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Large-scale economic dispatch by seeker optimization algorithm

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ABSTRACT

Seeker optimization algorithm (SOA), a novel heuristic population-based search algorithm, is utilized in this paper to solve different economic dispatch (ED) problems of thermal power units. 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. The effectiveness of the algorithm as tested on two large-scale test power systems to solve the ED problems. The results obtained by the SOA are compared to the other different algorithms published in the recent literatures to establish its superiority.

Introduction

Economic dispatch (ED) allocates generations among the committed generating units in the most economical manner subject to different operational constraints [1]. To date, various investigations on ED problems have been undertaken as better solutions would result in more saving in the operating cost. Increased interests are being paid by the researchers towards the application of the evolutionary optimization techniques for the solution of the ED problems. Genetic algorithm (GA) [2], artificial neural networks [3], simulated annealing (SA), Tabu search, evolutionary programming (EP), particle swarm optimization (PSO) [2], [4], ant colony optimization (ACO) [5], differential evolution (DE) [6], bacteria foraging with Nelder-Mead (BF-NM) [7], biogeography-based optimization (BBO) [8], a hybrid technique combining DE with BBO (DE-BBO) [9] are just a few among the numerous techniques adopted for this specific purpose.

Seeker optimization algorithm (SOA) [10] 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 present work focuses on the performance of SOA as an optimizing tool in solving the ED problems.

In view of the above, the main contribution of this paper can be summarized as follows:

(a) Two large-scale power systems test cases of ED problem are solved with the SOA and the best results obtained by the SOA are presented in this paper.

(b) The best results obtained by adopting the SOA are compared with those published in the recent papers.

(c) Considering the near-globality of the solution and the improved convergence speed obtained, application of the SOA in solving ED problems seems to be a promising alternative approach for solving the ED problems in practical power system.

Mathematical Modeling of the ED Problem

ED with Quadratic Cost Function

The problem of ED 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) [8], [9].

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

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

ED 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 [11] as given in (3)

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

Ripples in the heat-rate curves are introduced due to valve-point effects, and thereby, the number of local optima is increased. It is to be noted here that the fuel cost coefficients e_i and f_i are introduced to model the valve point discontinuities.

Constraints of ED Problems

The problems of ED are subject to the following constraints.

(i) Real Power Balance Constraint: The total generated power should be same as the total load demand (P_D) plus the line loss (P_L) and is modeled as in (4).

$$\sum_{i=1}^{ng} P_i - P_D - P = 0 \tag{4}$$

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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 (5) [4].

$$P_L = \sum_{i=1}^{ng}\sum_{j=1}^{ng} P_i B_{ij} P_j + \sum_{i=1}^{ng} B_{0i} P_i + B_{00} \quad (5)$$

(ii) Generation Capacity Constraints: The power output of each generator should be within its minimum ($P_i^{\min}$) and maximum ($P_i^{\max}$) limits. The generating capacity constraints are written as in (6).

$$P_i^{\min} \le P_i \le P_i^{\max} \quad (6)$$

(iii) Ramp Rate Constraints: The ramp-up and ramp-down limits may be represented by the following equation [2].

$$P_i - P_i^0 \le UR_i \text{ , and } P_i^0 - P_i \le DR_i \quad (7)$$

To consider the ramp rate limits and power output limits constrains at the same time, (6) and (7) can be written as a combined inequality constraint as given by the following equation [2].

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

(iv) Prohibited Operating Zone Constraints: The prohibited operating zones are the ranges 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 in (9) [8], [9].

$$\begin{aligned} & P_i^{\min} \le P_i \le P_{i,1}^{lower} \\ & P_{i,j-1}^{upper} \le P_i \le P_{i,j}^{lower}; \qquad j = 2,3,\ldots\ldots pz_i, \quad (9) \\ & P_{i,pz_i}^{upper} \le P_i \le P_i^{\max} \end{aligned}$$

Formulation of Objective Function

The objective function ($OF()$) is designed as in (10) that requires to be minimized.

