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

June 2013 Issue 15 Volume 5 Number 2 Pages 129-135

USING DSO METHOD FOR SOLVING DYNAMIC ECONOMIC DISPATCH INCLUDING PRACTICAL CONSTRAINTS AND RENEWABLE ENERGY SOURCE

M. Shahrokhi [1] K. Valipour [1] S.M.T. Bathaee [2]

1. Electrical Engineering Department, University of Mohaghegh Ardabili, Ardabil, Iran
shahrokhi.m66@gmail.com, kh_valipour@uma.ac.ir
2. Faculty of Electrical and Computer Engineering, K.N. Toosi University of Technology, Tehran, Iran
bathaee@kntu.ac.ir

Abstract- Dynamic economic dispatch (DED) is one of the most significant non-linear problems in power systems. The purpose is determining the optimal power outputs of available generating units in order to meet the load demand subject to satisfying various operational constraints over a certain period of time. In real power systems, the valve-point effects should be considered that makes the DED a non-smooth and non-convex optimization problem. In this paper a Directed Searching Optimization (DSO) algorithm is used to solve the DED where the valve-point effects, ramp-rate limits, power losses and initial power of units are taken into account. A renewable energy source and its impact are analyzed, too. A five-unit test system for a period of 24-hours is studied to validate efficiency of the used method. The results are compared with other approaches and demonstrate the superiority of the proposed method.

Keywords: Directed Searching Optimization (DSO) Algorithm, Dynamic Economic Dispatch (DED), Renewable Energy Sources, Practical Constraints.

I. INTRODUCTION

Dynamic economic dispatch (DED) is one of the major optimization issues in power system operations. Its objective is to schedule the available generator outputs with the predicted load demands over a certain period of time in order to operate in the best economical manner, while taking into consideration various operational equality and inequality constraints. The DED considers additional practical constraints such as upper and lower bounds on the ramp-rate limits of units because in real power systems, generating units will not respond to instantaneous load variations. In addition, considering the valve-point effects makes the DED problem a non-smooth and non-convex optimization problem.

Many kinds of methods have been proposed for solving the DED problem in literatures. Classical methods used deterministic techniques such as non-linear programming [1] and dynamic programming [2] to solve this problem. However, these methods may cause the dimensions of the DED problem to become extremely large when applied on large power systems, therefore requiring enormous computational efforts.

Over the last decades there has been a growing interest in algorithms inspired from the observation of natural phenomenon. It has been shown by many researches that these algorithms are good replacement as tools to solve complex computational problems [3]. Genetic Algorithm (GA) in [4], Particle Swarm Optimization algorithms (PSO) [5-7], Enhanced Bee Swarm Optimization (EBSO) [8], Simulated Annealing (SA) [9], Evolutionary Programming (EP) [10], Artificial Bee Colony (ABC) [11], and Quantum Evolutionary Algorithm (QEA) [12] have been used to obtain global or near global optimum solutions for DED problems. These methods are good for global searching due to their capability of exploring and finding promising regions in the search space at advantageous time, and they overcome the main limitations of deterministic techniques, e.g., getting trapped in local optimum.

In recent years, with increasing fuel prices and environmental concerns, the governments all over the world has interested towards renewable energy sources, e.g. wind, tidal, and photovoltaic. Many countries set up their renewable energy target. Due to clean and economical energy generation, a huge number of wind farms are going to be connected with the existing network in the near future. The wind farms produce uncontrollable and fluctuated power because of the stochastic nature of wind. It degrades their applicability as dispatch options [13]. Despite that, according to the Global Wind Energy Council (GWEC) [14], the global cumulative installed wind capacity is increasing exponentially (Figure 1).

In this paper, we used a Directed Searching Optimization algorithm (DSO) to solve the DED problem including practical constraints, e.g., the valve-point effects, ramp-rate limits, power losses, and initial powers. The proposed algorithm includes two important operations position updating and genetic mutation. The former can enhance the convergence of the DSO, and the latter can improve the capability of escaping from the local optimum. An attempt to integrate a renewable resource and analyze its impact is considered. To validate competence of the proposed method, a five-unit test system for a period of 24 hours is studied. The results are compared with other approaches and demonstrate the superiority of the proposed method.

The paper is organized as follows: Section II offers the mathematical formulation of the DED problem. The used DSO algorithm for the DED problem is described in Section III. The results and comparative study are presented in Section IV. The conclusions are shown in Section V.

