Solution of Economic Load Dispatch Problems by a Novel Seeker Optimization Algorithm

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Abstract: This article presents an efficient approach for solving economic load dispatch (ELD) problems in different test power systems using a novel seeker optimization algorithm (SOA) 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. In this paper, four test systems of the ELD problems are solved by adopting the SOA. A comparison of obtained simulation results by adopting the SOA is carried out with those published in the recent literatures. It is revealed from comparison that the optimization efficacy of the SOA over the prevailing optimization techniques for the solution of the multimodal, non-differentiable, highly non-linear, and constrained ELD problems is promising.

Keywords: Economic load dispatch; multiple fuel options; seeker optimization algorithm; transmission loss; valve point loading

1. Introduction

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 [1]. To date, various investigations on ELD problems have been undertaken as better solutions would result in more saving in the operating cost.

Several classical methods, such as the lambda iteration (LI) method and gradient method have been applied to solve the ELD problems. But unfortunately, these methods are not feasible in practical power systems owing to the non-linear characteristics of the generators and non-smooth cost functions. Consequently, many powerful mathematical optimization techniques that are fast and reliable, such as non-linear programming and dynamic programming have been employed to solve the ELD problems. But due to the non-differential and non-convex characteristics of the cost functions, these methods are also unable to locate the global optima. Among the artificial intelligence methods, Hopfield neural networks [2] have been applied to solve the non-linear ELD problems, but these methods suffer from excessive numerical iterations, resulting in huge computations. Complex constrained ELD problems have been solved by many population-based optimization techniques in recent years. Some of the population-based optimization methods are genetic algorithm (GA) [3], simulated annealing (SA) [4], Tabu search [5], improved fast evolutionary programming (EP) (IFEP) [6], particle swarm optimization (PSO) [3], ant colony optimization (ACO) [7], differential evolution (DE) [8], bacteria foraging with Nelder-Mead (BF-NM) [9], Seeker optimization algorithm (SOA) [12] is essentially a novel population based heuristic Biogeography-based optimization (BBO) [10], a hybrid technique combining DE with BBO (DE/BBO) [11].

Received: August 19th, 2010. Accepted: February 28th, 2011

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 highlighting characteristic features of this algorithm are the following:

a. Search direction and step length are directly used in this algorithm to update the position,
b. Proportional selection rule is applied for the calculation of the search direction, which can improve the population diversity so as to boost the global search ability and decrease the number of control parameters making it simpler to implement, and
c. Fuzzy reasoning is used to generate the step length because the uncertain reasoning of human searching could be the best described by natural linguistic variables, and a simple if-else control rule.

The algorithm is to model the cooperative manner of human being while performing the group dynamics. In view of the aforementioned underlying concepts of the SOA as an optimizer, can this algorithm be exploited for the solution of the ELD problems of different capacities and volumes? Are the results yielded by the SOA comparable to those reported in the recent literatures? Basically, the present work is an attempt to utilize the optimizing capability of the SOA for the solutions of highly constrained ELD problems.

The present work focuses on the performance of the SOA as an optimizing tool in solving different ELD problems. The main contribution of the paper can be summarized as follows:

1. Four test cases of the ELD problems are solved with the help of the SOA and the best results obtained are presented in this paper.
2. The best results obtained for the test cases considered by adopting the SOA are compared with those published in the recent papers.
3. Based on the quality and the improved convergence speed of the solution as obtained and presented in this paper, the applicability of the SOA in solving the practical ELD problems of power systems is proposed.

The rest of the paper is organized as follows. In Section 2, mathematical modeling of the ELD problem is done. In Section 3, an objective function is formulated which requires to be optimized. The SOA is narrated in Section 4. Test cases and simulation results are presented in Section 5 to demonstrate the performance of the algorithm for the ELD problems. Section 6 focuses on conclusions of the present work.

2. Mathematical Modeling of the ELD Problem

A. ELD with Quadratic Cost Function and Transmission Loss

The problem of the ELD is multimodal, non-differentiable and highly non-linear. Mathematically, the problem can be stated as in (1) [1, 6].

$$Min\ F_T(P) = \sum_{i=1}^{NG} F_i(P_i) \quad \$/h;\ i = 1, \ldots\ldots\ldots, NG \qquad (1)$$

Subject to,

(i) Real Power Balance Constraint

The power balance operation can be modeled as in (2).

$$\sum_{i=1}^{NG} P_i - P_D - P_L = 0; \qquad i = 1, \ldots\ldots\ldots, NG \qquad (2)$$

The transmission loss (P_L) may be expressed as a quadratic function of generations (using B coefficient matrix) as given in (3).

$$P_L = \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_i B_{ij} P_j + \sum_{i=1}^{NG} B_{0i} P_i + B_{00};\ i = 1, \ldots\ldots\ldots, NG \text{ , and } j = 1, \ldots\ldots\ldots, NG \qquad (3)$$

(ii) Generation Capacity Constraints

The generating capacity constraints are written as in (4).

$$P_i^{\min} \le P_i \le P_i^{\max}\ ; i = 1, ..., NG \tag{4}$$

B. ELD Problem with Valve Point Loading

For a more practical and accurate model of the cost function, multiple valve steam turbines are considered. Total cost of the generating units with valve point loading is given in (5) [6].

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \times \sin(f_i \times (P_i^{\min} - P_i)) \right|\ \$/h\ ; i = 1, ..., NG \tag{5}$$

It is to be noted here that the fuel cost coefficients e_i and f_i are introduced in (5) to model the valve point loadings.