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

The weighing factors are selected to make the corresponding terms competitive during the process of optimization. The unit of each weighing factor involved in (10) is \$/MWh.

Seeker optimization algorithms as applied to ED Problem

Seeker Optimization Algorithm

SOA [10, 12] is a population-based heuristic search algorithm. It regards optimization process as an optimal solution obtained by a seeker population. Each individual of this population is called *seeker*. The total population is randomly categorized into three subpopulations. These subpopulations search over several different domains of the search space. All seekers in the same subpopulation constitute a neighborhood. This neighborhood represents the social component for social sharing of information.

Steps of Seeker Optimization Algorithm

In 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 number of variable to be optimized

Calculation of Search Direction, $d_{ij}(t)$

It is the natural tendency of the swarms to reciprocate in a cooperative manner while executing their needs and deeds. Normally, there are two extreme types of cooperative behavior prevailing in the swarm dynamics. One, egotistic, is entirely pro-self and another, altruistic, is entirely pro-group [13]. Every seeker, as a single sophisticated agent, is uniformly egotistic [13]. 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 in (11).

$$\vec{d}_{i,\,ego}(t) = sign(\vec{p}_{i,\,best}(t) - \vec{x}_i(t)) \quad (11)$$

In (11), $sign(.)$ is a signum function on each dimension of the input vector. On the other hand, in altruistic behavior each seeker wants 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 (12)-(13).

$$\vec{d}_{i,\,alt1}(t) = sign(\vec{g}_{best}(t) - \vec{x}_i(t)) \quad (12)$$

$$\vec{d}_{i,\,alt2}(t) = sign(\vec{l}_{best}(t) - \vec{x}_i(t)) \quad (13)$$

In (12)-(13), $\vec{g}_{best}(t)$ 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 [14]. In addition, future behavior can be predicted and guided by past behavior [15]. 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 in (14).

$$\vec{d}_{i,\,pro}(t) = sign(\vec{x}_i(t_1) - \vec{x}_i(t_2)) \quad (14)$$

In (14), $t_1, t_2 \in \{t, t-1, t-2\}$ and it is assumed that $\vec{x}_i(t_1)$ is better than $\vec{x}_i(t_2)$. The aforementioned four empirical directions as shown in (11)-(14) direct human being to take a rational decision in the 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 dimension j of $\vec{d}_i(t)$ is selected by applying the following proportional selection rule (shown in Figure 1) as stated in (15).

$$d_{ij} = \begin{cases} 0, & if \quad r_j \le p_j^{(0)} \\ +1, & if \quad p_j^{(0)} \le r_j \le p_j^{(0)} + p_j^{(+1)} \\ -1, & if \quad p_j^{(0)} + p_j^{(+1)} \le r_j \le 1 \end{cases} \quad (15)$$

In (15), r_j is a uniform random number in [0, 1], $p_j^{(m)}$ $(m \in \{0, +1 -1\}$ is the percent of the number of "m" from the set $\{d_{ij,ego}, d_{ij,alt1}, d_{ij,alt2}, d_{ij,pro}\}$ on each dimension j of all the four empirical directions, i.e. $p_j^{(m)}$ = (the number of m) / 4.

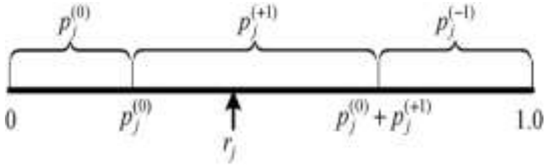

Figure 1. The proportional selection rule of search directions

Calculation of 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 the 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. $1, 2, \ldots\ldots, S$. The expression is presented as in (16).

$$\mu_i = \mu_{\max} - \frac{s - I_i}{s-1}(\mu_{\max} - \mu_{\min}) \tag{16}$$

In (16), 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 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 dimension 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. Thus, the minimum value $\mu_{\min} = 0.0111$ is set. Moreover, the parameter, $\vec{\delta}$, of the Bell membership function is determined by the following equation.

$$\vec{\delta} = \omega \times abs(\vec{x}_{best} - \vec{x}_{rand}) \tag{17}$$

In (17), the absolute value of the input vector as the corresponding output vector is represented by the symbol $abs(.)$. 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 *i*th 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.

