International Journal on "Technical and Physical Problems of Engineering" (IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

March 2012	Issue 10	Volume 4	Number 1	Pages 27-34

APPLICATION OF MOPSO FOR ECONOMIC LOAD DISPATCH SOLUTION WITH TRANSMISSION LOSSES

H. Shayeghi A. Ghasemi

Technical Engineering Department, University of Mohaghegh Ardabili, Ardabil, Iran, hshayeghi@gmail.com

Abstract- This paper presents a new multi objective heuristic algorithm for Dynamic Economic Load Dispatch (DELD) problem soultion with transmission losses based on new version of the Particle Swarm Optimization (PSO) algorithm, which called Multi Objective PSO (MOPSO) method. The proposed algorithm is based on multi objective meta-heuristics technique that evaluates a set of the Pareto solutions systematically and preserve the diversity of Pareto optimality by a crowding entropy diversity measure tactic. The crowding entropy strategy is able to measure the crowding degree of the solutions more accurately and efficentlly. The effectivness of the proposed method have been varified on two 6 and 15 units test systems with considered various demand for 24 hours. The numrical results demonstrates the capability of the proposed MOPSO approach to generate well distributed Pareto optimal non-dominated solutions of multi-objective DELD problem. The comparison with the recently reported results using Brent method reveals the superiority of the proposed MOPSO approach and confirms its potential for the solution of dynamic ELD problem in the real world power systems.

Keywords: MOPSO, Dynamic Economic Load Dispatch, Pareto Optimal Solution, Transmission Loss.

I. INTRODUCTION

The problem of allocating the customer's load demands among the available thermal power generating units in an economic, secure and reliable way has been received considerable attention since 1920 or even earlier [1-2]. Dynamic Economic Dispatch (DED) problem is one of the main issues of power system operation and control. The goal of practical DED problem is to determine the optimal schedule of output powers of online generating units over a certain period of time to meet a given load profile instead of fixed demand as in conventional economic dispatch problem at minimum operating cost subject to operational constraints of the generators such as valve-point loading effects, ramp rate limits, unit generating output limits and etc [3].

It is a dynamic optimization problem that includes nonlinear and complex characteristics with heavy equality and inequality constraints. These facts distinguish DED from the static economic load dispatch problem and which makes the challenge of finding global optimum barely because of its large dimensionality [4].

A number of the conventional techniques have been reported in the literature to solve DED problem namely: the Lagrangian relaxation approximate [5], Dynamic programming [6] and Dantzig-Wolfe decomposition method [7]. Unfortunately, the classical methods require heavy computation burden and are incapable of providing ideal results in the aspect of rapidity and precision. In addition, the search process is susceptible to be trapped in local minima and the solution obtained may not be optimal. So, many artificial intelligence based optimization methods, such as Tabu search, simulated annealing, Genetic Algorithms (GA), evolutionary programming and differential evolution have recently received much interest for achieving high efficiency and search global optimal solution in the problem space and they have been successfully applied to solve DED problem [8-12].

These evolutionary based methods are heuristic population-based search procedures that incorporate random variation and selection operators. Although, these methods seem to be good approaches to find a feasible and reasonable solution for the DED problem, however, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then they have degraded effectiveness to obtain the global optimum solution. In recent years, the particle swarm optimization (PSO) technique is used to find the optimal solution of DED problem [13].

Unlike GA and other heuristic methods, PSO has a well-balanced and flexible mechanism to improve and adapt the global and local exploration abilities. It usually results in faster convergence rates than the GA [14]. The ability of PSO to handle nonsmooth and nonconvex economic power dispatch problem was verified and reported [15, 16]. However, the problem was formulated as a conventional dispatch problem with the fuel cost as the only objective considered for optimization.

In order to overcome premature convergence and to speed up the searching process, a new Multi Objective PSO (MOPSO) technique is developed and proposed for the solution of the DED problem in this paper. In general changing standard single objective PSO to a MOPSO needs redefinition of global and local best particles in order to obtain a front of optimal solutions. There is no absolute global best in MOPSO, but rather a set of nondominated solutions. Also, there may be no single local best particle for each individual of the swarm. Selecting the global best and local best to guide the swarm particles becomes nontrivial task in multi-objective domain. Thus, for non-dominance solutions sorting the Pareto archive maintains approach and to ensure proper diversity amongst the solutions of the non-dominated solutions in Pareto archive maintains the crowding distance method is used, two approaches namely niche count and crowded distance method [17] are used.

To illustrate the robustness of the proposed MOPSO algorithm and their ability to provide efficient solution for the DED problem, it is tested on two test power systems, including 6 and 15 unit generating in comparison with the performance of Brent method [18]. The results evaluation reveals that the proposed MOPSO algorithm achieves good quality solution for DED problem and is superior to the Brent method one.

II. DYNAMIC ECONOMIC DISPATCH PROBLEM

Dynamic Economic Load Dispatch (DELD) is one of the main functions of modern Energy Management System (EMS), which determines the optimal real power settings of generating units with an objective of minimizing the total the total operating cost over a dispatch period, while achieving a set of constraints. Without loss of generality, we should consider a simple DED problem involving three types of constraints, the load demand balance in terms of equality constraints, ramp rates in terms of dynamic constraints and generation capacity in terms of inequality constraints [19]. This section describes the problem formulation of DED.