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

Considering both valve point loading effect and multiple fuels, the cost function [13] is as in (6).

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 + \left| e_{i1} \times \sin(f_{i1} \times (P_{i1}^{\min} - P_{i1})) \right|, & for\ fuel 1, P_i^{\min} \le P_i \le P_{i1} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 + \left| e_{i2} \times \sin(f_{i2} \times (P_{i2}^{\min} - P_{i2})) \right|, & for\ fuel 2, P_{i1} < P_i \le P_{i2} \\ . & \\ . & \\ . & \\ a_{ik} + b_{ik}P_i + c_{ik}P_i^2 + \left| e_{ik} \times \sin(f_{ik} \times (P_{ik}^{\min} - P_{ik})) \right|, & for\ fuel\ k, P_{ik-1} < P_i \le P_i^{\max} \end{cases} \tag{6}$$

3. Formulation of The Objective Function

The objective function ($OF()$) is designed as in (7) that requires to be minimized.

$$OF(\,) = \sum_{i=1}^{NG} F_i(P_i) + 100 \times P_L + 1000 \times abs\left(\sum_{i=1}^{NG} P_i - P_D - P_L \right) \tag{7}$$

The weighing factors are selected to make the corresponding terms competitive during the process of optimization. The unit of each weighing factor involved in (7) is \$/MWh.

4. Seeker Optimization Algoritm and Its Application to the ELD Problem

A. Seeker Optimization Algorithm

The SOA [12] is a population-based heuristic search algorithm. 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 ith seeker on each jth variable at each time step t, where $\alpha_{ij}(t) \ge 0$ and

$d_{ij}(t) \in \{-1,\ 0,\ 1\}$. Here, i represents the population number and j represents the optimizing variable number.

a) Calculation of the search direction, $d_{ij}(t)$: It is the natural tendency of the swarms to reciprocate in a cooperative manner while executing their needs and goals. Normally, there are two extreme types of cooperative behavior prevailing in swarm dynamics. One, egotistic, is entirely pro-self and another, altruistic, is entirely pro-group [14]. Every seeker, as a single sophisticated agent, is uniformly egotistic [14]. He believes that he should go toward his historical best position according to his own judgment. This attitude of ith seeker may be modeled by an empirical direction vector $\vec{d}_{i,\ ego}\ (t)$ as shown in (8).

$$\vec{d}_{i,\ ego}\ (t) = sign(\vec{p}_{i,\ best}(t) - \vec{x}_i(t)) \quad (8)$$

In (8), $sign\ (\cdot)$ is a signum function on each variable of the input vector. On the other hand, in altruistic behavior, seekers want to communicate with each other, cooperate explicitly, and adjust their behaviors in response to the other seeker in the same neighborhood region for achieving the desired goal. That means the seekers exhibit entirely pro-group behavior. The population then exhibits a self-organized aggregation behavior of which the positive feedback usually takes the form of attraction toward a given signal source. Two optional altruistic directions may be modeled as in (9)-(10).

$$\vec{d}_{i,\ alt1}\ (t) = sign(\vec{g}_{best}(t) - \vec{x}_i\ (t)) \quad (9)$$

$$\vec{d}_{i,\ alt\ 2}\ (t) = sign(\vec{l}_{best}(t) - \vec{x}_i\ (t)) \quad (10)$$

In (9)-(10), $\vec{g}_{best}(t)$ represents neighbors' historical best position, $\vec{l}_{best}(t)$ means neighbors' current best position.

Moreover, seekers enjoy the properties of pro-activeness; seekers do not simply act in response to their environment; they are able to exhibit goal-directed behavior. In addition, the future behavior can be predicted and guided by the past behavior. As a result, the seeker may be pro-active to change his search direction and exhibit goal-directed behavior according to his past behavior. Hence, each seeker is associated with an empirical direction called as pro-activeness direction as given in (11).

$$\vec{d}_{i,\ pro}\ (t) = sign(\vec{x}_i\ (t_1) - \vec{x}_i\ (t_2)) \quad (11)$$

In (11), $t_1, t_2 \in \{t,\ t-1,\ t-2\}$ and it is assumed that $\vec{x}_i\ (t_1)$ is better than $\vec{x}_i\ (t_2)$. Aforementioned four empirical directions as presented in (9)-(11) direct human being to take a rational decision in his search direction.

If the jth variable of the ith seeker goes towards the positive direction of the coordinate axis, $d_{ij}(t)$ is taken as +1. If the jth variable of the ith seeker goes towards the negative direction of the coordinate axis, $d_{ij}(t)$ is assumed as -1. The value of $d_{ij}(t)$ is assumed as 0 if the ith seeker stays at the current position. Every variable j of $\vec{d}_i\ (t)$ is selected by applying the following proportional selection rule (shown in Figure 1) as stated in (12).