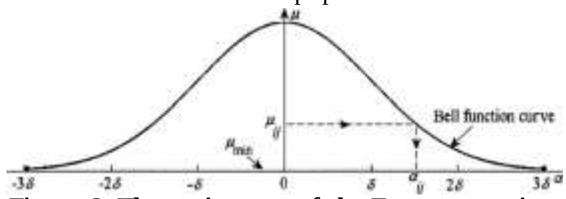

Figure 2. The *action* part of the Fuzzy reasoning

In order to introduce the randomness in each dimension and to improve local search capability, the following equation is introduced to convert μ_i into a vector $\vec{\mu}_i$.

$$\mu_{ij} = RAND(\mu_i, 1) \tag{18}$$

In (18), $RAND(\mu_i, 1)$ returns a uniformly random real number within $[\mu_i, 1]$. Equation (19) denotes the *action* part of the fuzzy reasoning and gives the *step length (* α_{ij} *) for* every dimension j.

$$\alpha_{ij} = \delta_j \sqrt{-\ln(\mu_{ij})} \tag{19}$$

Updating of Seekers' Position

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

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t) \times d_{ij}(t) \tag{20}$$

where,

$x_{ij}(t+1)$	the position of the *j*th variable of the *i*th seeker at time step $t+1$,
$x_{ij}(t)$	the position of the *j*th variable of the *i*th seeker at time step t,
$\alpha_{ij}(t)$	the step length of the *j*th variable of the *i*th seeker at time step t,
$d_{ij}(t)$	the search direction of the *j*th variable of the *i*th seeker at time step t.

Subpopulation 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 convergence. Subpopulations must learn from each other about the optimum information so far they have acquired in their domain. Thus, the positions of the worst seekers of each subpopulation are combined with the best one in each of the other subpopulations using the following binomial crossover operator as expressed in (21).

$$x_{k_n j,worst} = \begin{cases} x_{lj,\,best} & if \quad rand_j \le 0.5 \\ x_{k_{nj},\,worst} & else \end{cases} \tag{21}$$

In (21), $rand_j$ is a uniformly random real number within [0, 1], $x_{k_n j,worst}$ is denoted as the j dimension of the *n*th worst position in the *k*th subpopulation, $x_{l\,j,worst}$ is the *j*th dimension of the best position in the *l*th subpopulation with and n , k , $l = 1, 2, \ldots\ldots, K-1$ and $k \ne l$. 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.