A. Objective Function

The objective of ELD problem is to minimize the overall cost of generation units for a given load profile in interval T. The objective function for optimization used in this paper is defined as follows:

$$\min \sum_{t=1}^{T}\sum_{i=1}^{N} F_i(P_i^t) \tag{1}$$

where, N is number of generator and F_i is the fuel cost for the ith generating unit ($/h) and is expressed as the following quadratic function of active power generation:

$$F_i(P_i^t) = a_i + b_i P_i^t{}_i + c_i P_i^{t2} \tag{2}$$

where, P_i^t is power output of generator i in time interval t; a_i, b_i and c_i are cost function coefficients of generating unit i, respectively.

B. Equality Constraints

The condition of equality constrain for interval t can be given by:

$$\sum_{i=1}^{N} P_i^t - P_D{}^t - P_{loss}^t = 0 \tag{3}$$

with considering losses in DED problem, it is became a little complicated because the losses are depend to the power generated of any active unit and change by new generation. However one of the most important problems for ELD is expressing transmission loss as function of generator powers is through B-coefficients. This method used the fact that under normal operating condition, the transmission loss is quadratic in the injected bus real power. The general form of the loss formula using B-coefficient is for DED problem solution as expressed:

$$P_{loss}^t = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i^t B_{ij} P_j^t + \sum_{i=1}^{N} B_{i0} P_i^t + B_{00} \tag{4}$$

where, P_i^t, P_j^t are real power injection at the ith, jth buses and B_{ij} is loss coefficients and the B_{io} and B_{00} is matrix for loss in transmission which are constant under certain assumed conditions.

C. Generation Capacity Constraints

For unflinching operation, the generator outputs are restricted by lower and upper limits as follows:

$$P_i^{\min} \le P_i^t \le P_i^{\max} \tag{5}$$

where $P_i^{\min}$ and $P_i^{\max}$ is minimum and maximum active power of the ith generator.

D. Ramp Rate Limit Constraints

The actual operation of online generating unit range is limited by its ramp rate limits which can affect the operation of generating unit. The operational decision at the current hour may impact the operational decision at the later hour due to ramp rate limits. Due to variation in power demand from present hour to next hour three possible cases (steady state, increasing and decreasing operation conditions) exist in actual operation. First, during the steady state operation condition, the operation of the available unit is in steady state condition. Second, if the power demand is raised, the power generation of the generator also increased. Third, if the power demand is reduced then the power generation of the generator also decreased. The ramp rate limits with all possible situations are depicted in Figure 1.

The generator constraints due to ramp rate limits of ith generating units is given by

i) If power generation increases

$$P_i - P_i^0 \le UR_i \tag{6}$$

ii) If power generation decreases

$$P_i^0 - P_i \le DR_i \tag{7}$$

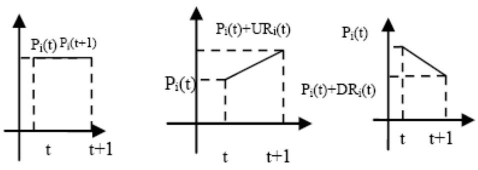
Thus, with considering ramp rate limits the capability of generate for ith unit can be described as follow:

$$\max(P_i^{\min}, P_i^0 - DR_i) \le P_i \le \min(P_i^{\max}, P_i^0 + UR_i) \tag{8}$$

Hence, the minimum and maximum output powers limits are modified as follows

$$P_i^{\min-ramp} = \max(P_i^{\min}, P_i^{t-1} - DR_i) \tag{9}$$

$$P_i^{\max-ramp} = \min(P_i^{\max}, P_i^{t+1} + UR_i) \tag{10}$$



a) b) c)

Figure 1. Ramp rate constraints of the generating unit
a) Steady state operation b) Increased operation c) Decreased operation

E. Line Flow Constraints

This constrains can be described as:

$$\left|P_{Lf,k}\right| \leq P_{Lf,k}^{\max}, k=1,2,...,L \tag{11}$$

where $P_{Lf,k}$ is the real power flow of line *k*; $P_{Lf,k}^{\max}$ is the power flow up limit of line *k* and *L* is the number of transmission lines.

III. MULTI OBJECTIVE PARTICLE SWARM OPTIMIZATION

A. PSO Overview

Kennedy and Eberhart [20] developed the PSO algorithm which models the social behavior of the birds flocking or fish schooling for food within a group. It searches in parallel using a group of individuals similar to other AI-based heuristic optimization techniques.