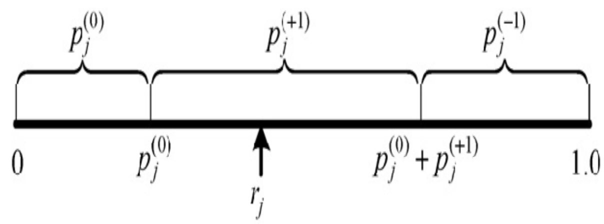

Figure 1. The proportional selection rule of search directions

$$d_{ij} = \begin{cases} 0, & if \quad r_j \le p_j^{(0)} \\ +1, & if \quad p_j^{(0)} \le r_j \le p_j^{(0)} + p_j^{(+1)} \\ -1, & if \quad p_j^{(0)} + p_j^{(+1)} < r_j \le 1 \end{cases} \tag{12}$$

In (12), r_j is a uniform random number in [0, 1], $p_j^{(m)}$ ($m \in \{0, +1\ -1\}$ is the percent of the numbers of "m" from the set $\{d_{ij,ego}, d_{ij,alt1}, d_{ij,alt2}, d_{ij,pro}\}$ on each variable j of all the four empirical directions, i.e. $p_j^{(m)}$ = (the number of m) / 4.

b) Calculation of the step length, $\alpha_{ij}(t)$: From the view point of human searching behavior, it is understood that one may find the near-optimal solutions in a narrower neighborhood of the point with lower fitness value and on the other hand, in a wider neighborhood of the point with higher fitness value.

A fuzzy system may be an ideal choice to represent the understanding and linguistic behavioral pattern of human searching tendency.

Different optimization problems often have different ranges of fitness values. To design a fuzzy system to be applicable to a wide range of optimization problems, the fitness values of all the seekers are sorted in descending manner (for minimization problem) / in ascending manner (for maximization problem) and turned into the sequence numbers from 1 to S as the inputs of fuzzy reasoning. The linear membership function is used in the conditional part since the universe of discourse is a given set of numbers, i.e. 1, 2, ..., S . The expression is presented as in (13).

$$\mu_i = \mu_{\max} - \frac{S - I_i}{S - 1}(\mu_{\max} - \mu_{\min}) \tag{13}$$

In (13), I_i is the sequence number of $\vec{x}_i(t)$ after sorting the fitness values, $\mu_{\max}$ is the maximum membership degree value which is equal to or a little less than 1.0. Here, the value of $\mu_{\max}$ is taken as 0.95.

A fuzzy system works on the principle of the control rule as "If {the conditional part}, then {the action part}. Bell membership function $\mu(x) = e^{-x^2/2\delta^2}$ (shown in Figure 2) is well utilized in the literature to represent the action part. For the convenience, one variable is considered. Thus, the membership degree values of the input variables beyond $[-3\delta, +3\delta]$ are less than 0.0111 ($\mu(\pm 3\delta) = 0.0111$), and the elements beyond $[-3\delta, +3\delta]$ in the universe of discourse can be neglected for a linguistic atom [15]. Thus, the minimum value $\mu_{\min} = 0.0111$ is set. Moreover, the parameter, $\vec{\delta}$ of the Bell membership function is determined by (14).

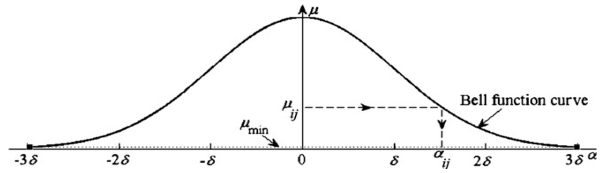

Figure 2. The action part of the fuzzy reasoning.

$$\vec{\delta} = \omega \times abs(\vec{x}_{best} - \vec{x}_{rand}) \quad (14)$$

In (14), the absolute value of the input vector as the corresponding output vector is represented by the symbol $abs(\cdot)$. The parameter ω is used to decrease the step length with increasing time step so as to gradually improve the search precision. In the present experiments, ω is linearly decreased from 0.9 to 0.1 during a run. The $\vec{x}_{best}$ and $\vec{x}_{rand}$ are the best seeker and a randomly selected seeker respectively from the same subpopulation to which the ith seeker belongs. It is to be noted here that $\vec{x}_{rand}$ is different from $\vec{x}_{best}$ and $\vec{\delta}$ is shared by all the seekers in the same subpopulation.

In order to introduce the randomness in each variable and to improve the local search capability, the following equation is introduced to convert μ_i into a vector $\vec{\mu}_i$ with elements as given by (15).

$$\mu_{ij} = RAND(\mu_i, 1) \quad (15)$$

In (15), $RAND(\mu_i, 1)$ returns a uniformly random real number within $[\mu_i, 1]$. Equation (16) denotes the action part of the fuzzy reasoning and gives the step length (α_{ij}) for every variable j.

$$\alpha_{ij} = \delta_j \sqrt{-\ln(\mu_{ij})} \quad (16)$$

c) Updating of seekers' position: In a population of size S, for each seeker i ($1 \le i \le S$), the position update on each variable j is given by the following equation.

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t) \times d_{ij}(t) \quad (17)$$

where

$x_{ij}(t+1)$	the position of the jth variable of the ith seeker at time step $t+1$;
$x_{ij}(t)$	the position of the jth variable of the ith seeker at time step t;
$\alpha_{ij}(t)$	the step length of the jth variable of the ith seeker at time step t; and
$d_{ij}(t)$	the search direction of the jth variable of the ith seeker at time step t.

d) Subpopulations learn from each other: Each subpopulation is searching for the optimal solution using its own information. It hints that the subpopulation may trap into local optima yielding a premature