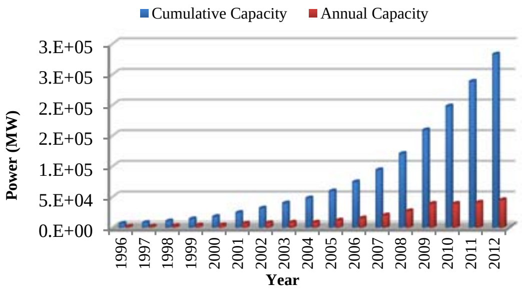

Figure 1. Global installed wind capacity [14]

II. MATHEMATICAL DESCRIPTION

A. Objective Function

The main goal of the DED problem is to minimize the following cost function:

$$F = \min \sum_{t=1}^{T} \sum_{i=1}^{N} f_i\left(P_i^t\right) \qquad (1)$$

where, F is the total generating cost over the whole dispatch period, $f_i(P_i)$ is fuel cost function of ith generator, T is the number of intervals in the scheduled horizon, N is the number of available units and P_i^t is the real power output of the ith generator at time t. With considering the valve-point effects, the above cost function is approximated by the absolute value of the sinusoidal function witch is superimposed on the quadratic fuel cost function as follows:

$$f_i\left(P_i\right) = a_i + b_i P_i + c_i P_i^2 + \left| d_i \times \sin\left(g_i \times \left(P_{i,\min} - P_i\right)\right)\right| \qquad (2)$$

where, a_i , b_i and c_i are the cost coefficients, d_i and g_i are constants from the valve-point effect of the ith generating unit, and $P_{i,\min}$ is minimum power output of ith unit in MW.

B. Constraints

The equality and inequality constraints are as follows:

- **Real Power Balance**

$$\sum_{i=1}^{N} P_i^t = P_D^t + P_L^t \quad , \quad t = 1,\ 2,\ ...,T \qquad (3)$$

Integration of a renewable energy source (RES) modifies equality constraint function to be as follow [11]:

$$\sum_{i=1}^{N} P_i^t = P_D^t + P_L^t - \sum_{RES=1}^{M} \mu_{RES} P_{RES}^t \quad , \quad t = 1,2,...,T \qquad (4)$$

where, $P_D{}^t$ and $P_L{}^t$ are the load demand and system losses at time t respectively in MW. The multiplier μ_{RES} is set to a permissible amount of active power injected by RES, $P_{RES}{}^t$ is the forecasted real power from RES at time t, and M is the number of RES. We assume the multiplier μ_{RES} is set to one, in this paper.

The transmission power losses at time t can be calculated as follows:

$$P_L^t = \sum_{j=1}^{N} \sum_{i=1}^{N} P_i^t B_{ij} P_j^t \quad , \quad t = 1,2,...,T \qquad (5)$$

where, $P_i{}^t$ and $P_j{}^t$ are the real power output of the ith and jth generating unit at time t, respectively, and B_{ij} is the loss coefficients matrix.

- **Real Power Generation Limit**

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

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

where, $P_{i,\max}$ is maximum power output of ith unit in MW.

- **Generating Unit Ramp-Rate Limit**

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 power demand is reduced then power generation of generator also decreased.

The generator constraints due to ramp rate limits of ith generating units are as follows:

$$\begin{aligned} &P_i^t - P_i^{t-1} \le UR_i \quad , \quad i = 1,2,...,N \\ &P_i^{t-1} - P_i^t \le DR_i \quad , \quad t = 1,2,...,T \end{aligned} \qquad (7)$$

where, UR_i and DR_i are the ramp-up and ramp-down-rate limits of ith unit, respectively. We should incorporate the real power output limit constraints (6) in the constraints of ramp-rate limits of units (7) to obtain the real power output of ith unit at time t [15], as follows:

$$\begin{aligned} P_{i,\min}^t &= \max(P_{i,\min}, P_i^{t-1} - DR_i) \\ P_{i,\max}^t &= \min(P_{i,\max}, P_i^{t-1} + UR_i) \end{aligned} \qquad (8)$$

- **Initial Power**

At the beginning of the schedule, initial power of all the units must be taken in to account. This constraint has not been considered at the many previous papers.

