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CONGESTION MANAGEMENT IN OPEN ACCESS ELECTRIC NETWORK USING ADAPTIVE REAL CODED BIOGEOGRAPHY-BASED OPTIMIZATION

A. Ramesh Kumar[1] and L. Premalatha[2]
[1]Department of Electrical and Electronics Engineering, S.A. Engineering College, Chennai, India
[2]School of Electrical Engineering, VIT University, Chennai Campus, Chennai, India
E-Mail: a_rameshkumar@live.com

ABSTRACT

Open access electric network faces severe congestions due to the increasing demand for power, multiple transactions in the transmission line and outage of network equipment, causing uncertainty and affecting the system security. In this article, different operating states are considered for congestion management in an electric power network. An effective algorithm to reschedule the generating units is implemented for relieving congestion as well as maintaining optimal settings of electrical parameters in the network. The main objective of our algorithm is to minimize rescheduling of power using generator sensitivity factor method and hence minimize congestion cost through the adjustment of generator price bids submitted by independent power producers. The proposed algorithm has been validated on IEEE 30-bus, IEEE 57-bus and IEEE 118-bus systems.

Keywords: biogeography-based optimization, differential evolution, generator sensitivity factor, optimal power flow, congestion management.

1. INTRODUCTION

Open-access electric energy market is a complex system with a diversity of participants. If the desire arises to produce and consume power in amounts causing the transmission system to operate at or beyond the transfer limits, the system is said to be congested. System congestion may occur on active limits of transmission lines, voltage levels and thermal limits. In the power market, system security plays a vital role from the operator's point of view. An independent system operator (ISO) is a regulating entity independent from the power producer and optimizes the overall system operations.

An OPF problem is generally a nonlinear and a multi-objective optimization problem, with more than one local optimum solution. Thus, local optimization techniques are lesser suitable for such complex problems, because they may not be able to provide a global optimum solution. Recently, many of the evolutionary algorithms have been successfully applied in solving OPF problems [1-8].

Elaborate literature on congestion management in competitive power market is available elsewhere [9]. Optimal rescheduling of generators has also been discussed by different evolutionary algorithms [10-13]. Voltage profile and transmission congestion management in open-access power market have also been described previously [14]. Sensitivity-based optimal power rescheduling of generators has been discussed earlier [15]. Congestion due to voltage instability and thermal overload has also been elaborated [16]. Network reconfiguration for congestion management by deterministic method and genetic algorithm has been described elsewhere [17].

In a congested power system, incremental or decremented change in power output may not affect power transmission alike. Therefore, no need arises to reschedule the output of generators that are less critical to congestion. In order for a generator to participate in congestion management, its sensitivity to the congested line must be considered. The objective is to choose generators in such a way that the number of participating generators may be limited.

The present article aims to explore the ability of adaptive real-coded biogeography-based optimization (ARCBBO) in solving the congestion problem. Bhattacharya and Chattopadhyay employed biogeography-based optimization (BBO) to solve OPF problems [4]. However, the BBO method was reported to lack exploration ability and poorly supports population diversity. In the ARCBBO approach, adaptive Gaussian mutation is integrated into the OPF problem, thereby avoiding premature convergence, improving population diversity, and enhancing the exploration ability.

2. REVIEW OF BIOGEOGRAPHY BASED OPTIMIZATION

Dan [18] proposed a comprehensive algorithm (BBO) for solving optimization problems based on the study of geographical distribution of species. A BBO algorithm has two main operators: migration operator and mutation operator.

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2.1 Migration

Migration is a process of probabilistically modifying each individual in the habitat randomly. A geographical area with high habitat suitability index (HSI) tends to have a large number of species, high emigration rate, and low immigration rate. Suitability index variables (SIVs) define the characteristics of a habitat. A habitat with a high HSI tends to be more static in its species distribution. Such a habitat signifies a good solution in terms of an optimization problem. Immigration rate, λ_k, and emigration rate, μ_k, are functions of the number of species in a habitat. For a habitat with no species, its immigration rate can be the highest. λ_k is given by:

$$\lambda_k = I\left(1 - \frac{k}{n}\right) \tag{1}$$

where I is the maximum possible immigration rate, k is the number of species of kth individual, and n is the maximum number of species. μ_k is given by:

$$\mu_k = E\left(\frac{k}{n}\right) \tag{2}$$

where E is the maximum possible emigration rate.

