A Seeker Optimization Algorithm for Economic Load Dispatch with Non-Smooth Cost Functions

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***Abstract* - In this paper, a novel heuristic population-based seeker optimization algorithm (SOA) is utilized for the optimal solution of different economic load dispatch (ELD) problems in power systems. In the SOA, the act of human searching capability and understanding are exploited for the purpose of optimization. The effectiveness of the algorithm is tested on a number of power systems, including the systems with 40, 10 and 15 generating units. The test power systems are having valve point effects, prohibited operating zones, ramp rate limits, as well as, transmission network loss, and multiple fuels with valve point effects. The obtained results are compared with those of the other state-of-the-art heuristic optimization techniques published in the literature. The outcome of the present work is to establish the SOA as a promising alternative approach to solving the ELD problems in practical power systems. Both the near-optimality of the solution and the convergence speed of the algorithm are promising.**

Keywords- economic load dispatch, multiple fuels, prohibited operating zones, ramp rate limits, seeker optimization algorithm, valve point effect.

I. INTRODUCTION

Economic load dispatch (ELD) is defined as the process of allocating generation levels to the generating units in such a manner, so that the system load is supplied entirely and most economically [25] Various classical methods such as gradient method, Lagrangian relaxation algorithm, lambda iteration method, non-linear programming, linear programming, dynamic programming and quadratic programming were proposed by the researchers to solve the ELD problems. Taking valve loading effect into account, the cost function of generator is of non-convex in nature [22]. The theoretical assumptions behind previous algorithms (except dynamic programming) may not be suitable for convexity and differentiability of the ELD problems. Furthermore, these methods are local optimizers in nature, i.e. if the initial guess is in the neighborhood of a local solution these methods converge to local solutions instead of the global ones.

generator is of non-convex in nature [23]. The theoretical assumptions behind previous algorithms (except dynamic programming) may not be suitable for convexity and differentiability of the ELD problems.

The dimensions of the ELD problem become extremely large for dynamic programming approach. Consequently, it imposes heavy computational burden. To alleviate these deficiencies, artificial intelligence methods such as binary genetic algorithm (GA) [12], improved GA with multiplier updating (MU) (IGA-MU) [9], real coded GA (RCGA) [2], Tabu search [14], Hopfield neural network [8], evolutionary strategy [19], particle swarm optimization (PSO), bacterial foraging with Nelder-Mead (BF-NM) algorithm [18], ant colony optimization (ACO) [20], and Biogeography-based optimization (BBO) [5] are being used to solve the ELD problems. Moreover, several hybrid methods like combination of GA, and pattern search (PS) with sequential quadratic programming (SQP) (GA-PS-SQP) [1]; chaotic differential evolution (DE) (CDE) [10]; modified DE (MDE) [3]; hybrid DE with BBO (DE-BBO) [4] are also proposed for this specific purpose.

Seeker optimization algorithm (SOA) [11] is, essentially, a novel population based heuristic search algorithm. It is based on human understanding and searching capability for finding an optimum solution. In the SOA, optimum solution is regarded as one which is searched out by a seeker population. The underlying concept of the SOA is very easy to model and relatively easier than other optimization techniques prevailing in the literature.

The rest of the paper is organized as follows. In Section II, mathematical modeling of the ELD problem is done. In Section III, an objective function is formulated which requires to be optimized. The SOA is narrated in Section IV. Test cases and simulation results are presented in Section V to demonstrate the performance of the algorithm for the different ELD problems. In Section VI, conclusions of the present work are drawn.