III. DIRECTED SEARCHING OPTIMIZATION ALGORITHM

We used an efficient algorithm named Directed Searching Optimization algorithm (DSO) to get feasible solutions of high quality for DED problem [16]. In short, the DSO algorithm works as follows:

i. Initialize the algorithm parameter

This algorithm consists of six parameters that are: The population size (PS), or the number of solution vectors; maximal number of iterations (k), or stopping criterion; forward probability P_α; forward coefficient α; backward coefficient β, and genetic mutation probability P_m.

ii. Initialize the population
The initial population is generated from a uniform distribution in the ranges $[x_{iL}, x_{iU}]$ (i=1,2,…,N):

$$P_{op}=\begin{pmatrix} x_1^1 & x_2^1 & \cdots & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_N^2 \\ \vdots & \vdots & & \vdots \\ x_1^{PS-1} & x_2^{PS-1} & \cdots & x_N^{PS-1} \\ x_1^{PS} & x_2^{PS} & \cdots & x_N^{PS} \end{pmatrix} \tag{9}$$

where, x_i^j is the ith component of the jth (j =1,2,...,PS) candidate solution vector.
iii. Update non-best solution vectors using position updating and genetic mutation.
iv. Apply selection criterion.
v. Save the best solution so far.
vi. Check the stopping criterion, if it is satisfied, computation is terminated, otherwise step 'iv' is repeated.
The pseudo code of updating solution vectors is as follows:

if rand $< P_\alpha$

$$x_V = x_i^j(k) + (1+\alpha)\times\left(x_i^{jg}(k) - x_i^j(k)\right)$$

if $x_V > x_{iU}$

$x_V = x_{iU}$

elseif $x_V < x_{iL}$

$x_V = x_{iL}$

end

$$x_i^j(k+1) = x_i^j(k) + r\times\left(x_V - x_i^j(k)\right)$$

else

$$x_S = x_i^j(k) - \beta\times\left(x_i^{jg}(k) - x_i^j(k)\right)$$

if $x_S > x_{iU}$

$x_S = x_{iU}$

elseif $x_S < x_{iL}$

$x_S = x_{iL}$

end

$$x_i^j(k+1) = x_i^j(k) + r\times\left(x_S - x_i^j(k)\right)$$

end

if rand $< P_m$

$$x_i^j(k+1) = x_{iL} + r\times\left(x_{iU} - x_{iL}\right)$$

end

where, j_g represents the index of the global best solution vector, P_α represents forward probability, α represents forward coefficient, β represents backward coefficient, P_m represents genetic mutation probability, and r is a random in the region [0, 1]. $x_i^j(k)$ is the ith component of the jth position vector in the kth iteration, and $x_i^j(k+1)$ is its corresponding updated component, $x_i^{jg}(k)$ represents the ith component of the global best position vector in the kth iteration. x_{iL} and x_{iU} are the lower bound and the upper bound of the ith position component, respectively. Figure 2 shows the schematic diagram of position updating which $x_i^j(k)$ locates at P, and $x_i^{jg}(k)$ locates at Q. x_v locates at V, and it is on the forward extension line of segment PQ.

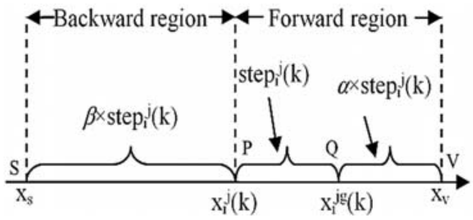

Figure 2. The schematic diagram of position updating

Thus, the region between P and V is defined as forward region. x_s locates at S, and it is on the backward extension line of segment PQ. Thus, the region between P and S is defined as backward region. In the PSO algorithm, the individuals are inclined to mimic their successful companions, which is beneficial to the convergence of the PSO. Inspired by the swarm intelligence of the PSO algorithm, in [16] is proposed a novel position updating strategy.

According to this strategy, $x_i^j(k)$ is inclined to mimic $x_i^{jg}(k)$, so the forward region is selected as its main searching region which is actually a region near $x_i^{jg}(k)$. P_α is used to determine the updating strategy of $x_i^j(k)$: if P_α is satisfied, the forward region is considered, otherwise, the backward region is considered. The backward region is an auxiliary region, and it is used to slow down the rapid convergence of the DSO algorithm, which is beneficial to prevent the premature convergence of the DSO. The $step_i^j(k)$ is defined as adaptive step.

In the early stage of optimization, all solution vectors are sporadic in solution space, so most adaptive steps, which is beneficial to the global search of the DSO algorithm; while in the late stage of optimization, most solution vectors are close to each other due to position updating. In this case, most adaptive steps are small, which is beneficial to the local search of the DSO algorithm; in short, dynamically adjusted $step_i^j(k)$ keeps a balance between the global search and the local search for the DSO algorithm.