In a physical-dimensional search space, the position and velocity of individual *i* are represented as the vectors $X_i=\left(x_{i1},...,x_{in}\right)$ and $V_i=\left(v_{i1},...,v_{in}\right)$ in the PSO algorithm, respectively. Let $Pbest_i=\left(x_{i1}^{Pbest},...,x_{in}^{Pbest}\right)$ and $Gbest_i=\left(x_{i1}^{Gbest},..,x_{in}^{Gbest}\right)$ be the best position of particle *i* and its neighbors' best position so far. Using this information, the updated velocity of particle is modified as follows:

$$\begin{aligned}V_i^{k+1}&=\omega V_i^k+c_1 rand_1\times\left(Pbest_i^k-X_i^k\right)+\\&+c_2 rand_2\left(Gbest^k-X_i^k\right)\end{aligned} \tag{12}$$

where, V_i^k is velocity of particle at iteration *k*; ω is weight parameter; c_1 and c_2 are weight factors; X_i^k is position of particle at iteration *k*; $Pbest_i^k$ is the best position of particle until iteration *k* and $Gbest_i^k$ is the best position of the group until iteration *k*.

In Equation (12) the first term shows the current velocity of the particle, second term presents the cognitive part of PSO where the particle changes its velocity is based on its own thinking and memory. The third term corresponds to the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge. Each particle moves from the current position to the next one by the modified velocity in (12) as follows:

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

Suitable chosen of the inertia weight provides a balance between global and local exploration and exploitation, and results in less iteration on average to find a suitably optimal solution. The linearly decreasing inertia weight factor is used as follows:

$$w=w_{\max}-\frac{w_{\max}-w_{\min}}{iter_{\max}}\times iter \tag{14}$$

where, w_{max} and w_{min} are both random numbers called initial and final weight, respectively; $iter_{max}$ is the maximum iteration number and *iter* is the current iteration number.

B. Multi Objective PSO (MOPSO)

A lot of realistic life problems entail simultaneous optimization of some objective functions. In general, these functions are non-commensurable and often competing and conflicting objectives. The application of a multi objective optimizer makes it possible to envisage the trade off among different conflicting objectives to direct the engineer in making his compromise and gives rise to a set of optimal solutions, in place of one optimal solution. The concept of Pareto dominance formulated by Vilfredo Pareto is used for the evaluation of the solutions [21].

This concept is defined as for a multi objective optimization problem, a solution u_1 dominates u_2 if and only if:

$$\begin{aligned}&a)\ \forall\ i\in\{1,2,...,Mobj\}: f_i(x_1)\leq f_i(x_2)\\&b)\ \exists j\in\{1,2,...,Mobj\}: f_j(x_1)<f_j(x_2)\end{aligned} \tag{15}$$

where, *M* is the dimension of the objective function. If u_1 dominates the solution u_2 then u_1 is called the non-dominated (NOD) solution. The solutions that are nondominated within the whole search space are signified as Pareto-optimal and constitute the Pareto-optimal set. This set is also known as Pareto optimal front.

Pareto dominance concept classifies solutions as dominated or non-dominated solutions and the "*best solutions*" are selected from the non-dominated solutions. The implemented algorithm is the non-dominated sorting PSO which is currently used in many other practical design problems. To sort non-dominated solutions, the first front of the non-dominated solution is assigned the highest rank and the last one is assigned the lowest rank. When comparing solutions that belong to a same front, another parameter called crowding distance [17] is calculated for each solution. The crowding distance is a measure of how close an individual is to its neighbors. Large average crowding distance will result in better diversity in the population.

In order to investigate multi-objective problems, some modifications in the PSO algorithm were made. A multi-objective optimization algorithm must achieve: guide the search towards the global Pareto-optimal front and maintain solution diversity in the Pareto-Optimal front. The main steps of the MOPSO algorithm for DED problem are explained in more detail as follows:

Step 1: Input parameters of system, and specify the lower and upper boundaries of each variable.

Step 2: Initialize randomly the speed and position of each particle and maintain the particles within the search space.

Step 3: For each particle of the population, employ the Newton-Raphson power flow analysis method to calculate power flow and system transmission loss, and evaluate each of the particles in the population.
Step 4: Store the positions of the particles that represent non-dominated vectors in the repository NOD.
Step 5: Generate hypercubes of the search space explored so far, and locate the particles using these hypercubes as a coordinate system where each particle's coordinates are defined according to the values of its objective function.
Step 6: Initialize the memory of each particle in which a single local best for each particle is contained.
Step 7: Update the time counter t=t+1.
Step 8: Determine the best global particle G_{best} for each particle i from the repository NOD. First, those hypercubes containing more than one particle are assigned a fitness value equal to the result of dividing any number x>1 by the number of particles that they contain. Then, we apply crowding distance method using these fitness values to select the hypercube from which we will take the corresponding particle. Once the hypercube has been selected, we select randomly a particle as the best global particle G_{best} for particle i within such hypercube.
Step 9: Compute the speed and its new position of each particle using Equations (12) and (13), and maintain the particles within the search space in case they go beyond its boundaries.
Step 10: Evaluate each particle in the population by the Newton-Raphson power flow analysis method.
Step 11: Update the contents of the repository NOD together with the geographical representation of the particles within the hypercubes.
Step 12: Update the contents of the repository P_{best}.
Step 13: If the maximum iterations *iter*max are satisfied then go to Step 14. Otherwise, go to Step 7.
Step 14: Input a set of the Pareto-optimal solutions from the repository NOD.

C. Non-Dominated Sort

The initialized population is sorted based on non-domination. The fast sort algorithm as given in [17] is used here for NOD.