II. MATHEMATICALMODELING of the ELD PROBLEM

The prime objective of the ELD problem is to minimize the total generation cost in power system (with an aim to deliver power to the end user at minimal cost) for a given load demand with due regard to the system equality and inequality constraints [25]

A. ELD with Quadratic Cost Function

The problem of ELD is multimodal, non-differentiable and highly non-linear. Mathematically, the problem can be stated as in (1). The simplified cost function of each generator unit can be represented as in (2).

$$Min\ F_T = \sum_{i=1}^{NG} F_i(P_i) \quad \$/h \tag{1}$$

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

In (1) and (2); F_T is total generation cost; F_i is cost function of the ith generator; a_i, b_i, c_i are cost coefficients of the ith generator; P_i power output of the ith generator; and NG is the number of generators.

B. ELD Problem with Valve Point Effect

The cost function of a fossil fired plant, owing to valve point effect, is highly non-linear. Hence, the cost function is realistically denoted as a recurring rectified sinusoidal function [22]. Each generator has multi-valve steam turbines and cost functions comprising of very different input-output curves. To consider the valve-point effect, a sinusoidal function is introduced into the quadratic cost function of (2) as given in (3).

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin(f_i \times (P_i^{\min} - P_i)) \right| \quad \$/h \tag{3}$$

It is to be noted here that the fuel cost coefficients e_i and f_i are introduced in (3) to model valve point effect for the ith generator. Ripples are introduced in the input-output curves due to the valve-point effect, and thereby, the number of local optima is increased. Variation of fuel cost $F_i(P_i)$ due to the valve-point effect with the change of generation value P_i is shown in Fig. 1.

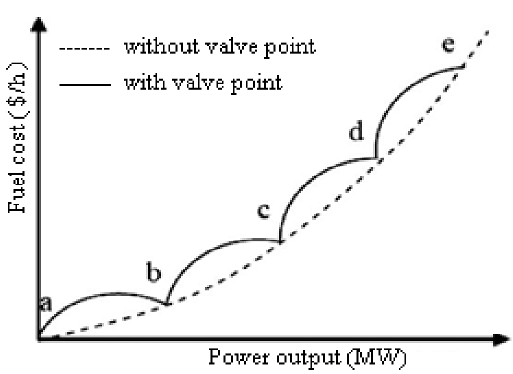

Fig. 1. Input-output curve with valve-point effects: a, b, c, d, e-valve points

C. ELD Problem with Valve Point Effect and Multiple Fuel Options

To model an accurate and practical ELD problem, both valve point effect and multiple fuel options are also taken into account in [9]. Units with multiple fuels option utilize "hybrid cost function". Each segment of the hybrid cost function bears some information about the fuel being burnt for the unit's operation. The single continuous quadratic function of each unit is replaced by several piecewise quadratic functions that reflect the effects of fuel type changes and the generators must identify the most economic fuel to be burnt. To frame the valve point effect and multiple fuels, the cost function [9] may be represented as

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1} P_i + c_{i1} P_i^2 + \left| e_{i1} \times \sin(f_{i1} \times (P_{i1}^{\min} - P_{i1})) \right|, \\ \quad for\ fuel\ 1,\ P_i^{\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2} P_i + c_{i2} P_i^2 + \left| e_{i2} \times \sin(f_{i2} \times (P_{i2}^{\min} - P_{i2})) \right|, \\ \quad for\ fuel\ 2,\ P_{i1} < P_i \le P_{i2} \\ \quad . \\ \quad . \\ a_{ik} + b_{ik} P_i + c_{ik} P_i^2 + \left| e_{ik} \times \sin(f_{ik} \times (P_{ik}^{\min} - P_{ik})) \right|, \\ \quad for\ fuel\ k,\ P_{i\,k-1} < P_i \le P_i^{\max} \end{cases} \tag{4}$$

where a_{ik}, b_{ik}, c_{ik} are the cost coefficients of ith generator for fuel type k; e_{ik}, f_{ik} are the cost coefficients of ith generator reflecting valve-point effects for fuel type k; and $P_{ik}^{\min}$ is the minimum output of ith generator using fuel type k. The discontinuous characteristics of the generators by considering the multiple fuel options are shown in Fig. 2.