Genetic mutation is also an efficient and necessary operation, for it can increase the diversity of individuals, which can effectively improve the performance of DSO in preventing premature convergence to local optimum.

IV. SIMULATION RESULTS AND DISCUSSION

A 5-unit test system for DED problem is studied to demonstrate effectiveness of the DSO method for solving this problem with valve-point effects and ramp-rate limits. The parameters of the algorithm are tuned after trial-and-error experiments, and are as follows: forward probability P_α = 0.8, forward coefficient α = 1; backward coefficient β = 10 and genetic mutation probability P_m = 0.001. The load demand in each time and the data of units which is extracted from [9] are given in Tables 1 and 2. The dispatch horizon T is selected as one day with 24 hours. All the simulation are carried out by Matlab on an Intel(R) Core(TM) i7-2630QM personal computer with 2.00 GHz speed and 6.00GB RAM. The results are obtained after carrying out 30 independent runs, and are compared with those obtained using other well-known approaches in the literatures.

Penalty factor method is used to violation handling of equality constraints. Two test cases are examined, and the results are compared with those of other well-known methods. Maximum iteration number is 1000 for the tests. The integration of a renewable energy source is considered in the second test case and its impacts have been shown in tables and figures.

Table 1. Load demand for the system

Hour	P_D (MW)	Hour	P_D (MW)
1	410	13	704
2	435	14	690
3	475	15	654
4	530	16	580
5	558	17	558
6	608	18	608
7	626	19	654
8	654	20	704
9	690	21	680
10	704	22	605
11	720	23	527
12	740	24	463

Table 2. Data for 10-unit system

U	a ($)	b ($/MW)	c ($/MW^2)	d ($)	$P_{\min}$ (MW)	$P_{\max}$ (MW)	UR (MW/h)	DR (MW/h)	P_0 (MW)
1	25	2	0.008	10	10	75	30	30	50.7118
2	60	1.8	0.003	140	20	125	30	30	40.9004
3	100	2.1	0.0012	160	30	175	40	40	100.0930
4	120	2	0.001	180	40	250	50	50	116.8943
5	40	1.8	0.0015	200	50	300	50	50	161.0431

The transmission loss coefficients matrix for the system is:

$$B_{ij} = 10^{-5}\begin{pmatrix} 4.9 & 1.4 & 1.5 & 1.5 & 2.0 \\ 1.4 & 4.5 & 1.6 & 2.0 & 1.8 \\ 1.5 & 1.6 & 3.9 & 1.0 & 1.2 \\ 1.5 & 2.0 & 1.0 & 4.0 & 1.4 \\ 2.0 & 1.8 & 1.2 & 1.4 & 3.5 \end{pmatrix} \quad (10)$$

Two test cases are described as follows:

A. Case Study 1

This test case, considers a system with five thermal generating units to demonstrate the working of the DSO approach. Table 3 provides the comparison the CPU execution time, as well as the best, worst and average total fuel cost, and standard deviation using the proposed algorithm and the other recent well-known methods reported in the literature. It shows that the proposed DSO performs much better than earlier methods in solving the DED problem. The best achieved total cost using the proposed algorithm is $45,379.28 for the population size of 200. A significant reduction in the required CPU time was obtained. Although both Hybrid Harmony Search (HHS) [17] and Adaptive PSO methods have achieved better results (less operating fuel costs) than that of the DSO algorithm, they disregarded the initial power of generating units, therefore the ramp-rate limit has not been fulfilled properly in some cases, and relaxed the accepted value for violating the equality constraints.

A high violation in equality constraint degraded the quality and practicality of the solutions by these two methods. As shown in Table 4, the violation of equality constraints using the proposed algorithm is better than the ABC* and that is near to zero in every time (maximum violation is 0.00003 MW). Furthermore, Figure 3 shows that the dispatch schedule of the generating units is more consistent using the DSO compared with ABC* and other methods.