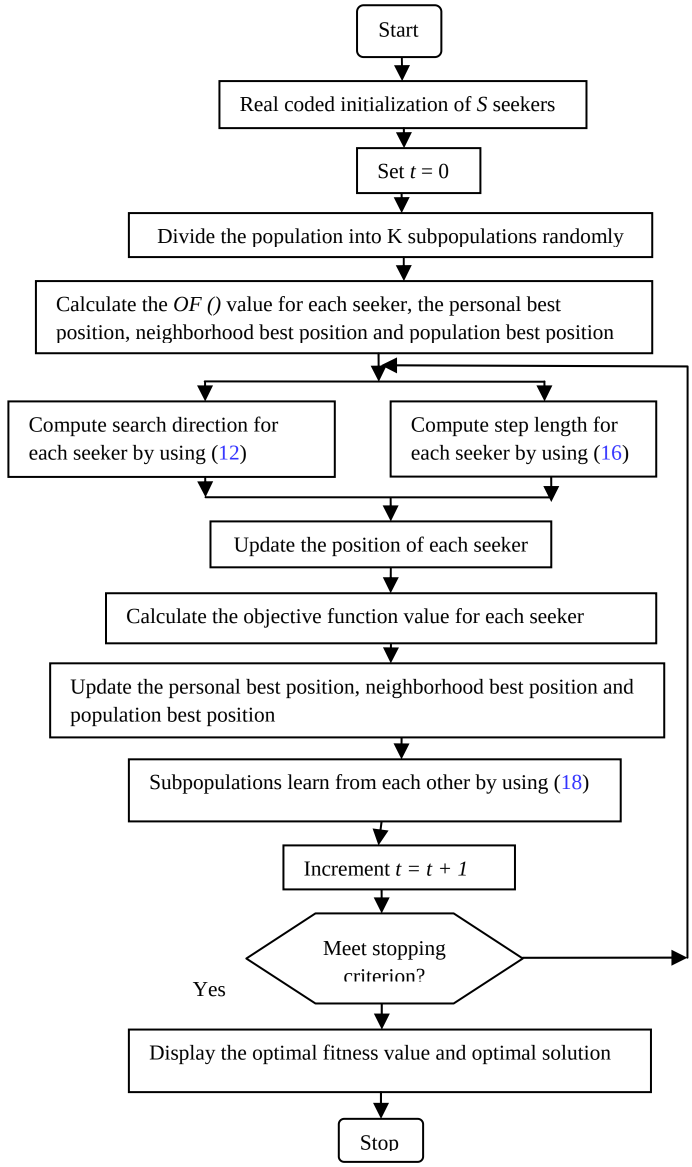

Figure 3. Flowchart of the seeker optimization

convergence. Subpopulations must learn from each other about the optimum information so far they have acquired in their respective domain. Thus, the position of the worst seeker of each subpopulation is combined with the best one in each of the other subpopulations using the following binomial crossover operator as expressed in (18).

$$x_{k_n j,worst} = \begin{cases} x_{lj,\,best}\,, & if\ \ rand_j \leq 0.5 \\ x_{k_n\, j,\,worst}\,, & else \end{cases} \tag{18}$$

In (18), $rand_j$ is a uniformly random real number within [0, 1], $x_{k_n j,\,worst}$ is denoted as the jth variable of the nth worst position in the kth subpopulation, $x_{lj\,best}$ is the jth variable of the best position in the lth subpopulation. Here, n, k, $l = 1, 2, ..., K-1$ and $k \neq l$. In order to increase the diversity in the population, good information acquired by each subpopulation is shared among the subpopulations. The flowchart of the algorithm is depicted in Figure 3.

Step 1	Initialization: Read input data, set number of run counter, read cost curves of machines and B coefficients, set maximum population number, set lower and upper limits of each generator output, read SOA parameters, set termination criteria (i.e. maximum iteration cycles).
Step 2	Initialize the positions of the seekers in the search space randomly and uniformly.
Step 3	Set the time step t = 0
Step 4	Compute the objective function of the initial positions. The initial historical best position among the population is achieved. Set the personal historical best position of each seeker to his current position.
Step 5	Let t = t + 1.
Step 6	Select the neighbor of each seeker.
Step 7	Determine the search direction and step length for each seeker, and update his position
Step 8	Update the position of each seeker.
Step 9	Compute the objective function for each seeker.
Step 10	Update the historical best position among the population and historical best position of each seeker.
Step 11	Subpopulations learn from each other.
Step 12	Repeat from Step 5 till the end of the maximum iteration cycles/stopping criterion.
Step 13	Determine the best string corresponding to optimum objective function value.
Step 14	Determine the optimal generation string corresponding to the grand optimum objective function value.

Figure 4. Implementation steps of the SOA algorithm for the ELD problems

B. Implementation of SOA for ELD Problem

The steps of the SOA, as implemented for the solution of the ELD problem of this work, are shown in Figure 4.

5. Test Cases and Solution Results

SOA has been applied to solve the ELD problems in four different test cases for investigating its optimization capability. The software has been 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 Cases

The following four test cases are considered in this work. In the different test cases, while comparing the costs obtained by the algorithms with that obtained by the SOA, the numbers within the {… } denote the minimum values of the total generation costs in $/h as reported in the referred literatures [...]. The values of the total generation cost are presented in the descending order.

a) Test case 1: 20-generating units without valve point loading: A system with 20 generators is taken as the test case 1. The system input data are available in [3, 16]. The valve point loading effect is not considered for this case but transmission loss is considered. For this test case load demand is 2500 MW. The best generation costs reported for the algorithms in the literature like BBO {62456.77926} [10], Lambda iteration (LI) {62456.6391} [2], Hopfield model (HM) {62456.6341} [2], and chaotic and Gaussian PSO (PSO-CG) {59804.0500} [16] are compared with the SOA-based best generation cost {59421}. The best solutions of the generation schedules, the generation costs etc as obtained from 50 trial runs of the SOA and other afore-mentioned algorithms are presented in Table 1. The convergence profile of the cost function is depicted in Figure 5.