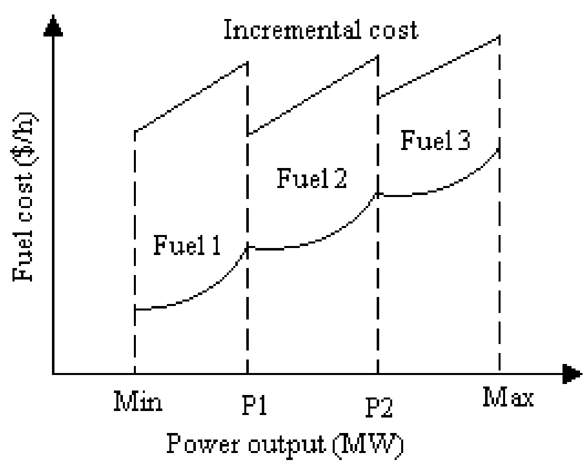

Fig. 2. Piecewise quadratic and incremental cost function of a generator.

D. Equality and Inequality Constraints of ELD Problems

The problems of ELD are subject to the following constraints.

1) *Real Power Balance Constraint*: The total generated power should be same as the total load demand (P_D) plus the line loss (P_L). The real power balance operation can be modeled as in (5).

$$\sum_{i=1}^{NG} P_i = P_D + P_L \quad (5)$$

The transmission loss is a function of active power generation of each generating unit for a given load demand. It may be expressed as a quadratic function of generations (using B coefficient matrix) as given by (6) [17]

$$P_L = \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{0i} P_i + B_{00} \quad (6)$$

where B_{ij} is the (*i-j*)th element of loss coefficient symmetric matrix (*B*); B_{i0} is the *i*th element of the loss coefficient vector; and B_{00} is the constant loss coefficient

2) *Generation Capacity Constraints*: The power output of each generator should be within its minimum and maximum limits. The generating capacity constraints are written as in (7)

$$P_i^{\min} \le P_i \le P_i^{\max} \quad (7)$$

where $P_i^{\min}$ and $P_i^{\max}$ are , respectively, the minimum and the maximum output of the *i*th generator.

3) *Ramp Rate Constraints*: Ramp rate constraints govern the actual operating ranges of all the online units. The ramp-up and ramp-down limits may be represented by the following equation

$$P_i - P_i^0 \le UR_i \text{ ,and } P_i^0 - P_i \le DR_i \quad (8)$$

where P_i^0 is the previous power output of the *i*th generating unit; UR_i and DR_i are the up-rate and the down rate limits of the *i*th generator respectively. To consider the ramp rate limits constraints and power output limits constraints at the same time, (7) and (8) can be written as an inequality constraint as given by the following equation.

$$\max\{P_i^{\min}, P_i^0 - DR_i\} \le P_i \le \min\{P_i^{\max}, P_i^0 + UR_i\} \quad (9)$$

4) *Prohibited Operating Zone Constraints:* The prohibited operating zones are the range of output power of a generator where the operation causes undue vibration of the turbine shaft. Normally, operation of a unit is avoided in such regions. Hence, mathematically the feasible operating zones of a unit can be described as follows

$$\begin{aligned} &P_i^{\min} \le P_i \le P_{i,1}^{lower} \\ &P_{i,j-1}^{upper} \le P_i \le P_{i,j}^{lower}; \qquad j = 2,3,\ldots\ldots pz_i, \quad (10) \\ &P_{i,pz_i}^{upper} \le P_i \le P_i^{\max} \end{aligned}$$

where j represents the number of prohibited operating zones of the *i*th unit; $P_{i,j}^{lower}$, $P_{i,j}^{upper}$ are the lower and the upper limits of the *j*th prohibited operating zone of the *i*th unit respectively,; pz_i is the total number of prohibited operating zone of the *i*th unit. By considering the prohibited operating zones, the discontinuous characteristics of the generators are shown in Fig. 3.