Table 3. Comparing the performance of DSO with other methods

Methods	Min. ($)	Avg. ($)	Max. ($)	Std. Dev.	CPU (s)
HHS [17]	44,677.3	–	–	–	–
APSO [7]	43,154.9	–	–	–	308.4
ABC [11]	51,102.8	51,462.8	51,868.9	229.2	280.4
ABC* [11]	48,848.2	49,814.3	50,195.9	288.1	221.5
SA [9]	47,356.0	–	–	–	351.9
DSO	45,379.3	45,820.6	46,669.4	277.6	107.2

Table 4. Comparison of results for case 1

H	APSO [7]		ABC* [11]		DSO Method	
	Violation	P_{loss} (MW)	Violation	P_{loss} (MW)	Violation	P_{loss} (MW)
1	0.00149	3.686	0.00009	3.687	0.00000	3.697
2	0.00016	4.056	0.00003	4.150	0.00000	3.983
3	0.01713	4.795	0.00008	4.854	0.00001	4.701
4	0.00016	5.906	0.00002	5.959	0.00001	6.036
5	0.00065	6.685	0.00009	6.579	0.00001	6.678
6	0.00006	7.885	0.00001	7.798	0.00000	7.930
7	0.00055	8.440	0.00002	8.271	0.00002	8.270
8	0.00068	9.185	0.00005	9.034	0.00000	8.922
9	0.00090	10.173	0.00010	10.152	0.00000	10.370
10	0.00020	10.559	0.00000	10.489	0.00001	10.614
11	0.00250	10.937	0.00010	10.891	0.00002	10.793
12	0.00000	11.454	0.00000	11.552	0.00000	11.633
13	0.00010	10.489	0.00000	10.379	0.00000	10.333
14	0.00110	10.168	0.00000	10.067	0.00000	10.070
15	0.00023	9.237	0.00005	9.251	0.00000	8.923
16	0.00157	7.230	0.00010	7.147	0.00000	6.969
17	0.03427	6.879	0.00006	6.656	0.00002	6.435
18	0.00005	7.931	0.00004	7.875	0.00000	7.728
19	0.00002	9.218	0.00001	9.096	0.00000	9.368
20	0.00040	10.598	0.00000	10.552	0.00000	10.864
21	0.00027	9.894	0.00009	9.819	0.00000	9.578
22	0.00068	7.873	0.00007	7.577	0.00000	7.657
23	0.00127	5.917	0.00003	5.760	0.00002	5.852
24	0.00069	4.690	0.00002	4.466	0.00003	4.647
Total Power loss (MW)	193.890		192.067		192.062	
Total Operating cost ($)	43,154.9		48,848.200		45,379.280	

The detailed results of the best solution are shown in Table 5, which confirms all of the constraints were satisfied.

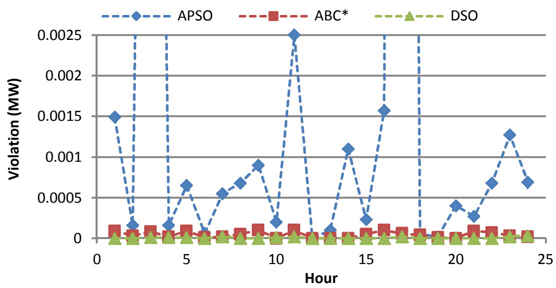

Figure 3. Comparison of different algorithms violations for case 1

Table 5. Best solutions obtained by the DSO for case 1 (without wind power)

H	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	$\sum P$
1	20.712	20.000	60.093	115.104	197.787	413.697
2	12.384	22.830	100.093	155.888	147.787	438.983
3	16.737	28.858	140.092	105.888	188.124	479.699
4	10.352	58.786	100.092	138.917	227.888	536.036
5	40.352	88.786	81.236	173.825	180.479	564.679
6	11.914	58.966	116.659	208.152	220.239	615.930
7	41.817	28.967	145.335	158.152	259.999	634.270
8	71.817	58.332	132.407	188.625	211.740	662.921
9	44.239	88.330	92.407	223.532	251.864	700.373
10	67.814	58.330	123.313	173.532	291.624	714.613
11	66.203	88.330	163.313	171.322	241.624	730.792
12	66.612	89.079	127.017	206.230	262.695	751.633
13	59.311	119.08	167.017	156.230	212.695	714.333
14	55.948	89.150	127.021	175.495	252.454	700.069
15	25.948	59.150	167.021	208.349	202.454	662.923
16	55.943	89.150	128.007	158.382	155.487	586.969
17	25.943	60.650	168.007	169.560	140.275	564.435
18	55.941	47.241	128.049	204.461	180.035	615.728
19	37.601	77.241	88.120	239.369	221.036	663.368
20	67.601	107.24	79.622	189.369	271.030	714.864
21	59.987	77.249	119.622	203.021	229.899	689.778
22	29.988	107.25	142.488	153.021	179.911	612.657
23	21.341	88.171	102.488	187.929	133.023	532.952
24	41.385	58.171	62.488	222.837	83.023	467.905
Total Operating Cost ($)						45,379.280
Total Power Loss (MW)						192.062