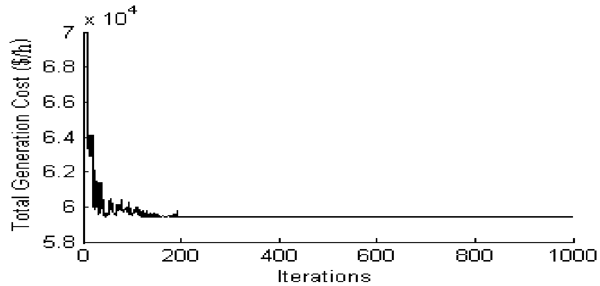

Figure 5. Convergence profile of the total generation cost for 20-generating units.

Table 1. Best results for 20-generating units with P_D = 2500 MW

Unit	BBO [10]	LI [2]	HM [2]	PSO-CG [16]	SOA
P_1	513.0892	512.7805	512.7804	563.3155	304.7058
P_2	173.3533	169.1033	169.1035	106.5639	90.1026
P_3	126.9231	126.8898	126.8897	98.7093	105.088
P_4	103.3292	102.8657	102.8656	117.3171	100.9737
P_5	113.7741	113.6386	113.6836	67.0781	111.9052
P_6	73.06694	73.5710	73.5709	51.4702	89.4554
P_7	114.9843	115.2878	115.2876	47.7261	97.5200
P_8	116.4238	116.3994	116.3994	82.4271	115.0051
P_9	100.6948	100.4062	100.4063	52.0884	166.0976
P_{10}	99.99979	106.0267	106.0267	106.5097	76.8435
P_{11}	148.9770	150.2394	150.2395	197.9428	246.2108
P_{12}	294.0207	292.7648	292.7647	488.3315	239.5819
P_{13}	119.5754	119.1154	119.1155	99.9464	111.9761
P_{14}	30.54786	30.8340	30.8342	79.8941	115.8576
P_{15}	116.4546	115.8057	115.8056	101.525	114.6967
P_{16}	36.22787	36.2545	36.2545	25.8380	72.4539
P_{17}	66.85943	66.8590	66.8590	70.0153	64.9063
P_{18}	88.54701	87.9720	87.9720	53.9530	107.2208
P_{19}	100.9802	100.8033	100.8033	65.4271	107.2200
P_{20}	54.2725	54.3050	54.3050	36.2552	88.4224
Total generation (MW)	2592.1011	2591.9670	2591.9670	2512.3343	2526.2430
Total transmission loss (MW)	92.1011	91.9670	91.9669	12.3343	26.2432
Power mismatch (MW)	0	-0.000187	0.000021	NR*	0
Total generation cost ($/h)	62456.77926	62456.6391	62456.6341	59804.0500	59421
Time/iteration (s)	0.29282	0.033757	0.006355	0.44	0.0238

Table 2. Best results for 38-generating units with $P_D = 6000$ MW

Unit	New-PSO [18]	PSO-TVAC [18]	BBO [10, 11]	DE/BBO [11]	SOA
P_1	550.000	443.659	422.230586	426.606060	318.4260
P_2	512.263	342.956	422.117933	426.606054	315.2351
P_3	485.733	433.117	435.779411	429.663164	277.6897
P_4	391.083	500.00	445.481950	429.663181	281.8220
P_5	443.846	410.539	428.475752	429.663193	262.0443
P_6	358.398	492.864	428.649254	429.663164	330.4357
P_7	415.729	409.483	428.115368	429.663185	305.7628
P_8	320.816	446.079	429.900663	429.663168	237.5684
P_9	115.347	119.566	115.904947	114.000000	346.8533
P_{10}	204.422	137.274	114.115368	114.000000	203.8684
P_{11}	114.000	138.933	115.418662	119.768032	250.0759
P_{12}	249.197	155.401	127.511404	127.072817	213.2689
P_{13}	118.886	121.719	110.000948	110.000000	338.2986
P_{14}	102.802	90.924	90.0217671	90.0000000	131.1207
P_{15}	89.039	97.941	82.0000000	82.0000000	148.7008
P_{16}	120.000	128.106	120.038496	120.000000	156.8968
P_{17}	156.562	189.108	160.303835	159.598036	214.0027
P_{18}	84.265	65.00	65.0001141	65.0000000	134.2227
P_{19}	65.041	65.00	65.0001370	65.0000000	136.6392
P_{20}	151.104	267.422	271.999591	272.000000	225.3016
P_{21}	226.344	221.383	271.872680	272.000000	192.5932
P_{22}	209.298	130.804	259.732054	260.000000	197.8333
P_{23}	85.719	124.269	125.993076	130.648618	153.4579
P_{24}	10.000	11.535	10.4134771	10.0000000	54.3421
P_{25}	60.000	77.103	109.417723	113.305034	87.6238
P_{26}	90.489	55.018	89.3772664	88.0669159	84.4932
P_{27}	39.670	75.000	36.4110655	37.5051018	52.2166
P_{28}	20.000	21.682	20.0098880	20.0000000	60.2310
P_{29}	20.995	29.829	20.0089554	20.0000000	56.9315
P_{30}	22.810	20.326	20.0000000	20.0000000	47.4167
P_{31}	20.000	20.000	20.0000000	20.0000000	35.3158
P_{32}	20.416	21.840	20.0033959	20.0000000	51.4590
P_{33}	25.000	25.620	25.0066586	25.0000000	53.4545
P_{34}	21.319	24.261	18.0222107	18.0000000	52.0196
P_{35}	9.122	9.667	8.00004260	8.00000000	16.7219
P_{36}	25.184	25.000	25.0060660	25.0000000	35.3188
P_{37}	20.000	31.642	22.0005641	21.7820891	27.0471
P_{38}	25.104	29.935	20.6076309	21.0621792	37.9999
Total generation (MW)	NR*	NR*	NR*	NR*	61247.7098
Total transmission loss (MW)	NR*	NR*	NR*	NR*	124.7098
Power mismatch (MW)	NR*	NR*	NR*	NR*	0
Total generation cost ($/h)	9516448.312	9500448.307	9417633.637644	9417235.78639	9.0012e+06
Time/iteration (s)	NR*	NR*	NR*	NR*	0.17