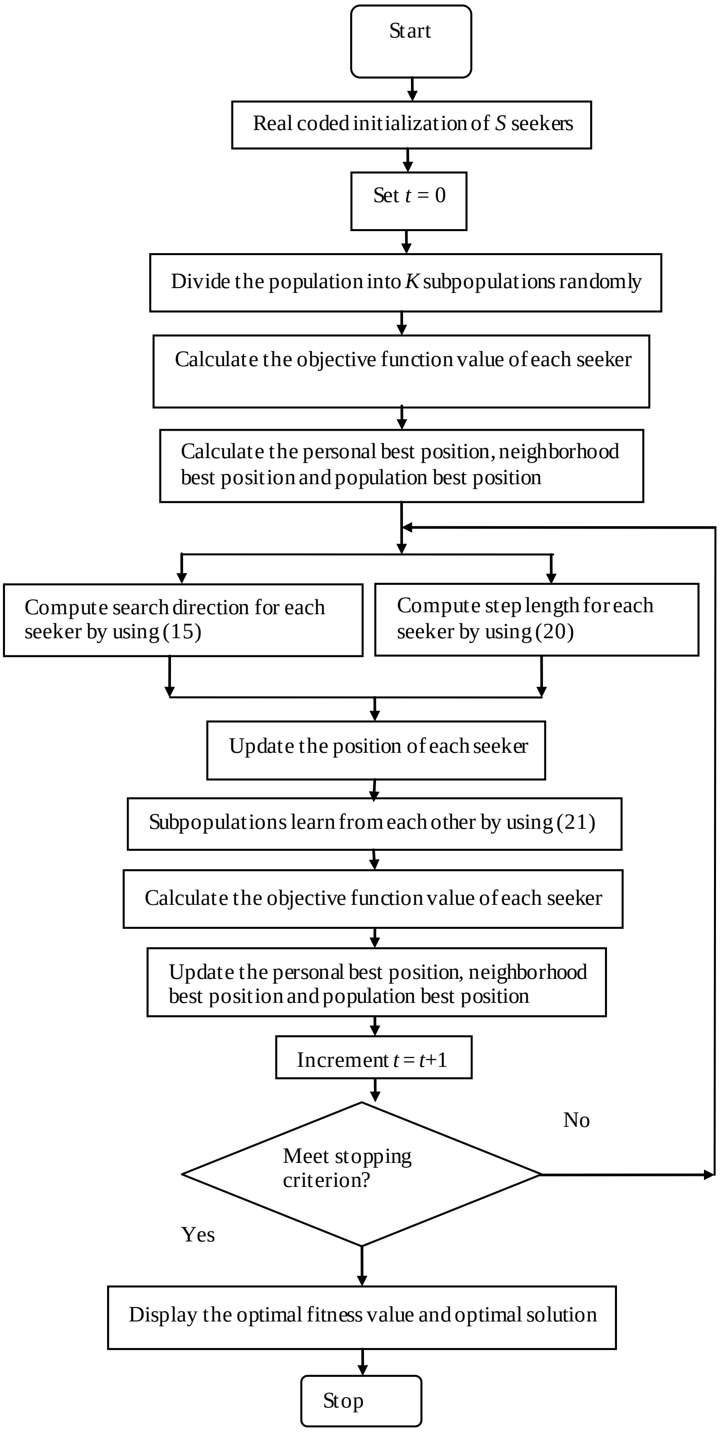

Figure 3. Flowchart of the seeker optimization algorithm

Numerical Examples and Solution Results

The SOA has been applied to solve the ED problems in two different large-scale test systems 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.

Test System 1: 40-Generating Units with Valve Point Loading

A system with 40 generators with valve point loadings and transmission loss is considered as the test system 1. The input data are given in [11]. The load demand is 10500 MW. The best solutions of the generation schedules and the total generation cost etc as obtained from 50 trial runs are presented in Table I. Convergence results of the different algorithms are also presented in Table II. The convergence profile of the total generation cost ($/h) is depicted in Figure 4.

Test System 2: A Large Scale Power System of Korea

A large scale power system of Korea with 140 generators is taken as the test system 2. Hydro and pump storage units are excluded. For this system ramp rate limits, valve point effect, and prohibited operating zones are considered but transmission network loss is not considered. The system input data are available in [19]. The system load demand is 49342 MW. The convergence results of the different algorithms for this test system are shown in Table III. The convergence profile of the total generation cost ($/h) is depicted in Figure 5

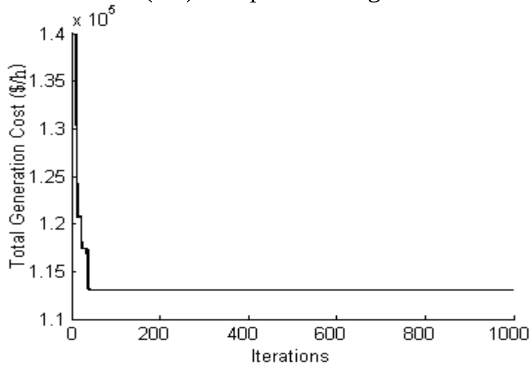

Figure 4. Convergence profile of the total generation cost for the 40-generating units