2.2 Mutation

Mutation tends to increase the diversity of a species in a habitat. Due to natural events, the HSI of a habitat can change dramatically, causing the species count to shift away from its equilibrium value. Species count may be a probability value (Pi). If this probability value is very low, an individual solution is thought to have been mutated with other solutions. So, mutation rate of an individual solution can be calculated using species count probability, given by:

$$\mathrm{M_i} = \mathrm{M_{max}} * \left(\frac{1 - \mathrm{P_i}}{\mathrm{P_{max}}}\right) \tag{3}$$

where M_i is the mutation rate; M_{max} is the maximum mutation rate, which is a user-defined parameter; and P_{max} is the maximum probability of species count. In BBO, a mutation characteristic function is given by:

$$X_i^{'} = X_i + rand\ (0,1) \times (X_i^{\max} - X_i^{\min}) \tag{4}$$

where Xi is the decision variable; Ximax and Ximin are the lower and upper limits of the decision variable, respectively.

3. ADAPTIVE REAL CODED BIOGEOGRAPHY BASED OPTIMIZATION

In BBO, Migration operator can improve the performance of BBO. It is used to modify habitat by simply replacing similar kind of habitat that means habitat shares less information from the others. Hence, migration operator is lacking of exploration ability.

Differential evolution (DE) is a direct real parameter optimization algorithm [19]. It uses the mutation operation to improve the quality of the solutions. In order to share more information between habitats, BBO is inspired with differential evolution. The migration operation is improved by applying a DE mutation strategy, which enhances the exploration ability. The following operation is used as migration operation in this paper,

$$X_i = X_{best} + F \times (X_{r1} - X_{r2}) \tag{5}$$

where X_i is the i-th habitat, X_{best} is the best habitat, X_{r1} and X_{r2} are the random habitats among the total population and F is the scaling factor. The value of scaling factor increases, exploration ability of the algorithm will be increased but their exploitation ability will be decreased and vice versa, therefore F is the vital role to balance the exploration and exploitation ability.

In BBO, individuals are encoded by a floating point for the continuous optimization problems and random mutation is used which deficient the exploration ability. In RCBBO [20], individuals are represented by a D-dimensional real parameter vector, and a probabilistically based Gaussian mutation operator is used, which improves the diversity of the population and its searching ability. The Gaussian mutation characteristic function is given by:

$$X_i^{'} = X_i + N(\mu, \sigma_i^2) \tag{6}$$

where $N(\mu,\sigma_i^2)$ represents the Gaussian random variable with mean μ and variance σ^2. The values of mean and variance are considered 0 and 1, respectively [20].

Generally, a probability-based mutation operation affects the convergence characteristics. Therefore, adaptive Gaussian mutation is applied in the present work to improve the solution of worst half of individuals in the population. In equation (6), $\mu=0$ and σ_i is found using the following equation [21]:

$$\sigma_i = \beta \times \sum_{i=1}^{n} \frac{F_i}{f_{\min}} \times (X_i^{\max} - X_i^{\min}) \tag{7}$$

where β is the scaling factor or mutation probability; F_i is the fitness value of i-th individual; and f_{min} is the minimum fitness value of the habitat in the population. Adaptive mutation probability is given by

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$$\beta = \beta_{\max} - \frac{\beta_{\max} - \beta_{\min}}{T_{\max}} \times T \tag{8}$$

where βmax=1, βmin=0.005, Tmax is the maximum iteration, and T is the current iteration.

The adaptive Gaussian mutation has the ability to prevent premature convergence and hence to produce a smooth convergence. This method of mutation can be easily used with real-coded variables, which have been widely used in evolutionary programming (EP), and hence to carry out local as well as global searches. It is namely adaptive real coded biogeography-based optimization (ARCBBO).