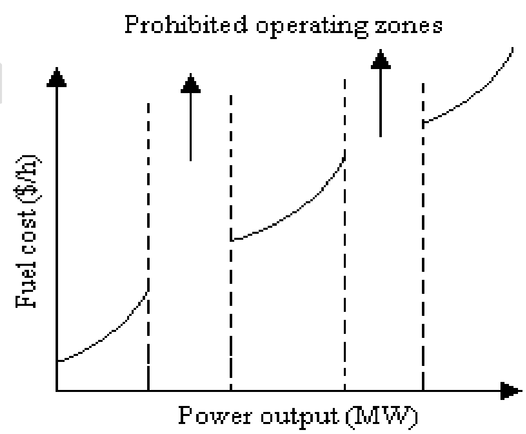

Fig. 3. Input-output curve with prohibited operating zones.

III. FORMULATION OF THE OBJECTIVE FUNCTION

In order to treat the problem as a normalized maximization function, the objective function ($OF(\cdot)$) is framed as in (11).

$$OF(\,) = \frac{10^6}{\sum_{i=1}^{NG} F_i(P_i) + 100 \times P_L + 1000 \times abs\left(\sum_{i=1}^{NG} P_i - P_D - P_L\right)} \quad (11)$$

In (11), the weighing factor in the numerator (10^6) is selected to bring the value of $OF(\cdot)$ within two/three digit figure. The factors 100 and 1000 in (11) are arbitrary weighting factors to amplify the associated terms properly to partly compete with the cost term.

IV. SEEKER OPTIMIZATION ALGORITHM AND ITS APPLICATION TO THE ELD PROBLEM

A. Seeker Optimization Algorithm

The SOA [11] is a population-based heuristic search algorithm. In the SOA, the act of human searching capability and understanding are exploited for the purpose of optimization. In this algorithm, the search direction is based on empirical gradient by evaluating the response to the position changes and the step length is based on uncertainty reasoning by using a simple fuzzy rule. It regards the optimization process as an optimal solution obtained by a seeker population. Each individual of this population is called a *seeker*. The total population is randomly categorized into three subpopulations. These subpopulations search over several different domains of the search space. All the seekers in the same subpopulation constitute a neighborhood. This neighborhood represents the social component for the social sharing of information.

B. Steps of Seeker Optimization Algorithm

In the SOA, a search direction ($d_{ij}(t)$) and a step length ($\alpha_{ij}(t)$) are computed separately for each *i*th seeker on each *j*th variable at each time step t, where $\alpha_{ij}(t) \geq 0$ and $d_{ij}(t) \in \{-1,\ 0,\ 1\}$. Here, *i* represents the population number and *j* represents the optimizing variable number.

V. TEST CASES AND SOLUTION RESULTS

The software of the present work is written in MATLAB-7.3 language and executed on a 3.0-GHz Pentium IV personal computer with 512-MB RAM.

A. Description of the Test Systems

To assess the efficiency and to establish the efficacy of the SOA, the following three test systems are considered

Test system 1:	40-generating units with valve point effect;
Test system 2:	10-generating units with valve point effect and multiple fuels; and
Test system 3:	15-generating units with prohibited operating zones, ramp rate limits, and transmission network loss but no valve point effect ;

Test System 1: A system with 40 generators with valve point effect and transmission network loss but no ramp rate limits and prohibited operating zones is considered as the test system 1. The input data are given in [22]. The load demand is 10500 MW. The best results obtained from the SOA are compared with those obtained by using improved fast evolutionary programming (EP) (IFEP) [22], hybrid EP with SQP (EP-SQP) [1], PSO with local random search (PSO-LRS) [21], CDE [10], new PSO (NPSO) [21], NPSO with LRS (NPSO-LRS) [21], combined PSO with real-valued mutation (CPSO-RM) [15], ACO [20], self-organizing hierarchical PSO (SOH-PSO) [6], GA-PS-SQP [1], quantum PSO (QPSO) [16], BBO [5], BF-NM [18], DE-BBO [4], RCGA [2], improved coordinated aggregation-based PSO (ICA-PSO) [24], and PSO with both chaotic sequences and crossover operation (CCPSO) [17]. The best solution of the generation schedules and the total generation cost etc for this test system as obtained from 50 random trial runs of the SOA are presented in Table 1. Convergence results for the different algorithms with the same P_D are also presented in Table 2. Table 3 shows the frequency of attaining the minimum cost within different ranges for this test system out of 50 independent trials. The convergence profile of the cost function is depicted in Fig. 4.