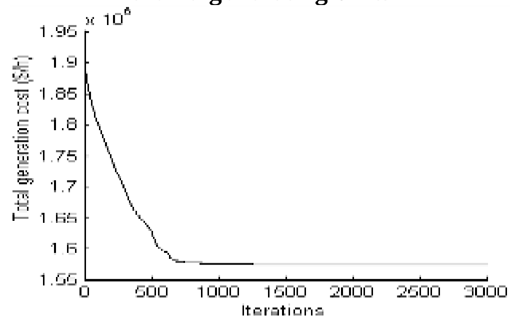

Figure 5. Convergence profile of the total generation cost for the large scale power system of Korea

Discussions of Results

Solution Quality: It is noticed from Tables II, and III that the minimum cost achieved by applying the SOA is the least one as compared to those achieved by earlier reported algorithms as mentioned in the respective tables.

Comparison of Best Generation Costs: It may be observed from Tables II, and III that the minimum costs achieved by the SOA based method for the test systems 1 and 2, are 113120 $/h, 1571700 $/h, respectively. Again, power mismatches are the least ones in the SOA as compared to those in others. Hence, it can be concluded that for all the two test systems the performance of the SOA is found to be the best one.

Computational Efficiency: Apart from yielding the minimum cost by the SOA, it may also be noted that the SOA yields 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.

Conclusion

In this paper, the SOA has been successfully implemented to solve two different large-scale ED 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 algorithms. Thus, this algorithm may become a very promising tool for solving some more complex engineering optimization problems for future researchers.

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Table I 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	98.4760	P_{11}	304.0025	P_{21}	438.7379	P_{31}	172.0005
P_2	106.2378	P_{12}	292.9607	P_{22}	436.0573	P_{32}	178.5031
P_3	110.7931	P_{13}	413.3226	P_{23}	441.0579	P_{33}	168.2835
P_4	158.2180	P_{14}	391.8817	P_{24}	425.0123	P_{34}	187.7960
P_5	91.8640	P_{15}	400.7214	P_{25}	427.9365	P_{35}	171.5563
P_6	127.2495	P_{16}	401.5576	P_{26}	452.8892	P_{36}	178.2705
P_7	236.0978	P_{17}	409.0213	P_{27}	110.2229	P_{37}	97.2393
P_8	286.5869	P_{18}	468.3763	P_{28}	140.5338	P_{38}	87.7159
P_9	236.7750	P_{19}	509.7511	P_{29}	122.5079	P_{39}	93.5632
P_{10}	260.7015	P_{20}	509.1169	P_{30}	87.2678	P_{40}	498.2079
						Total Generation (MW)	10729.07
						Total Transmission Loss (MW)	229.06
						Power Mismatch (MW)	0.01
						Total Generation Cost ($/h)	113120
						Time/Iteration (s)	0.05

Table II convergence results (50 trial runs) of the different algorithms for the test system 1 with pd = 10500 mw

Algorithms	Total Generation Cost ($/h)		
	Minimum	Maximum	Average
QPSO [16]	121448.21	NR*	122225.07
BBO [8]	121426.953	121688.6634	121508.0325
BF-NM [7]	121423.63792	NR*	122295.1278
DE-BBO [9]	121420.8948	121420.8968	121420.8952
RCGA [17]	121418.5425	121628.5987	121504.1169
ICA-PSO [18]	121413.20	121453.56	121428.14
CCPSO [19]	121403.5362	121525.4934	121445.3269
SOA	113120	114000	113250
NR* means not reported in the referred literature			

Table III convergence results (50 trial runs) of the different algorithms for the test system 2with pd = 49342 mw

Algorithms		Total Generation Cost ($/h)		
		Minimum	Maximum	Average
CTPSO [19]		1657962.73	1658002.79	1657964.06
CSPSO [19]		1657962.73	1657962.85	1657962.74
COPSO [19]		1657962.73	1657962.73	1657962.73
CCPSO [19]		1657962.73	1657962.73	1657962.73
SOA		1571700.00	1571700.00	1571700.00