Table 6. Best solutions obtained by the DSO for case 2 (with wind power)

H	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	$\sum P$
1	33.456	70.828	83.018	72.536	111.982	371.821
2	20.959	100.828	43.024	78.363	151.753	394.928
3	50.940	71.707	81.910	124.909	101.837	431.303
4	20.994	41.715	121.622	155.809	141.572	481.712
5	21.314	71.712	84.740	142.431	187.382	507.578
6	51.271	41.712	124.733	177.36	158.339	553.401
7	60.295	63.765	164.733	172.818	108.340	569.952
8	40.734	68.976	130.309	207.802	148.058	595.880
9	10.857	98.410	90.340	242.155	187.819	629.582
10	23.853	68.423	130.290	192.166	227.353	642.086
11	53.853	98.423	92.688	225.801	186.299	657.065
12	61.397	102.388	128.505	246.866	136.367	675.523
13	31.915	72.581	166.020	196.866	174.562	641.945
14	61.915	102.572	167.224	151.063	146.185	628.960
15	31.959	72.572	127.242	178.742	185.326	595.841
16	61.953	102.531	87.251	140.688	135.329	527.752
17	32.998	72.541	127.216	99.537	175.139	507.431
18	62.959	42.568	167.191	64.164	216.691	553.574
19	40.006	51.090	132.974	114.164	257.738	595.973
20	70.000	81.062	92.975	147.292	250.896	642.229
21	40.012	76.865	132.969	169.060	200.898	619.804
22	39.822	63.140	92.988	203.970	150.925	550.845
23	69.815	93.134	53.028	160.204	103.036	479.217
24	39.909	63.317	30.023	144.591	142.730	420.570
Total Operating Cost ($)						42,525.025
Total Power Loss (MW)						155.658

B. Case Study 2

Renewable energy sources usage increase in current power systems, therefore its impacts to conventional thermal unit should be investigated. In this test case, we consider the impact of integrating a renewable energy sources (wind power) on the system used in case 1. It assumed the wind-power farm supply 10% of the load demand. The DSO algorithm with the previous parameters is employed. As shown in Table 6, solving the DED by considering a renewable energy source decreases the total operating cost (6.29%) and the power losses of system (18.95%). In addition, a reduction in the required CPU time was obtained (28.66 s). The cost saving in the operation and power losses reduction is shown in Figure 4. The load demand, the total input power of system before and after integration of RES is shown in Figure 5. As shown in this figure, the power generation of units in the points of the peak load curve was decreased more. Generation of each unit in 24 hours before and after integration of RES (wind power) is shown in Figure 6.