b) Test case 2: 38-generating units without valve point loading: A system with 38 generators is taken as the test case 2. Fuel cost characteristics are quadratic. Transmission loss is considered. The input data of the system are taken from [17]. The load demand is 6000 MW. The best generation cost {9.0012e+06} obtained by using the SOA has been compared with those by using simple PSO (SPSO) {9543984.777} [18], PSO with Crazy (PSO-Crazy) {9520024.601} [18], New PSO {9516448.312} [18], PSO with time varying acceleration coefficient (PSO-TVAC) {9500448.307} [18], BBO {9417633.637644} [10], and DE/BBO {9417235.78639} [11]. The best solutions of the generation schedules and the generation costs etc as obtained from 100 trial runs of the different algorithms are shown in Table 2. The convergence profile of the cost function is depicted in Figure 6.

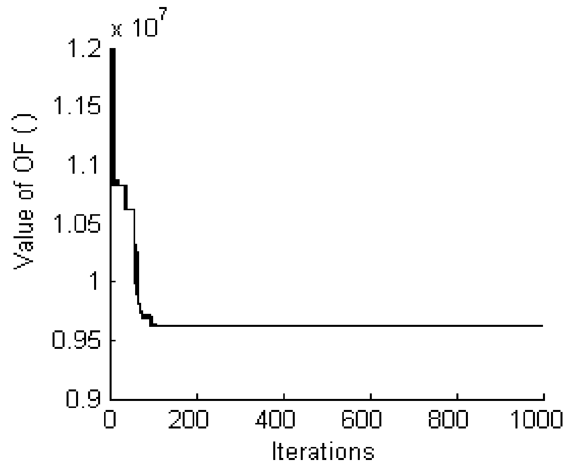

Figure 6. Convergence profile of the total generation cost for 38-generating units

c) Test case 3: 40-generating units with valve point loading: A system with 40 generators with valve point loadings and transmission loss is considered as the test case 3. The input data are given in [6]. The load demand is 10500 MW. The best generation cost{113120}obtained by the SOA is compared to those obtained by using IFEP {122624.3500} [6], hybrid EP and sequential quadratic programming (SQP) (EP-SQP) {122324} [19], PSO with local random search (LRS) (PSO-LRS) {122035.7946} [20], DE combination with SQP (DEC-SQP) {121741.9793} [8], new PSO (NPSO) {121704.7391} [20], new PSO with LRS (NPSO-LRS) {121664.4308} [20], combined PSO with real-valued mutation (CBPSO-RVM) {121555.32} [21],

ACO {121532.41} [7], self-organizing hierarchical PSO (SOH-PSO) {121501.14} [22], hybrid GA-pattern search-SQP (GA-PS-SQP) {121458.14} [19], quantum PSO (QPSO) {121448.21} [23], BBO {121426.953} [10], BF-NM {121423.63792} [9], DE/BBO {121420.8948} [11], real-coded GA (RCGA) {121418.5425} [24], improved coordinated aggregation-based PSO (ICA-PSO) {121413.20} [25], and PSO with both chaotic-sequence and crossover (CCPSO) {121403.5362} [26]. The best solutions of the generation schedules and the generation costs etc as obtained from 50 trial runs of the different algorithms are presented in Table 3. The convergence profile of the cost function is depicted in Figure 7.

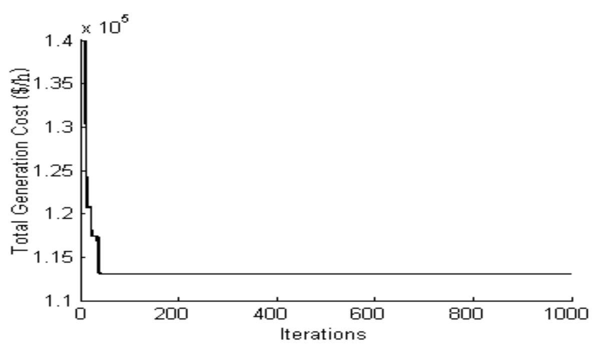

Figure 7. Convergence profile of the total generation cost for 40-generating units