Test System 2: A system comprising of 10 thermal units with valve point effect and multiple fuels option is considered as the test system 2. The input data are taken from [9]. The load demand is 2700 MW. Transmission loss is not considered in this case. The best results obtained by the SOA are compared with those obtained by IGA-MU [9], conventional GA with MU (CGA-MU) [9], PSO-LRS [21], NPSO [21], NPSO-LRS [21], RCGA [2], ACO [20], BBO [5], and DE-BBO [4]. The best solution of the generation schedules and the total generation cost etc for this test system as obtained from 100 independent trial runs of the algorithms are shown in Table 4. Convergence results for the algorithms with the same P_D are presented in Table 5. Table 6 shows the frequency of attaining minimum cost within different ranges for this test system out of 100 independent trials. The convergence profile of the cost function is depicted in Fig. 5.

Test System 3: Experiments are conducted on 15-generating unit power systems. In this test power systems; the prohibited operating zones, ramp rate limits, and transmission network losses are considered. The system input data and *B* coefficients are taken from [12]. Units 2, 5, and 6 have three prohibited zones while that for unit 12 is of two. For this test system load demand is 2630 MW. The best results obtained by the SOA are compared to those obtained by GA [12], PSO [12], CPSO1 [13], CPSO2 [13], BF-NM [18], SOH-PSO [6], parallel asynchronous PSO (PAPSO) [23], PSO with modified stochastic acceleration factors (PSO-MSAF) [23], MDE [3], PSO with chaotic sequences (CSPSO) [17], conventional PSO with the constraint treatment strategy (CTPSO) [17], and PSO with crossover operation (COPSO) [17]. The best solutions of the generation schedule, the total optimal generation cost etc for this test system as obtained from 50 independent trial runs of the SOA are presented in Table 7. Convergence results for the algorithms with the same P_D are presented in Table 8. The convergence profile of the cost function is depicted in Fig. 6

TABLE 1
SOA-BASED BEST RESULTS FOR THE TEST SYSTEM 1 WITH P_D=10500 MW

Unit	Generation (MW)	Unit	Generation (MW)	Unit	Generation (MW)	Unit	Generation (MW)
P_1	93.3423	P_{11}	308.7892	P_{21}	508.1364	P_{31}	167.7709
P_2	97.4103	P_{12}	277.1260	P_{22}	501.0253	P_{32}	149.3685
P_3	101.2452	P_{13}	392.8826	P_{23}	506.5673	P_{33}	167.6685
P_4	164.2993	P_{14}	395.1955	P_{24}	487.7431	P_{34}	160.6820
P_5	84.0175	P_{15}	381.0143	P_{25}	480.5522	P_{35}	169.2923
P_6	123.2729	P_{16}	380.9107	P_{26}	505.1173	P_{36}	165.5492
P_7	255.7977	P_{17}	437.8174	P_{27}	112.9493	P_{37}	99.6996
P_8	263.8875	P_{18}	445.1430	P_{28}	124.1613	P_{38}	86.2462
P_9	280.2526	P_{19}	451.5323	P_{29}	117.1892	P_{39}	89.7858
P_{10}	264.0890	P_{20}	460.1727	P_{30}	90.1045	P_{40}	412.0431
					Total generation (MW)		10759.85
					Total transmission loss (MW)		259.83
					Power mismatch (MW)		0.02
					Total generation cost ($/h)		**113890**
					Time/iteration (s)		0.05