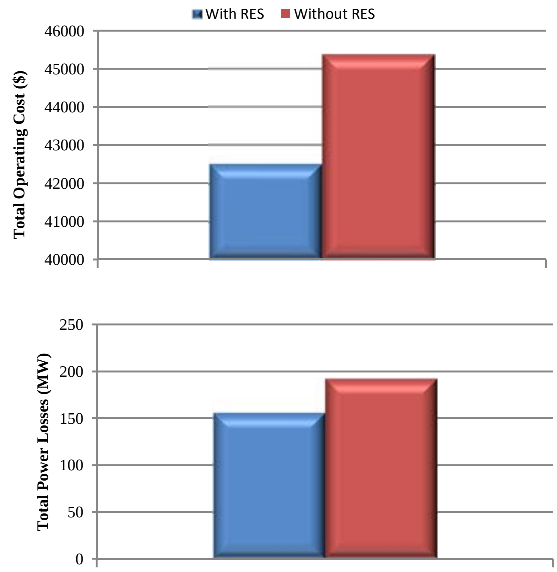

Figure 4. Reduction in operating fuel cost and power losses due to 10% RES

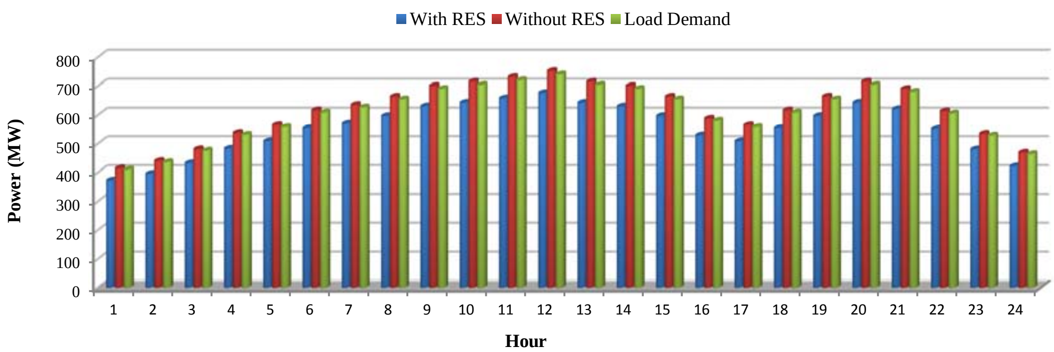

Figure 5. load demand and total input power supply before and after integration of RES

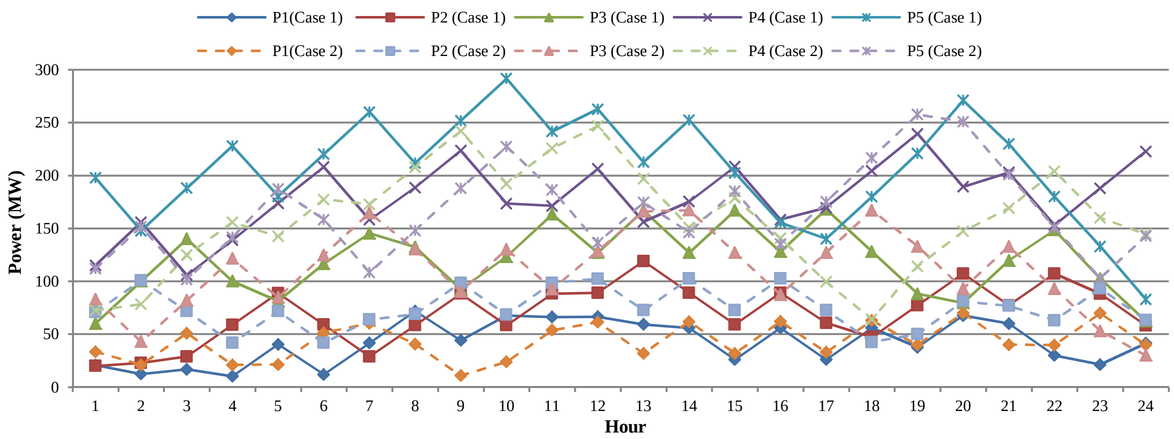

Figure 6. Generation of each unit before and after integration of RES

V. CONCLUSIONS

In this paper, we employed the DSO algorithm to solve the DED problem. In solving this problem, we considered the power losses, valve-point effects, ramp-rate limits, and initial power of generating units. Simulation results illustrate that the DSO algorithm has strong convergence due to the utilization of new position updating strategy. The results also illustrate that the DSO algorithm has strong capability of escaping from the local optimum due to the utilization of genetic mutation. Also, we analyzed the impacts of a renewable energy source on power losses and total operating cost of DED problem. There was a significant reduction in total operating cost and losses.

REFERENCES

[1] P.P.J. Van Den Bosch, "Optimal Dynamic Dispatch Owing to Spinning-Reserve and Power-Rate Limits", IEEE Transactions on Power Apparatus and Systems, Vol. PAS-104, Issue 12, pp. 3395-3401, Dec. 1985.

[2] D.W. Ross, S. Kim, "Dynamic Economic Dispatch of Generation", IEEE Transactions on Power Apparatus and Systems, Vol. PAS-99, Issue 6, pp. 2060-2068, Nov. 1980.

[3] 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, September 2011.

[4] W. Ongsakul, J. Tippayachai, "Parallel Micro Genetic Algorithm Based on Merit Order Loading Solutions for Constrained Dynamic Economic Dispatch", Electric Power Systems Research, Issue 2, Vol. 61, No. 2, pp. 77-88, March 2002.

[5] T. Aruldoss Albert Victoire, A. Ebenezer Jeyakumar, "Deterministically Guided PSO for Dynamic Dispatch Considering Valve-point Effect", Electric Power Systems Research, Issue 3, Vol. 73, No. 3, pp. 313-322, March 2005.