Table 3. Best results for 40-generating units with P_D=10500 MW

Unit	NPSO-LRS [20]	SOH-PSO[22]	QPSO[23]	BBO [10]	DE/BBO[11]	ICA-PSO [25]	CCPSO [26]	SOA
P_1	113.9761	110.80	111.20	111.0465	110.7998	110.80	110.7998	98.4760
P_2	113.9986	110.80	111.70	111.5915	110.7998	110.80	110.7999	106.2378
P_3	97.4241	97.40	97.40	97.60077	97.3999	97.41	97.3999	110.7931
P_4	179.7327	179.73	179.73	179.7095	179.7331	179.74	179.7331	158.2180
P_5	89.6511	87.80	90.14	88.30605	87.9576	88.52	87.7999	91.8640
P_6	105.0444	140.00	140.00	139.9992	140.00	140.00	140.0000	127.2495
P_7	259.7502	259.60	259.60	259.6313	259.5997	259.60	259.5997	236.0978
P_8	288.4534	284.60	284.80	284.7366	284.5997	284.60	284.5997	286.5869
P_9	284.6460	284.60	284.84	284.7801	284.5997	284.60	284.5997	236.7750
P_{10}	204.8120	130.00	130.00	130.2484	130.00	130.00	130.0000	260.7015
P_{11}	168.8311	94.00	168.80	168.8461	168.7998	168.80	94.0000	304.0025
P_{12}	94.0000	94.00	168.8	168.8239	94.00	94.00	94.0000	292.9607
P_{13}	214.7663	304.52	214.76	214,7038	214.7598	214.76	214.7598	413.3226
P_{14}	394.2852	304.52	304.53	304.5894	394.2794	394.28	394.2794	391.8817
P_{15}	304.5187	394.28	394.28	394.2461	394.2794	394.28	394.2794	400.7214
P_{16}	394.2811	398.28	394.28	394.2409	304.5196	304.52	394.2794	401.5576
P_{17}	489.2807	489.28	489.28	489.2919	489.2794	498.28	489.2794	409.0213
P_{18}	489.2832	489.28	489.28	489.4188	489.2794	489.28	489.2794	468.3763
P_{19}	511.2845	511.28	511.28	511.2997	511.2794	511.28	511.2794	509.7511
P_{20}	511.3049	511.27	511.28	511.3073	511.2794	511.28	511.2794	509.1169
P_{21}	523.2916	523.28	523.28	523.417	523.2794	523.28	523.2794	438.7379
P_{22}	523.2853	523.28	523.28	523.2795	523.2794	523.28	523.2794	436.0573
P_{23}	523.2797	523.28	523.29	523.3793	523.2794	523.28	523.2794	441.0579
P_{24}	523.2994	523.28	523.28	523.3225	523.2794	523.28	523.2794	425.0123
P_{25}	523.2865	523.28	523.29	523.3661	523.2794	523.28	523.2794	427.9365
P_{26}	523.2936	523.28	523.28	523.4262	523.2794	523.28	523.2794	452.8892
P_{27}	10.0000	10.00	10.01	10.05316	10.00	10.00	10.0000	110.2229
P_{28}	10.0001	10.00	10.01	10.01135	10.00	10.00	10.0000	140.5338
P_{29}	10.0000	10.00	10.00	10.00302	10.00	10.00	10.0000	122.5079
P_{30}	89.0139	97.00	88.47	88.47754	97.00	96.39	87.8000	87.2678
P_{31}	190.0000	190.00	190.00	189.9983	190.00	190.00	190.0000	172.0005
P_{32}	190.0000	190.00	190.00	189.9881	190.00	190.00	190.0000	178.5031
P_{33}	190.0000	190.00	190.00	189.9663	190.00	190.00	190.0000	168.2835
P_{34}	199.9998	185.20	164.91	164.8054	164.7998	164.82	164.7998	187.7960
P_{35}	165.1397	164.80	165.36	165.1267	200.00	200.00	194.3976	171.5563
P_{36}	172.0275	200.00	167.19	165.7695	200.00	200.00	200.0000	178.2705
P_{37}	110.0000	110.00	110.00	109.9059	110.00	110.00	110.0000	97.2393
P_{38}	110.0000	110.00	107.01	109.9971	110.00	110.00	110.0000	87.7159
P_{39}	93.0962	110.00	110.00	109.9695	110.00	110.00	110.0000	93.5632
P_{40}	511.2996	511.28	511.36	511.2794	511.2794	511.28	511.2794	498.2079
TG*	NR*	NR*	NR*	NR*	NR*	NR*	NR*	10729.07
TTL*	NR*	NR*	NR*	NR*	NR*	NR*	NR*	229.06
PM*	NR*	NR*	NR*	NR*	NR*	NR*	NR*	0.01
TGC*	121664.4308	121501.14	121448.21	121426.95	121420.89	121413.2	121403.5362	113120
TI*	NR*	NR*	NR*	0.11	0.06	0.22	NR*	0.05

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 (s), NR* means not reported in the referred literature

d) Test case 4: 10-generating units with valve point loading and multiple fuel options : A system comprising of 10 thermal units with valve point loading and multiple fuels option is considered as the test case 4. The input data are taken from [13]. The load demand is 2700 MW. Transmission loss is not considered in this case. The best generation cost {564.7591} obtained by the SOA is compared to those obtained by the combined improved GA with multiplier updating (MU) (IGA-MU) {627.5178} [13], conventional GA with MU (CGA-MU {624.7193} [13], PSO-LRS {624.2297} [20], NPSO {624.1624} [20], NPSO-LRS {624.1273} [20], RCGA {623.8281} [24], ACO {623.7000} [7], BBO {605.6387} [10] and DE-BBO {605.6230} [11]. The best solutions of the generation schedules and the generation costs etc as obtained from 100 trial runs of the algorithms are shown in Table 4. The convergence profile of the cost function is depicted in Figure 8. The results of interest are bold faced in the respective tables.