D. Crowding Distance

Once the non-dominated sort is complete, the crowding distance is assigned. As the individuals are selected based on rank and crowding distance all the individuals in the swarm are assigned a crowding distance value. Crowding distance is allocated front wise and comparing the crowding distance between two individuals in different front is meaningless. The algorithm as given in [17] is used here for the crowding distance. The flowchart of the proposed MOPSO algorithm is shown in Figure 2.

IV. RESULTS AND DISCUSSIONS

In order to illustrate the efficiency of the proposed MOPSO algorithm for the solution of the DED problems, two test cases, including 6 and 15 generating units are considered. In these studied systems, the generators constraints and transmission losses were taken into account for the practical application. The results obtained from the proposed method were compared in terms of the solution quality and computation efficiency with the Brent method [18] in the literature. The MOPSO algorithm is implemented in MATLAB software. In each test system, 30 independent runs were made for each of the optimization methods.

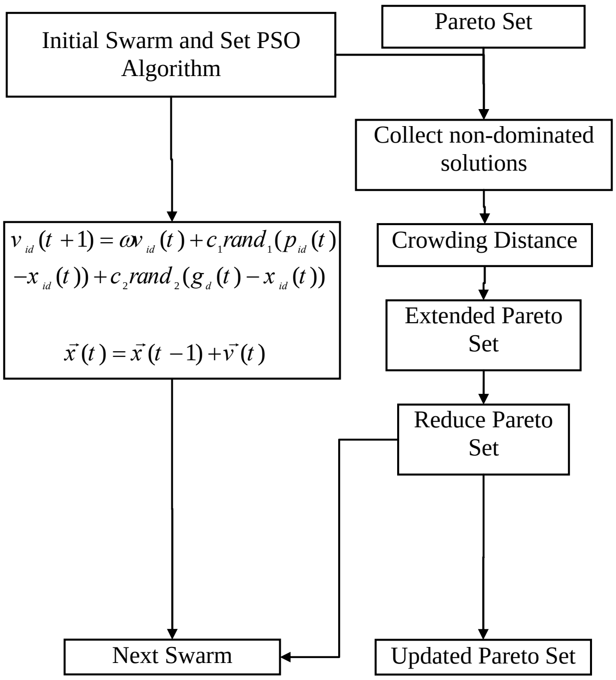


Figure 2. The flowchart of the proposed MOPSO algorithm

Case 1: The proposed method is applied to the electrical network on IEEE 30 bus including six thermal generating units as shown in Figure 3 to assess the suitability of the algorithm. The fuel cost (in \$/hr), ramp rate limits and data of predicted power demands is extracted from [3] are given in Tables 1-3, respectively.

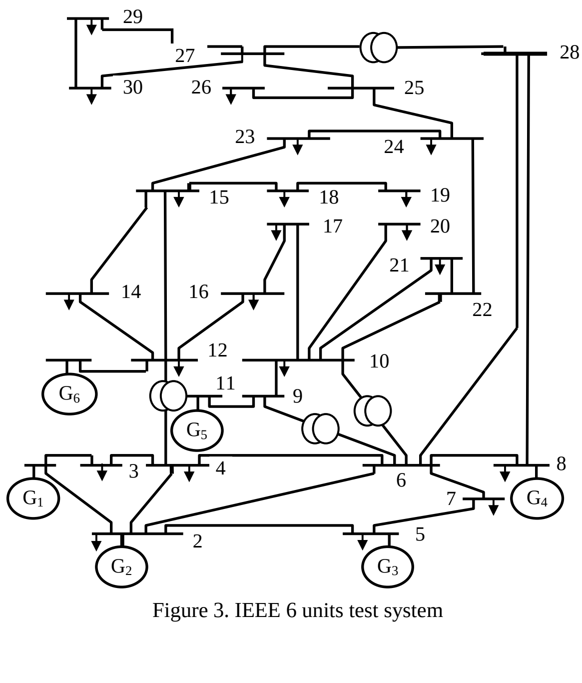


Figure 3. IEEE 6 units test system

Table 1. Fuel cost data of six units system

U	a_i ($)	b_i ($/MW)	c_i ($/MW2)	P_i^{min} (MW)	P_i^{max} (MW)
1	240	7	0.007	100	500
2	200	10	0.0095	50	200
3	220	8.5	0.009	80	300
4	200	11	0.009	50	150
5	220	10.5	0.008	50	200
6	190	12	0.0075	50	120

Table 2. Ramp rate limits of six units system

Unit	P_i^0 (MW)	UR_i (MW/h)	DR_i (MW/h)
1	340	80	120
2	134	50	90
3	240	65	100
4	90	50	90
5	110	50	90
6	52	50	90

Table 3. Prdicted power demand of six units system in 24 hours

H	1	2	3	4	5	6	7	8
PD (MW)	955	942	935	930	935	963	989	102.3
H	9	10	11	12	13	14	15	16
PD (MW)	112	6115	0120	1123	5119	0125	1126	3125
H	17	18	19	20	21	22	23	24
PD (MW)	122	1120	2115	9109	2102.3	984	975	960