[6] H. Shayeghi, A. Ghasemi, "Application of MOPSO for Economic Load Dispatch Solution with Transmission Losses", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 10, Vol. 4, No. 1, pp. 27-34, March 2012.

[7] B.K. Panigrahi, V. Ravikumar Pandi, Sanjoy Das, "Adaptive Particle Swarm Optimization Approach for Static and Dynamic Economic Load Dispatch", International Journal Energy Conversion and Management, Issue 6, Vol. 49, No. 6, pp. 1407-1415, June 2008.

[8] T. Niknam, F. Golestaneh, "Enhanced Bee Swarm Optimization Algorithm for Dynamic Economic Dispatch", IEEE Journal of System, Issue 99, April 2012.

[9] C. Panigrahi, P. Chattopadhyay, R. Chakrabarti, M. Basu, "Simulated Annealing Technique for Dynamic Economic Dispatch", Electric Power Components and Systems, Issue 5, Vol. 34, pp. 577-586, Feb. 2006.

[10] A.M.A.A. Joned, I. Musirin, T.K. Abdul Rahman, "Solving Dynamic Economic Dispatch Using Evolutionary Programming", IEEE International Power and Energy Conference, pp. 144-149, Nov. 2006.

[11] F.S. Abu-Mouti, M.E. El-Hawary, "Optimal Dynamic Economic Dispatch Including Renewable Energy Source Using Artificial Bee Colony Algorithm", IEEE International System Conference (SysCon), pp. 1-6, Mar. 2012.

[12] G.S.S. Babu, D.B. Das, C. Patvardhan, "Dynamic Economic Dispatch Solution Using an Enhanced Real-Quantum Evolutionary Algorithm", IEEE International Conference on Power System Technology, pp. 1-6, 12-15 Oct. 2008.

[13] I.A. Farhat, M.E. El-Hawary, "Dynamic Adaptive Bacterial Foraging Algorithm for Optimum Economic Dispatch with Valve-Point Effects and Wind Power", Generation, Transmission and Distribution, IET, Issue 9, Vol. 4, No. 9, pp. 989-999, Sep. 2010.

[14] www.gwec.net/global-figures/graphs/ .

[15] T. Aruldoss Albert Victoire, A. Ebenezer Jeyakumar, "A Modified Hybrid EP-SQP Approach for Dynamic Dispatch with Valve-Point Effect", International Journal of Electrical Power & Energy Systems, Issue 8, Vol. 27, No. 8, pp. 594-601, Oct. 2005.

[16] D. Zou, H. Liu, "Directed Searching Optimization Algorithm for Constrained Optimization Problems", International Journal of Expert System with Applications, Issue 7, Vol. 38, pp. 8716-8723, July 2011.

[17] M. Fesanghary, M.M. Ardehali, "A Novel Meta-Heuristic Optimization Methodology for Solving various

Types of Economic Dispatch Problem", International Journal of Energy, Issue 6, Vol. 34, No. 6, pp. 757-766, 2009.
[18] B.K. Panigrahi, V. Ravikumar Pandi, S. Das, "Adaptive Particle Swarm Optimization Approach for Static and Dynamic Economic Load Dispatch", International Journal Energy Conversion and Management, Issue 6, Vol. 49, No. 6, pp. 1407-1415, 2008.

BIOGRAPHIES

Mohsen Shahrokhi was born in Kerman, Iran in May 1987. He received his B.Sc. degree in Electrical Engineering Department, Shahid Bahonar University, Kerman, Iran, in 2010 and M.Sc. degree in Electrical Engineering Department, Mohaghegh Ardabili University, Ardebil, Iran, in 2012. His areas of interest in research are power system control and operation and applications of heuristic techniques in power systems. Currently, he is working on power system planning.

Khalil Valipour received the B.Sc., M.S.E. and Ph.D. degrees in Electrical Engineering, respectively. Currently, he is an Assistant Professor at Technical Engineering Department, University of Mohaghegh Ardabili, Ardabil, Iran. His research interests are in the electric machines design, power system transient and dynamic.

Seyed Mohammad Taghi Bathaee was born in Iran, July 1950. He received the B.Sc., M.Sc. and Ph.D. degrees in Math and Electrical Engineering from K.N. Toosi University (Tehran, Iran), Tehran University, (Tehran, Iran), George Washington University (USA) and Amir Kabir University (Tehran, Iran), respectively. His research interest is in power system analysis and control. Currently, he is an Assistant Professor at Faculty of Electrical and Computer Engineering in K.N. Toosi University of Technology.