The pseudo code of an ARCBBO algorithm

Initialize the ARCBBO parameters
Generate the individuals (SIV) randomly within their feasible region
$X_k = X_k^{\min} + rand\ (0,1) \times (X_k^{\max} - X_k^{\min})$
Calculate the fitness (HSI) value for each habitat in the population
While halting criteria is not satisfied do
Sort the SIVs from best to worst according the fitness value
Map the HSI values to the number of species
Compute immigrate rate and emigration rate for each individual
For i=1 to NP
Select Xi according to immigration rate λi
For j=1 to NP
Generate two integer randomly r1≠r2
Select Xj according to emigration rate μi
If rand (0, 1) <μi
$X_i = X_j$
Else
$X_i = X(HSI_{best}) + F \times (X_{r1} - X_{r2})$
End If
End For
End For
//Adaptive Gaussian Mutation
For i = (NP/2) +1 to NP
For j=1 to Nvar
$\sigma_{ij} = \beta \frac{F_i}{F_{\min}} \times (X_i(j) - X_i(j))$
$X_{ij}^{'} = X_{ij} + Normrnd\ (0, \sigma_{ij}^2)$
End For
End For
Compute HSI for new habitats
Sort SIV from best to worst
End While

4. PROBLEM FORMULATION

As mentioned earlier, generators in the system under consideration have different sensitivities to power flow on the congested line. A change in power flow in a transmission line connected between bus j and bus k due to change in power generation by generator i can be termed generator sensitivity. Mathematically, generator sensitivity factor (GSF) for bus j to bus k may be written as

$$GSF_i = \frac{\Delta P_{jk}}{\Delta P_{Gi}} \tag{9}$$

where P_{ji} is the active power flow in the congested transmission line between buses j and k, and P_{Gi} is the active power produced by unit-i.

For congestion management, it is preferable to choose generators with non-uniform and large magnitudes of sensitivity values because these are the ones most sensitive to power flow on the congested line. Based on the bids received from participating power producers, the amount of rescheduling required is computed by solving the following optimization problem. The flowchart for congestion management by ARCBBO is shown in Figure-1.

4.1 Objective function

- Minimization of fuel cost

It represents the quadratic cost function whose objective function is expressed as follows:

$$f = FC = \sum_{i=1}^{Ng} \left(a_i + b_i\left(P_{Gi}\right) + c_i\left(P_{Gi}^2\right)\right) \tag{10}$$

Where FC is the total fuel cost; N_g is the number of generating units; P_{Gi} is the generated active power; and a_i, b_i and c_i are fuel cost coefficients of the ith unit.

- Minimizing the Congestion Cost

$$f = \sum_{i=1}^{Ng} C_i^+ \Delta P_{Gi}^+ - \sum_{i=1}^{Ng} C_i^- \Delta P_{Gi}^- \tag{11}$$

where C_i^+ and C_i^- are the incremental and decremented bidding cost submitted by independent power producer of unit-i, respectively. ΔP_{Gi}^+ and ΔP_{Gi}^- are the change in active power from preferred schedule.

4.2 Constraints

$$\sum_{i=1}^{Ng} (GSF_i \times \Delta P_{Gi}) + MVA_k^0 \le MVA_k^{\max} \quad k = 1, \cdots Nl \tag{12}$$

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$$\sum_{i=1}^{Ng} \Delta P_{Gi} = 0 \tag{13}$$

$$P_{Gi} - P_{Di} - \sum_{j=1}^{Nb} V_i V_j \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)\right] = 0 \tag{14}$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{Nb} V_i V_j \left[G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)\right] = 0 \tag{15}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad i = 1,2,...,N_g \tag{16}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad i = 1,2,...,N_g \tag{17}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad i = 1,2,...,N_g \tag{18}$$

$$T_i^{\min} \le T_i \le T_i^{\max} \qquad i = 1,2,...,N_t \tag{19}$$

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \qquad i = 1,2,...,N_C \tag{20}$$