The transmission losses are calculated by B matrix loss formula which for 6-unit system is given as [18]:

$$B_{ij} = 10^{-3} \begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -2.0 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0.0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0.0 & 0.24 & -0.6 & -0.8 \\ -0.5 & -0.6 & -0.1 & -0.6 & 12.9 & -0.2 \\ -2.0 & -1.0 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix}$$

$$B_{0j} = 10^{-3}\left[0.3908 \ \text{-}1.297 \ 7.047 \ 0.591 \ 2.161 \ \text{-}6.635\right]$$

$$B_{00} = 0.056$$

The optimal output powers and power loss for all power demands using the proposed MOPSO method in comparison than the Brent method are shown in Figures 4-5 for 24 hours that satisfies the generator constraints. Also, Table 4 shows the computational time and the fuel cost. From this above results, it can be seen that the proposed MOPSO technique provided superior solutions for DED problem compared with the other reported methods in the literature.

Table 4. Simulation results of Lambda iterative, Brent method and proposed optimization in case 1

Methods	Lambda iterative method [18]	Brent Method [18]	MOPSO
Fuel cost ($)	313405.648	313405.403	313278.232
Time (S)	0.125	0.078	0.064

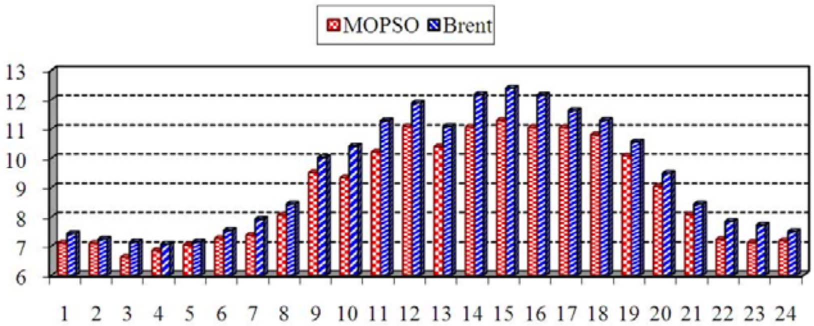


Figure 4. Power loss for all power demands of 6-unit system in MW

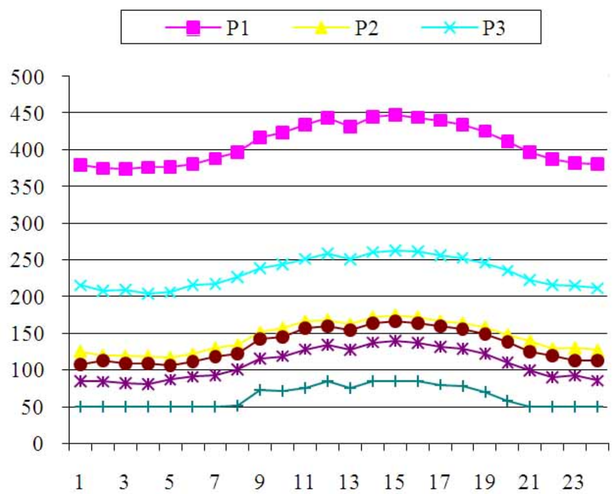


Figure 5. Generation each unit of 6-unit system in 24 hours

Case 2: 15-unit system

The system contains 15 thermal units whose data and loss coefficients matrix are given in [12]. The predicted load demand of the system for 24 hours is shown in Figure 6. The output power of each generation unit and power loss for all power demands using the MOPSO method shown in Table 5 that also satisfies the system constrains. Figures 7 and 8 depict the transmission loss and fuel cost for all power demands using the MOPSO method in comparison with the Brent approach. It is clear that the MOPSO reveals its supremacy in optimal solution quality than the Brent method for DED problem. Also, generation of each unit in 24 hours is shown in Figure 9. It can be evident that the units 1, 2, 6 and 7 have minimum cost for generation and working with full capacity in most time and units 5 set to network with most value in peak demand times, but other units have maximum cost for generation and working with minimum capacity or working near to upper constrain.

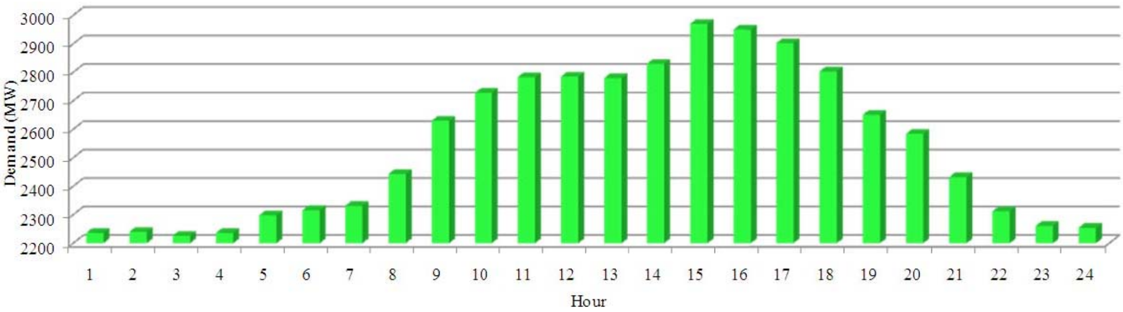


Figure 6. Load demand for 24 hours in case 2

Table 5. Output power and power loss for all power demand of 15 -unit test system

