1052668	1053771	---
MHEP-SQP	1050054	1052349	---
ISPO	1046275	1048145	---
SA-CLONAL	1018612	1018879	1029510
Mean time (t)	3.79		

generation cost increases. However, as can be seen, there is a significant reduction in total generation cost based on the SA-Clonal algorithm.

Test Case C: 10 Thermal Unit with Multi Fuel Option

In the same way, the third system consists of 10 thermal units and load demand is assumed to be P_D = 2700 MW. However, multi fuel option has been added to the constraints instead of ramp rate limit. The best, average and the worst results of different methods tested on the same system are compared in Table 3.

Table 3: Average, Worst and Best Results Comparison with Different Methods for Case C

Methods	Total Generation Cost ($)		
	Best	Average	Worst
CGA-MU [20]	624.7193	627.6087	633.8652
IGA-MU [20]	624.5178	625.8692	630.8705
DE [21]	624.5146	624.5246	624.5458
RGA [21]	624.5081	624.5079	624.5088
PSO [21]	624.5074	624.5074	624.5074
PSO-LRS [20]	624.2297	625.7887	628.3214
NPSO [20]	624.1624	625.218	627.4237
NPSO-LRS [20]	624.1273	624.9985	626.9981
CBPSO-RVM [20]	623.9588	624.0816	624.293
RCGA [20]	623.8281	623.8495	623.8814
SA-CLONAL	623.8143	623.8356	623.848
Mean time (t)	0.56		

It is notable that deviations of the best and average solutions of the SA-Clonal algorithm from the corresponding average result for each test system of ED problem are very low, which shows another reason for ability of the proposed method.

CONCLUSION

In this study, SA-Clonal algorithm is presented as a new solution of the Economic load Dispatch problem with valve-point effects. This method tries to gather all the positive features of both algorithms in order to make a fast reliable hybrid stochastic search technique with high performance in solving the optimization problems. The obtained results show that the proposed method is an effective approach for solving the ED problem in comparison with other stochastic search algorithms. Moreover, fast convergence rate and ability of skipping local optima traps are the most important advantages of the presented method.

REFERENCES

1. Arani A B, Yousefian R, Khajavi P and Monsef H (2011), "Load Curve Charactristics Improvement by Means of Optimal Utilization of Demand Response Programs", in in 10th International Conference on Environment and Electrical Engineering (EEEIC), May 8-11, pp. 1-5.
2. Chen G L, Wang X F and Zhuang Z Q (1996), "Genetic Algorithms and its Applications", Beijing Posts and Telecom, Beijing, China.
3. Davoudi M, Cecchi V and Romero Agüero J (2016), "Network Reconfiguration with Relaxed Radiality Constraint for Increased Hosting Capacity of Distribution Systems", *Power and Energy Society General Meeting*, IEEE, July, pp. 1-5.
4. Davoudi M, Sadeh J and Kamyab E (2015), "Parameter-Free Fault Location for Transmission Lines Based on Optimisation",

Generation, Transmission Distribution, IET, Vol. 9, No. 11, pp. 1061-1068.

5. Dodu J C, Martin P, Merlin A and Pouget J (1972), "An Optimal Formulation and Solution of Short-Range Operating Problems for a Power System with Flow Constraints", *Proc IEEE*, Vol. 60, No. 1, pp. 54-63.

6. Elyas S H, Akbari Foroud A and Chitsaz H (2013), "A Novel Method for Maintenance Scheduling of Generating Units Considering the Demand Side", *International Journal of Electrical Power & Energy*, Vol. 51, pp. 201-212.

7. Elyas S H, Mandal P, Haque A U, Giani A and Tzu-Liang T (2014), "A New Hybrid Optimization Algorithm for Solving Economic Load Dispatch Problem with Valve-Point Effect", *North American Power Symposium (NAPS)*, pp. 1-6.

8. Kirkpatrick S, Gelatt C D and Vecchi M P (1983), "Optimization by Simulated Annealing", *Sci. J.*, Vol. 220, No. 4598, pp. 671-680.

9. Lowery P G (1996), "Generating Unit Commitment by Dynamic Programming", *IEEE Trans Power Apparat Syst*, PAS-85, No. 5, pp. 422-426.

10. Manoharan P S, Kannan P S, Baskar S and Iruthayarajan M W (2008), "Penalty Parameter-Less Constraint Handling Scheme Based Evolutionary Algorithm Solutions to Economic Dispatch", *IET Gen., Transm.,Distrib.*, Vol. 2, No. 4, pp. 478-490.

11. Morsali R, Ghadimi N, Karimi M and Mohajeryami S (2014), "Solving a Novel Multiobjective Placement Problem of Recloser and Distributed Generation Sources in Simultaneous Mode by Improved Harmony Search Algorithm", Complexity.

12. Nanda J, Hari L and Kothari M L (1994), "Economic Emission Load Dispatch with Line Flow Constraints Using a Classical Technique", *IEE Proc Gener Transm Distrib*, Vol. 141, No. 1, pp. 1-10.

13. Naziri I and Karrari M (2011), "A Novel Method for State Estimation in Large Power Systems Using Phasor Measurement Units", *International Review of Automatic Control*, Vol. 4, No. 2, pp. 253-258.

14. Nejad S B, Elyas S H, Khamseh A, Moghaddam I N and Karrari M (2012), "Hybrid CLONAL Selection Algorithm with PSO for Valve-Point Economic Load Dispatch", Electrotechnical Conference (MELECON), 16th IEEE Mediterranean, pp. 1147-1150.

15. Park J, Lee K, Shin J and Lee K (2005), "A Particle Swarm Optimization for Economic Dispatch with Nonsmooth Cost Functions", *IEEE Trans. Power Syst.*, Vol. 20, No. 1, pp. 34-42.

16. Pereira-Neto A, Unsihuay C and Saavedra O R (2005), "Efficient Evolutionary Strategy Optimization Procedure to Solve the Nonconvex Economic Dispatch Problem with Generator Constraints", *Proc. Inst. Elect.Eng., Gen., Transm., Distrib.*, Vol. 152, No. 5, pp. 653-660.

17. Rahimi K and Famouri P (2013), "Performance Enhancement of Automatic

Generation Control for a Multi-Area Power System in the Presence of Communication Delay", *North American Power Symposium (NAPS)*, September 22-24, pp.1,6.

18. Rahimi K and Famouri P (2014), "Assessment of Automatic Generation Control Performance Index Criteria", in T&D Conference and Exposition, IEEE PES, April 14-17, pp. 1-5.

19. Selvakumar A I and Thanushkodi K (2007), "A New Particle Swarm Optimization Solution to Nonconvex Economic Dispatch Problems", *IEEE Trans. Power Syst.*, Vol. 22, No. 1, pp. 42-51.

20. Seyyed H Elyas and Wang Z (2016), "A Multi-Objective Optimization Algorithm for Bus Type Assignments in Random Topology Power Grid Model", Annual Hawaii International Conference on System Science (HICSS), January, Grand Hyatt, Kauai.

21. Vasileios K Karakasis and Andreas Stafylopati (2008), "Efficient Evolution of Accurate Classification Rules Using a Combination of Gene Expression Programming and Clonal Selection", *IEEE Transactions on Evolutionary Computation*, Vol. 12, No. 6.

22. Yousefian R and Monsef H (2011), "DG-Allocation Based on Reliability Indices by Means of Monte Carlo Simulation and AHP", in 10th International Conference on Environment and Electrical Engineering (EEEIC), May 8-11, pp. 1-4.