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max} \qquad i = 1,2,...,N_{pq} \tag{21}$$

$$MVA_k \le MVA_k^{\max} \tag{22}$$

where ΔP_{Gi} is the active power adjustment at bus i and MVA_k^0 is the power flow in kth transmission line at base case. P_{Gi} and Q_{Gi} are the active and reactive power injected at bus i, P_{Di} and Q_{Di} are the active and reactive power demand at bus i, V_i and δ_i are the magnitude and phase angle of voltage at bus i, G_{ij} and B_{ij} are the real and imaginary part of admittance of transmission line, MVA_k^{max} is the power flow capacity of kth transmission line, min and max represents the minimum and the maximum limits of the parameter, respectively

$$Min\ F = f + \lambda_{Pg}(P_{Gi} - P_{Gi}^{\lim})^2 + \sum_{i \in Ng} \lambda_{Qg}(Q_{Gi} - Q_{Gi}^{\lim})^2 + \sum_{i \in Npq} \lambda_V (V_{Li} - V_{Li}^{\lim})^2 + \sum_{i \in NL} \lambda_{Pf}(MVA_i - MVA_i^{\max})^2 \tag{23}$$

where λ_{Pg}, λ_{Qg}, λ_V and λ_{Pf} are penalty factors.

If $P_{G1} > P_{G1}^{\max}$ then $P_{Gi}^{\lim} = P_{G1}^{\max}$, elseif $P_{G1} < P_{G1}^{\min}$ then $P_{Gi}^{\lim} = P_{G1}^{\min}$

If $Q_{Gi} > Q_{G1}^{\max}$ then $Q_{Gi}^{\lim} = Q_{G1}^{\max}$, elseif $Q_{Gi} < Q_{G1}^{\min}$ then $Q_{Gi}^{\lim} = Q_{G1}^{\min}$

If $V_{Li} > V_{Li}^{\max}$ then $V_{Li}^{\lim} = V_{Li}^{\max}$, elseif $V_{Li} < V_{Li}^{\min}$ then $V_{Li}^{\lim} = V_{Li}^{\min}$

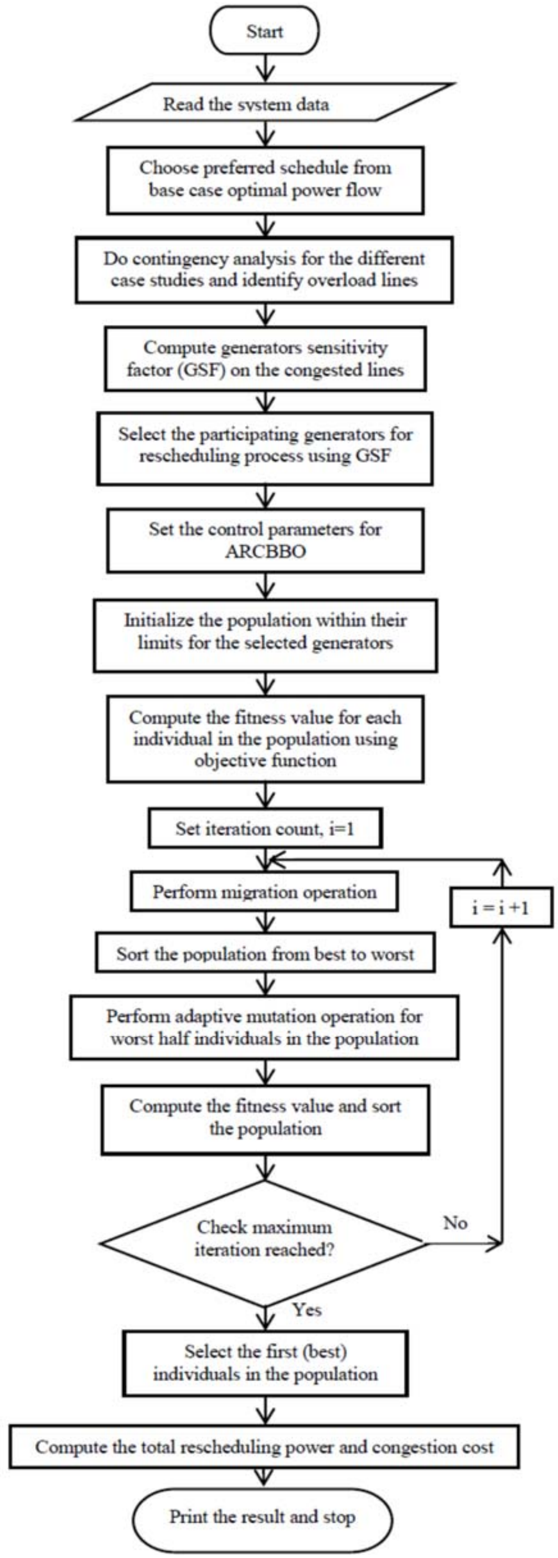

Figure-1. Flow chart for congestion management using ARCBBO.