H	Output powers (MW)															Loss (MW)
	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	P_{13}	P_{14}	P_{15}	
1	204.43	388.14	130.00	90.96	190.56	460.00	454.37	60.00	66.01	33.71	66.74	21.16	25.00	20.44	46.15	21.6640
2	172.45	455.00	130.00	130.00	202.60	361.28	406.86	76.11	47.08	25.00	80.00	60.35	77.00	16.94	19.42	19.7916
3	155.32	402.06	91.55	120.52	162.68	460.00	452.56	65.56	65.09	25.00	36.62	80.00	58.14	53.17	17.51	19.5049
4	313.71	196.95	130.00	130.00	195.49	399.55	465.00	60.00	43.43	25.00	80.00	80.00	76.07	44.87	15.07	18.8160
5	322.28	455.00	82.35	130.00	193.91	460.00	397.14	60.00	30.44	25.00	68.62	27.81	34.97	16.30	15.04	20.5173
6	185.72	449.02	130.00	116.93	173.32	453.32	465.00	60.00	34.23	48.05	40.61	80.00	31.64	33.24	36.31	21.0411
7	246.93	381.80	130.00	130.00	158.21	460.00	465.00	60.00	88.46	26.52	67.02	80.00	28.08	15.22	15.00	20.9092
8	261.95	455.00	130.00	130.00	177.51	460.00	465.00	60.00	83.43	25.02	63.73	80.00	25.00	34.13	15.86	22.1049
9	455.00	455.00	114.44	112.68	207.20	460.00	465.00	67.36	35.76	40.60	55.34	80.00	46.83	44.00	17.10	26.3608
10	455.00	455.00	130.00	130.00	248.08	460.00	465.00	67.46	84.45	31.01	80.00	80.00	31.32	22.89	16.84	28.0837
11	455.00	455.00	130.00	130.00	254.67	460.00	465.00	60.00	25.34	145.2	80.00	70.34	25.00	15.00	15.00	31.1440
12	455.00	455.00	129.94	129.26	262.74	457.85	444.69	60.10	25.25	150.15	80.63	65.07	25.01	15.01	15.03	31.2921
13	455.00	455.00	127.73	128.32	265.11	429.34	465.00	63.31	76.49	55.31	68.77	80.00	25.63	15.94	16.23	29.2897
14	455.00	455.00	130.00	130.00	280.85	457.04	465.00	64.81	26.93	157.60	77.81	75.07	25.00	15.00	15.00	33.4710
15	455.00	452.64	128.03	127.40	390.00	460.00	458.91	70.00	25.70	157.88	75.05	75.72	26.32	15.22	15.78	39.3182
16	455.00	455.00	130.00	130.00	360.23	460.00	465.00	65.00	75.53	160.00	80.00	80.00	25.95	15.00	15.20	40.4463
17	450.00	451.29	128.07	126.44	370.00	455.00	455.55	62.80	35.15	158.22	76.98	78.27	25.06	15.16	15.57	37.9225
18	455.00	455.00	130.00	130.00	290.23	457.76	465.00	60.00	25.00	134.23	80.00	73.19	25.00	15.00	15.00	32.3263
19	455.00	455.00	128.97	130.00	185.43	460.00	465.00	56.44	25.00	123.56	80.00	43.54	25.54	15.78	15.01	28.0054
20	454.43	454.87	127.98	128.99	150.00	460.00	465.00	60.00	25.00	93.54	69.56	38.65	25.00	15.00	15.00	25.6883
21	455.00	435.43	129.76	129.90	136.98	404.32	455.00	60.00	25.00	49.34	44.76	61.54	25.00	15.00	15.00	22.5091
22	435.65	445.00	130.00	130.00	150.00	373.76	430.54	60.00	25.00	25.21	27.76	20.00	25.00	15.00	15.00	21.2422
23	455.00	231.98	111.00	68.42	156.32	460.00	309.33	91.29	42.96	66.96	77.35	62.23	77.36	47.70	22.45	19.4106
24	95.62	325.49	130.00	125.10	184.70	380.16	460.07	60.00	42.95	26.42	67.23	80.00	35.40	42.00	18.92	19.3458