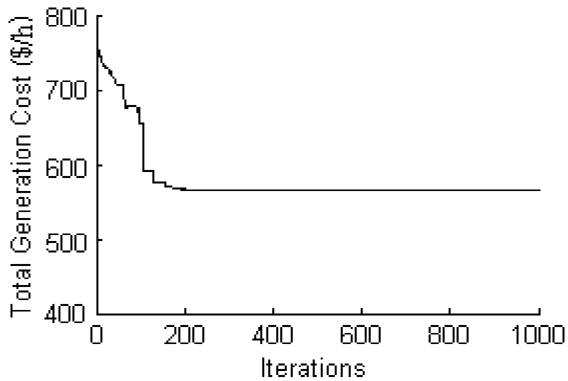

Figure 8. Convergence profile of the total generation cost for 10-generating units

Table 4. Best Results for 10-Generating Units with P_D=2700 MW

Unit	IGA-MU [13]		NPSO-LRS [20]		BBO[10]		DE/BBO [11]		SOA	
	Generation (MW)	**Fuel Type**	**Generation (MW)**	**Fuel Type**	**Generation (MW)**	**Fuel Type**	**Generation (MW)**	**Fuel Type**	**Generation (MW)**	**Fuel Type**
P_1	219.126	2	223.335	2	212.9	2	213.4589	2	203.9230	1
P_2	211.164	1	212.195	1	209.4	1	209.4836	1	215.5536	2
P_3	280.657	1	276.216	1	332.0	3	332.0000	3	488.2478	1
P_4	238.477	3	239.418	3	238.3	3	238.0269	3	206.4783	1
P_5	276.417	1	274.647	1	269.2	1	269.1423	1	281.1896	1
P_6	240.467	3	239.797	3	237.6	3	238.0269	3	241.6517	2
P_7	287.739	1	285.538	1	280.6	1	280.6144	1	344.2351	1
P_8	240.761	3	240.632	3	238.4	3	238.1613	3	250.1840	1
P_9	429.337	3	429.263	3	414.8	3	414.7001	3	166.7617	3
P_{10}	275.851	1	278.954	1	266.3	1	266.3850	1	388.9654	1
TG*	2700		2700		2700		2700		2700	
TTL*	0		0		0		0		0	
PM*	0		0		0		0		0	
TGC*	624.517		624.127		605.6387		605.6230127		564.7591	
TI*	7.25		0.52		0.80		0.48		0.14	

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 (S), NR* means not reported in the referred literature

B. Discussions on the Results of the Test Cases

Solution quality: It is noticed from Tables 1-4 that the minimum cost achieved by applying the SOA is the least one as compared to those achieved by the earlier reported algorithms. It is to be recalled here that the highlighting characteristic features of the SOA are (i) the direct usage of search direction and step length to update the position, (ii) the application of proportional selection rule for the calculation of the search direction which can improve the population diversity so as to boost the global search ability and decrease the number of control parameters making it simpler to implement, and (iii) adaptation of fuzzy reasoning to generate the step length because the uncertain reasoning of human searching could be the best described by natural linguistic variables. These features in the SOA help the algorithm to yield better solutions. It emphasizes on the fact that the SOA offers the best near-optimal solution for the ELD problems considered.

Comparison of the best generation costs: Comparing the minimum costs achieved by the reported algorithms as may be observed from Tables 1-4, the minimum costs achieved by the SOA are the least values given by 59421 \$/h, 9.0012e+06 \$/h, 113120 \$/h, and 564.7591\$/h for the test cases 1-4 respectively. Power mismatches are also the least ones in the SOA as compared to those in others. Hence, it can be concluded that for all the four test cases the optimization performance of the SOA is found to be the best one.

Testing of robustness: The performance of any heuristic search based optimization algorithm is best judged through repetitive trial runs so as to compare the robustness/consistency of the algorithm. For this specific goal, the frequency of convergence to the minimum cost at different ranges of generation cost with fixed load demand is to be recorded. While experimenting the same for the four test cases, it is observed that the frequency of convergence to the minimum generating cost of less than 120×10^3 \$/h is 50 out of 50 independent trial runs for the test case 2, and the same of less than 605.5 \$/h is 100 out of 100 independent trial runs for the test case 4. These frequency figures of attaining the minimum costs with minimum variations are the maximum ones as compared to the other algorithms of the referred literatures for these two test cases. The same for the test cases 1 and 2 are not included in the referred literatures. But, the authors of the present have tested the same with the SOA for the test cases 1 and 2 also and it is noticed that the convergence to the minimum value of the cost function with a minimum variation is achieved with high frequency values. The frequency of converging to the better solution is always higher in the SOA as compared to the other methods. Thus, it may be inferred that the SOA is the most consistent and robust in achieving the lowest cost in all the runs

Computational efficiency: Apart from yielding the minimum cost by the SOA, it may also be noted that the SOA yields the minimum cost at comparatively lesser time of execution of the program. Thus, this approach is also efficient as far as the computational time is concerned.

6. Conclusion

In this article a novel seeker optimization algorithm, based on the act of human searching capability and understanding while performing any task, is applied to the solution of the constrained, multimodal, non-differentiable, and highly non-linear economic load dispatch problem of small, as well as, large size test power systems. It is revealed 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 algorithms. The simulation results clearly reveal that the SOA may be used as an excellent optimizer for the solution of practical economic load dispatch problems of power systems.

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