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5. RESULT AND DISCUSSIONS

To compare the performance of the proposed ARCBBO method with DE, and BBO, experiments were performed on IEEE 30-bus, IEEE 57-bus and IEEE 118-bus systems. Fifty trails were performed independently with both algorithms and the results (best, mean, worst and standard deviation) of the objective function are presented. MATPOWER 4.1 package was used for calculations [24]. Simulations were carried out in MATLAB 10a programming environment on Core i3 2.53 GHz, 2.0 GB RAM personal computer.

Optimal power flow was carried out using proposed ARCBBO method. The control parameter settings for the proposed method were obtained by number of simulation results and hence optimal control parameters were chosen, scaling factor = 0.6, habitat size = 50, habitat modification probability = 1, immigration probability = 1, maximum immigration and emigration rate = 1 and maximum number of iterations for IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems were taken as 200, 500 and 1000, respectively. Simulation results obtained by the proposed ARCBBO for different test cases are presented in Table-1.

Table-1. Simulation results obtained by ARCBBO for OPF.

System	**Fuel cost** ($/h)		
	Best	**Average**	**Worst**
IEEE 30-bus system	799.0828	799.0904	799.1096
IEEE 57-bus system	41679.9467	41697.1934	41724.77896
IEEE 118-bus system	129630.2758	129722.8237	129890.6305

In the present congestion management problem, preferred schedule was obtained from ARCBBO-based OPF. The parameter settings for DE [2] and BBO [4] method were taken from the literature, they were scaling factor =0.9 and crossover probability =0.5. And BBO parameters were habitat modification probability = 1, immigration probability = 1, maximum immigration and emigration rate = 1, mutation probability = 0.005. Number of population and iterations were considered as 50 and 200, respectively for both optimization methods.

5.1 IEEE 30-bus system

The system consists of 6 generator buses, 24 load buses and 41 transmission lines. Shunt VAR compensator were connected at buses 10, 12, 15, 17, 20, 21, 23, 34 and 29 [23]. Bus 1 is taken as slack bus. The system load is 283.4 MW and 126.2 MVAR. The system has 25 control variables, comprises 6 generator active power outputs and bus voltages, 4 transformer tap settings, and 9 shunt compensator VAR injections. The bus data, line data and generator cost coefficient [22] and the minimum and maximum limits for control variables [23] were obtained from literature. Generator price bidding data were taken from publication [12].

Case A: Sudden load variation

Congestion is created by stepwise loading incremental at bus-14 and also thermal limit of line 26 (connected between buses 10 and 17) is reduced to 6.99 MVA, due to that line 26 is congested. Unconstrained power flow at line 26 is 7.01 MVA Therefore, congestion has to be relieved by active power generation rescheduling of generators. Generator sensitivity factors for this case are shown in Table-2. From the table, we understand that all generators showed high sensitivity to congested lines except slack bus, due to the system being small in size. Therefore, all generators can participate in the rescheduling process. Rescheduled power and congestion cost calculated using various methods are presented in Table 3, which shows best, mean and worst value of congestion cost. It is observed that best cost obtained by the proposed method is lesser than DE and BBO. In this case, the sum of change in rescheduled power is 8.1554 MW which is equivalent to sum of load increment at bus-14 and excess line loss due to load variation.

Table-2. Generator sensitivity factor for case A.

Gen. No.	GSF	Gen. No.	GSF	Gen. No.	GSF
1	0	5	-0.1320	11	-0.3034
2	0.0567	8	-0.3202	13	-0.2605

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Table-3. Comparison of simulation results of congestion management for case a.