TABLE 2
CONVERGENCE RESULTS (50 TRIAL RUNS) FOR THE TEST SYSTEM 1 WITH P_D = 10500 MW

Algorithms	Total generation cost ($/h)			Algorithms	Total generation cost ($/h)		
	Minimum	Maximum	Average		Minimum	Maximum	Average
IFEP	122624.3500	125740.6300	123382.0000	GA-PS-SQP	121458.14	NR*	122039
EP-SQP	122324	NR*	122379	QPSO	121448.21	NR*	122225.07
PSO-LRS	122035.7946	123461.6794	122558.4565	BBO	121426.953	121688.6634	121508.0325
CDE	121741.9793	NR*	121814.9465	BF-NM	121423.63792	NR*	122295.1278
NPSO	121704.7391	122995.0976	122221.3697	DE-BBO	121420.8948	121420.8968	121420.8952
NPSO-LRS	121664.4308	122981.5913	122209.3186	RCGA	121418.5425	121628.5987	121504.1169
CPSO-RM	121555.32	123094.98	122281.14	ICA-PSO	121413.20	121453.56	121428.14
ACO	121532.41	121679.64	121606.45	CCPSO	121403.5362	121525.4934	121445.3269
SOH-PSO	121501.14	122446.30	121853.57	SOA	**113890**	114000	113250

NR* means not reported in the referred literature

TABLE 3
FREQUENCY OF CONVERGENCE IN 50 TRIAL RUNS FOR 40-GENERATING UNITS WITH P_D = 10500 MW

Algorithms	Range of total generation cost ($\times$ 10^3, $/h)										
	<120.0	120.0-121.5	121.5-122.5	122.5-123.0	123.0-123.5	123.5-124.0	124.0-124.5	124.5-125.0	125.0-125.5	125.5-126.0	>126.0
SOA	**50**	0	0	0	0	0	0	0	0	0	0
DE-BBO	0	50	0	0	0	0	0	0	0	0	0
BBO	0	38	12	0	0	0	0	0	0	0	0
QPSO	0	2	27	20	1	0	0	0	0	0	0
SOH-PSO	0	0	50	0	0	0	0	0	0	0	0
NPSO-LRS	0	0	40	10	0	0	0	0	0	0	0
NPSO	0	0	37	13	0	0	0	0	0	0	0
PSO-LRS	0	0	26	17	7	0	0	0	0	0	0
CPSO-RM	0	41	8	1	0	0	0	0	0	0	0
IFEP	0	0	0	11	25	9	2	2	0	0	0