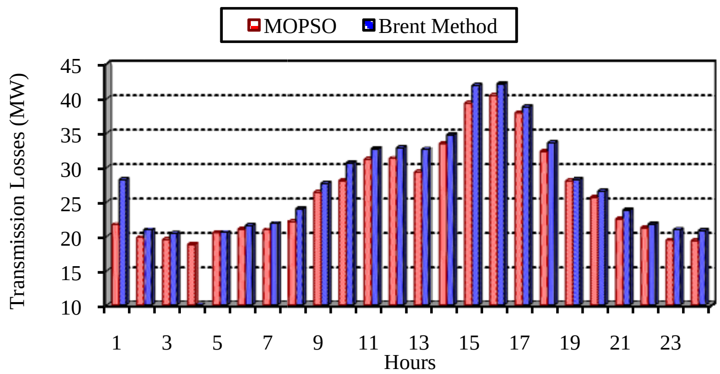


Figure 7. Transmission losses for 15-unit test system

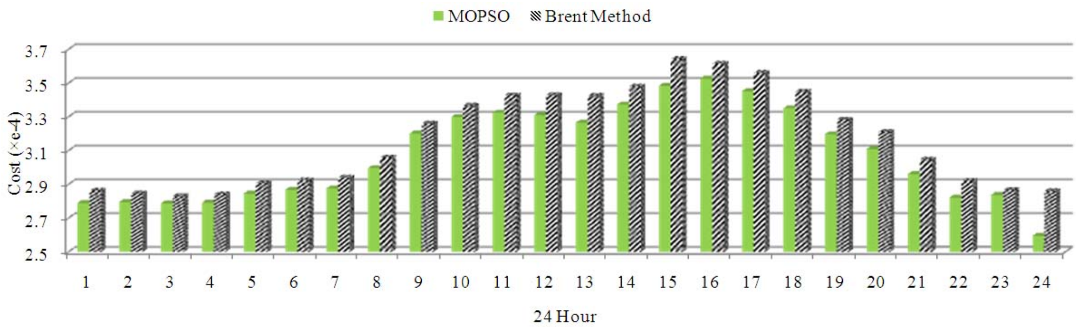


Figure 8. Fuel cost for 24 hours in case 2

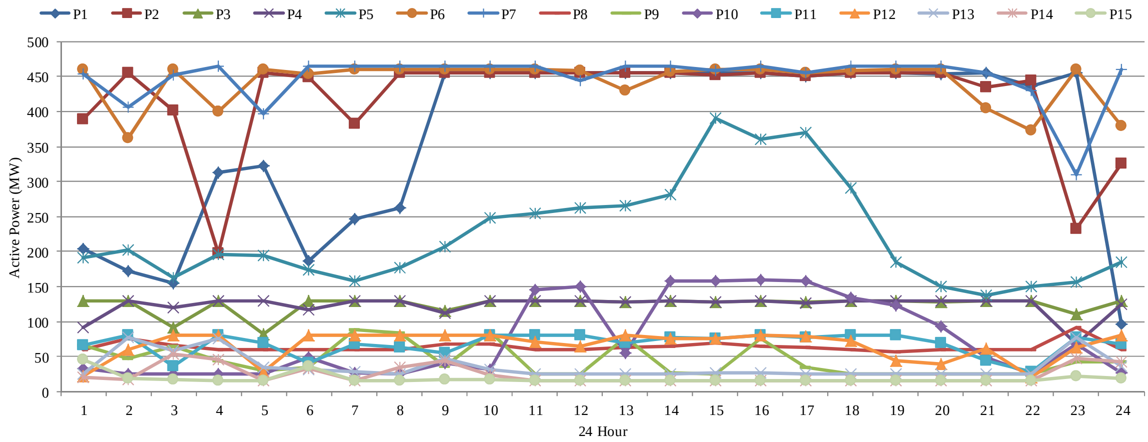


Figure 9. Generation each unit for 24 hours in case 2

V. CONCLUSIONS

A MOPSO optimization technique has been successfully applied for the solution of the dynamic economic dispatch in power system in this paper. For realistic generator operation, several nonlinear constraints of the generator, such as ramp rate limits, generation limits and transmission losses are all into in the proposed approach accounted. The proposed MOPSO algorithm addresses is a multiobjective version of the standard PSO technique and make uses of its efficacy for the solution of multiobjective optimization problems. The DED problem has been formulated with competing fuel cost and transmission losses objectives.

The comprehensive numerical results on two 6 and 15 unit test systems confirm the successful implementation and efficiency of the proposed MOPSO algorithm to solve multiobjective DED problems. The comparable studied that of the recent represented algorithms show the effectiveness of the proposed MOPSO technique and their capability to provide superior quality solution and high computation efficiency.

In addition, the computational times of the proposed approach much less than the lambda iterative and Brent methods. From these comparative studies, it is apparent that the MOPSO can be successfully applied to solve DED problems in the real-world power systems.