Parameter	ARCBBO	DE	BBO
ΔP_{G1}(MW)	0.0001	0.0184	0.3900
ΔP_{G2}(MW)	0.0390	0.0944	0.3454
ΔP_{G5}(MW)	0.0227	0.1683	0.0791
ΔP_{G8}(MW)	7.2886	6.9944	6.0444
ΔP_{G11}(MW)	0	0.0604	0.3392
ΔP_{G13}(MW)	0.8050	0.8207	1.0000
Rescheduled power (MW)	8.1554	8.1566	8.1981
Best Congestion cost ($/h)	332.7778	333.8845	338.9445
Mean Congestion cost ($/h)	333.8706	334.6615	342.2011
Worst Congestion cost ($/h)	334.0863	336.4360	348.0776
Std. Congestion cost	0.4720	0.6394	4.0172
Simulation time (sec)	129.58	147.71	106.11

5.2 IEEE 57-bus system

The system consists of 7 generator buses, 50 load buses and 80 transmission lines. Shunt VAR compensators were connected at buses 18, 25 and 53 [4]. Bus 1 is taken as slack bus. The system has 34 control variables, comprises 7 generator active power outputs and bus voltages, 17 transformer tap settings, and 3 shunt compensator VAR injections. The system data were taken from [26]. The voltage magnitude limits for generator buses are in the range of 0.9-1.1 p.u., and the voltage magnitude limits for load buses are in the range of 0.94-1.06 p.u. The system active and reactive power demand were 1250.8 MW and 336.4 MVAR, respectively. Line limits and generator price bidding data were taken from publication [13].

Case B: Transformer outage

Transmission lines 8 (connecting buses 8 and 9) and 10 (connecting buses 9 and 11) were congested due to transformer (placed at line connecting buses 24-26) outage. Unconstrained power flow at lines 8 and 10 were 201.1383 MVA and 50.3248 MVA respectively, but thermal limits of those lines are as 200 MVA and 50 MVA respectively and hence total power violation was 1.4633 MVA. GSF for this case is presented in Table-4. Generators 6, 8, 9 and 12 have shown high sensitivity with respect to congested line, so these generators have been participated in active power rescheduling process. Rescheduled active power is presented in Table-5. Total rescheduled power obtained by the proposed method is 4.2842 MW and hence congestion cost is 179.6299, which is lesser than that obtained by DE and BBO methods.

Case C: Transmission line outage

Transmission line 8 was congested due to transmission line 5 (connecting bus 4 and bus 6) outage. Unconstrained power flow at lines 8 was 201.5280 MVA, but thermal limit of this line is 200 MVA and hence total power violation was 1.5281 MVA. Congestion has to be managed by strong influence generators with respect to congested line from Table-4. Rescheduled active power is presented in Table-6. Total rescheduled power calculated by the proposed method is 4.0159 MW which is lesser than previous case, so congestion cost also minimum. It is observed that congestion cost varies with respect to rescheduling power.

Table-4. GSF for IEEE 57-bus system.

Gen. No.	Case B	Case C	Gen. No.	Case B	Case C
1	0	0	8	0.6252	0.6643
2	0.0201	0.0148	9	-0.2099	-0.1807
3	0.0812	0.0597	12	-0.0896	-0.0714
6	0.3811	0.4658	-	-	-

Table-5. Comparison of simulation results for Case B.

Parameter	ARCBBO	DE	BBO
ΔP_{G1}(MW)	2.1302	2.1033	0.7887
ΔP_{G6}(MW)	0	0.0001	-0.2700
ΔP_{G8}(MW)	-1.7744	-1.7733	-2.3021
ΔP_{G9}(MW)	-0.0005	-0.0021	-1.1441
ΔP_{G12}(MW)	0.3791	0.4059	3.5428
Reschedule power (MW)	4.2842	4.2847	8.0477
Best Congestion cost ($/h)	179.6299	179.6482	336.1192
Mean Congestion cost ($/h)	179.9562	180.0902	346.5134
Worst Congestion cost ($/h)	180.4227	181.1316	354.2035
Std. Congestion cost	0.2995	0.4013	6.4686
Simulation time (sec)	94.2	97.38	82.69

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Table-6. Comparison of simulation results for Case C.