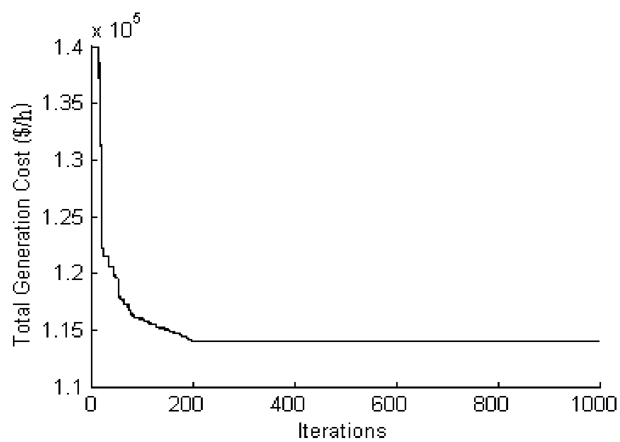

Fig.4. Convergence profile of the total generation cost for the test system1

TABLE 4

BEST RESULTS FOR THE TEST SYSTEM 2 WITH P_D = 2700 MW

Unit	SOA		DE-BBO		BBO		NPSO-LRS		IGA-MU	
	Generation (MW)	Fuel Type	Generation (MW)	Fuel Type	Generation (MW)	Fuel Type	Generation (MW)	Fuel Type	Generation (MW)	Fuel Type
P_1	186.4532	1	213.4589	2	212.9	2	223.335	2	219.126	2
P_2	102.1240	2	209.4836	1	209.4	1	212.195	1	211.164	1
P_3	399.4492	1	332.0000	3	332.0	3	276.216	1	280.657	1
P_4	185.6678	1	238.0269	3	238.3	3	239.418	3	238.477	3
P_5	358.6526	1	269.1423	1	269.2	1	274.647	1	276.417	1
P_6			238.0269	3	237.6	3	239.797	3	240.467	3
P_7	197.4176	2	280.6144	1	280.6	1	285.538	1	287.739	1
P_8	420.7243	1	238.1613	3	238.4	3	240.632	3	240.761	3
P_9	206.8849	1	414.7001	3	414.8	3	429.263	3	429.337	3
P_{10}	315.4986	3	266.3850	1	266.3	1	278.954	1	275.851	1
TG*		2700		1		2700		2700		2700
TTL*		0		0		0		0		0
PM*		0		0		0		0		0
TGC*		**536.0225**		605.6230127		605.6387		624.127		624.517
TI*		0.14		0.48		0.80		0.52		7.25

TG* means total generation (MW), TTL* means total transmission loss (MW), PM* means power mismatch (MW), TGC* means total generation cost ($/h), TI* means time/iteration

TABLE 5

CONVERGENCE RESULTS (100 TRIAL RUNS) FOR THE TEST SYSTEM 2 WITH P_D = 2700 MW

Algorithms	Total generation cost ($/h)			Algorithms	Total generation cost ($/h)		
	Minimum	Maximum	Average		Minimum	Maximum	Average
IGA-GA	627.5178	630.8705	625.8692	RCGA	623.8281	623.8814	623.8495
CGA-MU	624.7193	633.8652	627.6087	ACO]	623.70	624.09	623.90
PSO-LRS	624.2297	628.3214	625.7887	BBO]	605.6387	605.9103	605.8622
NPSO	624.1624	627.4237	625.2180	DE-BBO]	605.6230	605.6231	605.6252
NPSO-LRS	624.1273	626.9981	624.9985	SOA	**536.0225**	601.2624	600.0214

TABLE 6

FREQUENCY OF CONVERGENCE IN 100 TRIAL RUNS FOR 10-GENERATING UNITS WITH P_D = 2700 MW

Algorithms	Range of total generation cost ($/h)												
	<605.5	605.5–623.5	623.5–624.5	624.5–625.5	625.5–626.5	626.5–627.5	627.5–628.5	628.5–629.5	629.5–630.5	630.5–631.5	631.5–632.5	632.5–633.5	633.5–634.5
SOA	**100**	0	0	0	0	0	0	0	0	0	0	0	0
DE-BBO	0	100	0	0	0	0	0	0	0	0	0	0	0
BBO	0	100	0	0	0	0	0	0	0	0	0	0	0
NPSO-LRS	0	0	20	58	17	5	0	0	0	0	0	0	0
NPSO	0	0	18	54	16	12	0	0	0	0	0	0	0
PSO-LRS	0	0	5	37	36	17	5	0	0	0	0	0	0
IGA-MU	0	0	0	39	45	11	2	2	0	1	0	0	0
CGA-MU	0	0	0	5	20	31	21	10	7	3	2	0	1