REFERENCES

[1] K. Nekooei, M.M. Farsangi, H. Nezamabadi-pour, "An Improved Harmony Search Approach to Economic Dispatch", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 8, Vol. 3, No. 3, pp. 25-31, Sep. 2011.
[2] B.H. Chowdhury, S. Rahman, "A Review of Recent Advances in Economic Dispatch", IEEE Trans. on Power Systems, Vol. 5, No. 4, pp. 1248-1259, 1990.
[3] H. Saadat, "Power System Analysis", McGraw-Hill, New York, 1999.
[4] Y.H. Song, I. Yu, "Dynamic Load Dispatch with Voltage Security and Environmental Constraints", Electric Power System Research, Vol. 43, pp. 53-60, 1997.
[5] D.W. Ross, S. Kim, "Dynamic Economic Dispatch of Generation", IEEE Trans. on Power Apparatus Systems, Vol. 99, No. 6, pp. 2060-7, 2002.
[6] F.N. Lee, L .Lemonidis, K. Liu, "Price-Based Ramp-Rate Model for Dynamic Dispatch and Unit Commitment", IEEE Trans. on Power Systems, Vol. 9, No. 3, pp. 1233-42, 1994.
[7] X.S. Han, H.B. Gooi, D.S. Kirschen, "Dynamic Economic Dispatch: Feasible and Optimal Solutions", IEEE Trans. on Power Systems, Vol. 16, No. 1, pp. 22-28, 2002.
[8] S. Pothiya, I. Ngamroo, W. Kongprawechnon, "Application of Multiple Tabu Search Algorithm to Solve Dynamic Economic Dispatch Considering Generator Constraints", Energy Conversion and Management, Vol. 49, pp. 506-516, 2008.
[9] C.K. Panigrahi, P.K. Chattopadhyay, R.N. Chakrabarti, M. Basu, "Simulated Annealing Technique for Dynamic Economic Dispatch", Electric Power Components Systems, Vol. 34, pp. 577-586, 2006.
[10] F. Li, R. Morgan, D. Williams, "Hybrid Genetic Approaches to Ramping Rate Constrained Dynamic Economic Dispatch", Electric Power Systems Research, Vol. 43, pp.97-103, 1997.
[11] G. Ravi, R. Chakrabarti, S. Choudhuri, "Nonconvex Economic Dispatch with Heuristic Load Patterns Using Improved Fast Evolutionary Program", Electric Power Components and Systems, Vol. 34, pp. 37-45, 2006.
[12] B. Balamurugan, R. Subramanian, "Differential Evolution Based Dynamic Economic Dispatch of Generating Units with Valve Point Effects", Electric Power Components Systems, Vol. 36, pp. 828-843, 2008.
[13] B.K. Panigrahi, V. Ravikumar Pandi, D. Sanjoy, "Adaptive Particle Swarm Optimization Approach for Static and Dynamic Economic Load Dispatch", Energy Conversion and Management, Vol. 49, pp. 1407-1415, 2008.
[14] A. Safari, H. Shayeghi, H.A. Shayanfar, "Optimization Based Control Coordination of STATCOM and PSS Output Feedback Damping Controller Using PSO Technique", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 5, Vol. 2, No. 4, pp. 6-12, Dec. 2010.

[15] A. Safari, H. Shayeghi, “Iteration Particle Swarm Optimization Procedure for Economic Load Dispatch with Generator Constraints”, Expert System with Applications, Vol. 38, pp. 6043-48, 2011.
[16] C.K. Panigrahi, P.K. Chattopadhyay, R. Chakrabarti, “Load Dispatch and PSO Algorithm for DED Control”, International Journal of Automation and Control, Vol. 1, pp 195- 206, 2007.
[17] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, “A Fast and Elitist Multi-Objective Genetic Algorithm: NSGA-II”, IEEE Trans. on Evolutionary Computation, Vol. 6, No. 2, pp. 182-197, 2002.
[18] K. Chandram, N. Subrahmanyam, M. Sydulu, “Brent Method for Dynamic Economic Dispatch with Transmission Losses”, Iranian Journal of Electrical and Computer Engineering, Vol. 8, No. 1, pp. 16-22, 2009.
[19] X. Xia, A.M. Elaiw, “Dynamic Economic Dispatch: A Review”, The Online Journal on Electronics and Electrical Engineering, Vol. 2, No. 2, pp. 234-245, 2010.
[20] J. Kennedy, R. Eberhart, Y. Shi, “Swarm Intelligence”, Morgan Kaufmann Publishers, San Francisco, 2001.
[21] E. Zitzler, L. Thiele, “An Evolutionary Algorithm for Multiobjective Optimization: The Strength Pareto Approach”, Swiss Federal Institute of Technology, TIK-Report, No. 43, 1998.

BIOGRAPHIES

Hossein Shayeghi received the B.S. and M.S.E. degrees in Electrical and Control Engineering in 1996 and 1998, respectively. He received his Ph.D. degree in Electrical Engineering from Iran University of Science and Technology, Tehran, Iran in 2006. Currently, he is an Associate Professor in Technical Engineering Department of University of Mohaghegh Ardabili, Ardabil, Iran. His research interests are in the application of robust control, artificial intelligence and heuristic optimization methods to power system control design, operation and planning and power system restructuring. He is author of of five books in electrical engineering area, power systems analysis, MATALAB, electric circuits, electric DC machines, and electric installations (all in Persian). Also, he is co-authored of a book chapter “A Review on Load Frequency Control Strategies” in the book “Complex Behaviour of the Distributed Generation System: Intelligent Management of the Renewable Energy Resources for assuring the DG System Power Quality and a Sustainable Development”. He has been published more than 175 papers in international journals and conference proceedings. He is a member of Iranian Association of Electrical and Electronic Engineers (IAEEE) and IEEE.

Ali Ghasemi received the B.S. and M.S.E. degrees in Electrical Engineering from Esfahan University of Technology, Esfahan, Iran and University of Mohaghegh Ardabili, Ardabil, Iran in 2009 and 2011, respectively. His areas of interest in research are the application of heuristic optimization to power system control.