Parameter	ARCBBO	DE	BBO
ΔP_{G1}(MW)	0	0.0027	3.6560
ΔP_{G6}(MW)	0	-0.0150	-0.9926
ΔP_{G8}(MW)	-1.6413	-1.6325	-2.3021
ΔP_{G9}(MW)	2.3742	2.3680	0.1967
ΔP_{G12}(MW)	0.0004	0.0097	0.0742
Reschedule power (MW)	4.0159	4.0279	7.2216
Best Congestion cost ($/h)	168.4931	168.9607	299.2879
Mean Congestion cost ($/h)	169.8000	170.4851	332.4405
Worst Congestion cost ($/h)	170.6044	171.9241	351.5941
Std. Congestion cost	0.5280	0.9028	8.8419
Simulation time (sec)	117.48	124.11	104.69

5.3 IEEE 118-bus system

The system consists of 54 generators, 99 loads, and 186 transmission lines. The system load is 4242 MW and 1438 MVAR. Bus 69 has taken as slack bus. Generator price bidding data were taken from report [25]. Bus data, line data, and generator fuel cost coefficient were taken from publication [26]. Line limits were taken from web [27].

Case D: Generator outage

Transmission lines 37 (connecting bus 8 and bus 30) and 54 (connecting bus 30 and bus 38) were congested due to outage of generator number 5 (at bus 10). Unconstrained power flow at lines 37 and 54 were 241.3834 MVA (limit 175 MVA) and 189.9339 MVA (limit 175 MVA) respectively. Therefore, total power flow violation was 81.3174 MVA. GSF for this case is presented in Table-7. First fifteen generators have shown high sensitivity with respect to congested lines and hence can participate in the rescheduling process. Generator number 5 is the largest capacity in this system and hence total rescheduled power is also very high in this case, which is 401.2025 MW. Change in active power and congestion cost calculated using various methods are presented in Table-8. Best congestion cost obtained by the proposed method is 10748 $/h which is lesser than other methods.

Table-7. Generator sensitivity factor for Case D.

Gen. No.	GSF	Gen. No.	GSF	Gen. No.	GSF
1	0.5398	42	-0.0090	80	0.0179
4	0.5517	46	-0.0032	85	0.0210
6	0.5429	49	-0.0062	87	0.0210
8	0.5752	54	-0.0097	89	0.0204
10	0.5752	55	-0.0100	90	0.0204
12	0.5322	56	-0.0098	91	0.0203
15	0.4332	59	-0.0128	92	0.0202
18	0.4553	61	-0.0141	99	0.0191
19	0.4077	62	-0.0137	100	0.0196
24	0.3618	65	-0.0168	103	0.0196
25	0.4926	66	-0.0124	104	0.0196
26	0.5317	69	0.0253	105	0.0196
27	0.4756	70	0.1066	107	0.0196
31	0.4811	72	0.2403	110	0.0196
32	0.4691	73	0.1287	111	0.0196
34	0.0018	74	0.0710	112	0.0196
36	-0.0025	76	0.0457	113	0.4995
40	-0.0106	77	0.0250	116	0

Table-8. Comparison of simulation results of congestion management for Case D.

Parameter	ARCBBO	DE	BBO
ΔP_{G1}(MW)	**74.4074**	**74.4074**	**74.4074**
ΔP_{G4}(MW)	0.0001	0	0
ΔP_{G6}(MW)	0.0026	0.4459	0.6483
ΔP_{G8}(MW)	0	0.3644	1.000
ΔP_{G12}(MW)	98.6686	92.7299	97.8425
ΔP_{G15}(MW)	6.9724	7.4693	6.1853
ΔP_{G18}(MW)	0.0024	0.2462	0.5727
ΔP_{G19}(MW)	0.0002	0.0449	1.6066
ΔP_{G24}(MW)	0.0013	1.5554	2.0000
ΔP_{G25}(MW)	4.5938	7.5888	32.9042
ΔP_{G26}(MW)	132.8522	132.8531	131.8531
ΔP_{G27}(MW)	0	0.2043	-0.0645
ΔP_{G31}(MW)	0.0012	1.1402	0.0387
ΔP_{G32}(MW)	83.7003	82.6614	55.7003
ΔP_{G69}(MW)	0	-0.2418	-2.0959