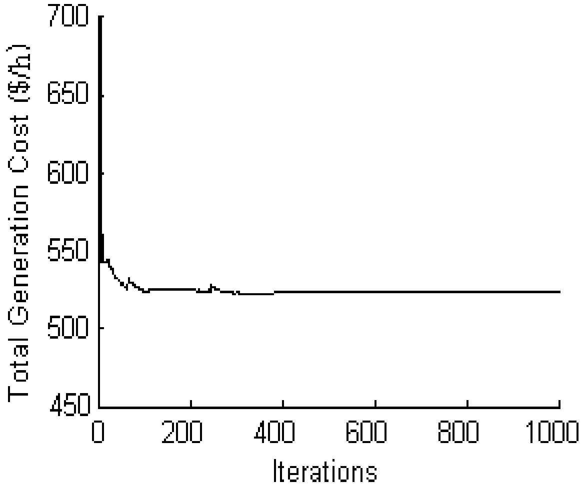

Fig.5. Convergence profile of the total generation cost for the test system 2.

TABLE 7
SOA-BASED RESULTS FOR THE TEST SYSTEM 3 WITH P_D = 2630 MW

Unit	Generation (MW)	Unit	Generation (MW)	Unit	Generation (MW)
P_1	436.2674	P_6	425.7442	P_{11}	67.8607
P_2	402.9568	P_7	415.7284	P_{12}	34.1385
P_3	117.1075	P_8	158.1469	P_{13}	74.0977
P_4	107.3267	P_9	74.1429	P_{14}	33.5093
P_5	251.6046	P_{10}	29.9969	P_{15}	33.2253
			Total generation (MW)		2656.5
			Total transmission loss (MW)		26.4731
			Power mismatch (MW)		2.0354e-04
			Total generation cost ($/h)		**32703**
			Time/iteration (s)		0.021

TABLE 8
CONVERGENCE RESULTS (50 TRIAL RUNS) FOR THE TEST SYSTEM 3 WITH P_D = 2630 MW

Algorithms	Total generation cost ($/h)			Algorithms	Total generation cost ($/h)		
	Minimum	Maximum	Average		Minimum	Maximum	Average
GA	33,113	33,337	33,228	PSO-MSAF	32 713.09	32798.25	32759.64
PSO	32,858	33,331	33,039	MDE	32704.9	32711.5	32708.1
CPSO1	32,835	33,318	33,021	CSPSO	32704.4514	32704.4514	32704.4514
CPSO2	32,834	33,318	33,021	CTPSO	32704.4514	32704.4514	32704.4514
BF-NM	32784.5	NR*	32796.8	COPSO	32704.4514	32704.4514	32704.4514
SOH-PSO	32,751	32,945	32,878	COPSO	32704.4514	32704.4514	32704.4514
PAPSO	32715.67	32852.14	32789.28	SOA	**32703**	32703	32703

NR* means not reported in the referred literature

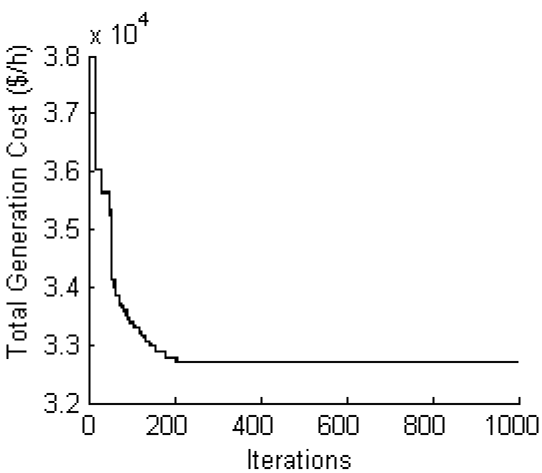

Fig. 6. Convergence profile of the total generation cost for the test system 3
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CONCLUSION

In this paper, a novel evolutionary optimization technique, SOA has been successfully implemented to solve different ELD problems. It has been observed that the SOA has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics and robustness than other prevailing techniques reported in the recent literatures. It is also clear from the results obtained by different trials that the SOA is free from the shortcoming of premature convergence exhibited by the other optimization techniques. Thus, this SOA technique may become very promising for solving some more complex engineering optimization problems for future researchers.

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