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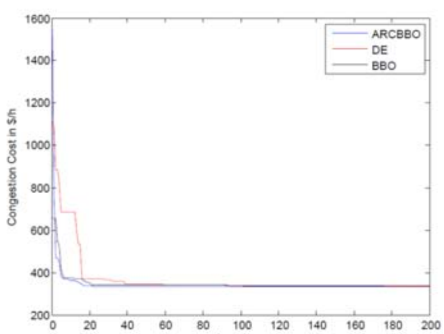
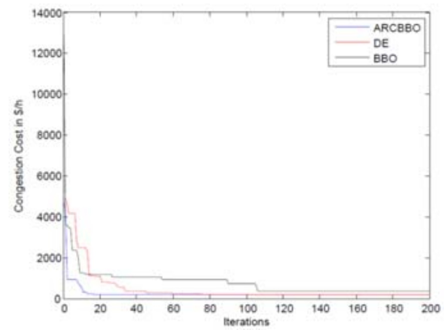
Rescheduled power (MW)	401.2025	401.9530	406.9195
Best Congestion cost ($/h)	10748	10869	11053
Mean Congestion cost ($/h)	10787	10910	11089
Worst Congestion cost ($/h)	10805	10923	11125
Std. Congestion cost	7.3616	11.4317	22.3831
Simulation time (sec)	230.89	245.14	175.03

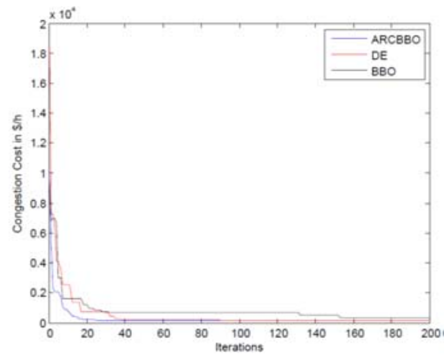
For each case study, power flows in congested line before and after rescheduling is presented in Table-9. The comparisons of convergence characteristics of ARCBBO, DE and BBO for congestion management are shown in Figure-2. Simulation time is presented in each case which represents time taken for 200 iterations per trail. Simulation time taken by BBO is lesser than ARCBBO and DE, but ARCBBO provides much better results than BBO and DE even in the first 50 iterations, it can be observed from Figure-5, which shows the exploration ability of the proposed method. Congestion cost and standard deviation of congestion cost obtained by ARCBBO are lesser than DE and BBO in all case studies, which represent accuracy and reliability of the proposed method.



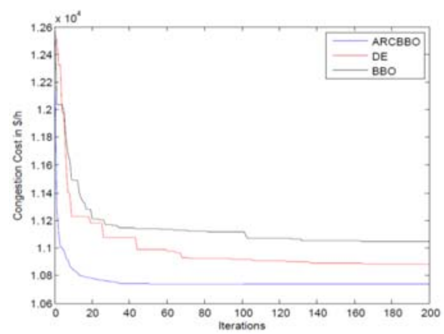
(a)



(b)



(c)



(d)

Figure-2. Convergence characteristics of optimization methods (a) Case A. (b) Case B. (c) Case C. (d) Case D.

Table-9. Power flow in congested line.

	Congested lines	**Power flow before rescheduling** (MVA)	**Power flow after rescheduling** (MVA)		
			ARCBBO	**DE**	**BBO**
Case A	10 - 17	7.01	6.99	6.99	6.99
Case B	8 -9	201.13	200	199.99	199.51
	9 -11	50.32	50	50	49.64
Case C	8 - 9	201.52	199.99	199.99	199.45
Case D	8 - 30	241.38	143.63	146.1	143.83
	30 - 38	189.93	71.57	71.31	71.85

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6. CONCLUSIONS

Using case studies approach, ARCBBO has been implemented successfully in different power systems for congestion management. From the results of 50 trails, it is evident that this algorithm has better convergence characteristics, computational efficiency, and robustness, compared with other approaches. This algorithm is ideal for independent system operators to solve different objective functions in deregulated environments. Whether this technique may be implemented in more complex multi-objective problems is worthy to investigate.

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