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Solution of Combined Economic and Emission Dispatch problems using Galaxy-based Search Algorithm.

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The Galaxy-based Search Algorithm (GbSA) is an optimization technique developed recently by Hamed Shah-Hosseini at Shahid Beheshti University-Iran [1, 2]. GbSA is a meta-heuristic that uses a modified Hill Climbing algorithm as a local search and resembles the spiral arms of some galaxies to search the optimum.
In this paper, GbSA is proposed for solving the Combined Economic and Emission Dispatch (CEED) problem under some equality and inequality constraints. The equality constraints are the active power flow balance equations, while the inequality constraints are the minimum and maximum power output of each unit. The voltage levels and security are assumed to be constant. The CEED problem is obtained by considering both the economy and emission objectives. This bi-objective problem is converted into a single objective function using a price penalty factor.
The validity of GbSA is tested on two sample systems and the results are compared to those reported in the recent literature. The study results are quite encouraging showing the good applicability of GbSA for CEED problem.

Keywords: Economic dispatch, emission dispatch, Combined Economic and Emission Dispatch, Galaxy-based Search Algorithm.

1. Introduction

In recent years the economic dispatch problem has taken a suitable twist as the public has become increasingly concerned with environmental matters. The absolute minimum cost is not anymore the only criterion to be met in the electric power generation and dispatching problems. The generation of electricity from the fossil fuel releases several contaminants such as sulfur oxides (SO_2) and oxides of nitrogen (NO_X) into the atmosphere. These gaseous pollutants cause harmful effects on human beings as well as on plants and animals [3].

The economic dispatch problem in a power system is to determine the optimal combination of power outputs for all generating units which will minimize the total cost while satisfying the constraints. When the environmental concerns that arise from the emissions produced by fossil-fueled electric power plants are combined with the EDP then the problem becomes Combined Economic and Emission Dispatch (CEED) problem. This problem considers two objectives such as minimization of the cost and emission from the thermal power plants with both equality and inequality constraints.

The economic load dispatch is one of the major problems in power system operation and planning. It is a large-scale highly non-linear constrained optimization problem. The traditional methods used to solve this economic load dispatch problem are Lambda iteration method, Gradient, Newton, linear programming and interior point method. Recently, meta-

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heuristic techniques such as Simulated Annealing, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Tabu search algorithm are used to solve this problem [4].

In this paper, a new meta-heuristic technique called “Galaxy-based Search Algorithm” (GbSA) has been proposed to solve the CEED problem. The bi-objective CEED problem is converted into a single-objective function using a price penalty factor.

In order to show the effectiveness of the proposed algorithm, it has been implemented on two different test systems. Satisfactory simulation results are demonstrated and also compared with the results obtained by other algorithms in the literature.

2. Problem formulation

2.1. Economic dispatch

The optimal Economic dispatch is the important component of power system optimization. It is defined as the minimization of the combination of the power generation, which minimizes the total cost while satisfying the power balance relation. The problem of economic dispatch can be formulated as minimization of the cost function subjected to the equality and inequality constraints [5].

In power stations, every generator has its input/output curve. It has the fuel input as a function of the power output. But if the ordinates are multiplied by the cost of \$/Btu, the result gives the fuel cost per hour as a function of power output [6].

The fuel cost of generator i may be represented as a polynomial function of real power generation:

$$F(P_{Gi}) = \sum_{i=1}^{ng}(a_i P_{Gi}^2 + b_i P_{Gi} + c_i)\,(i = 1,2,\dots,ng) \tag{1}$$

Where F is the total fuel cost of the system, ng is the number of generators, a_i , b_i and c_i are the cost coefficients of the i-th generating unit.

2.2. Emission dispatch

The emission function can be defined as the sum of all types of emission considered, such as NO_x, SO_2, CO_2, particles and thermal emissions, ect, with suitable pricing of weighting on each pollutant emitted [7].

In this paper, only NO_x emission function is taken into account. This function is illustrated by equation (2) if the valve point effect is not taken into account.

$$E(P_{Gi}) = \sum_{i=1}^{ng}(\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i) \tag{2}$$

Where E is the total NO_x emission of the system, α_i , β_i and γ_i are the emission coefficients of the i-th generating unit.

2.3. Constraints

During the minimization process, some equality and inequality constraints must be satisfied. In this process, an equality constraint is called a power balance and an inequality constraint is called a generation capacity constraint.

A.1 Equality constraint

The total power generation must supply the total power demand P_d and the total power transmission losses in the network P_L. Hence,

$$\sum_{i=1}^{ng} P_{Gi} - P_d - P_L = 0 \tag{3}$$

A.2 Inequality constraints

According to those constraints, the power output of each generator is restricted by minimum P_{Gimin} and maximum P_{Gimax} power limits.

$$P_{Gimin} \le P_{Gi} \le P_{Gimax} \tag{4}$$

2.4. Combined economic and emission dispatch (CEED)

Optimization of Combined Economic and Emission Dispatch (CEED) problem can be formulated as:

$$Min[\,F(P_{Gi}),E(P_{Gi})\,] \tag{5}$$

CEED engages the concurrent optimization of fuel cost and emission control that are contradictory ones. The bi-objective economic and emission dispatch problem is converted into single optimisation problem by introducing price penalty factor P_f as follows:

$$Min \quad T(P_{Gi}) = F(P_{Gi}) + P_f E(P_{Gi}) \tag{6}$$

Subject to the power constraints given by (3) and (4).

The price penalty factor P_f is the ratio between the maximum fuel cost and maximum emission of corresponding generator [8].

$$P_{fi} = \frac{F(P_{Gimax})}{E(P_{Gimax})} \tag{7}$$

The steps to determine the price penalty factor for a particular load demand are:

1. Find the ratio between maximum fuel cost and maximum emission of each generator.
2. Arrange P_{fi} $(i = 1,2...,ng)$ in ascending order.
3. Add the maximum capacity of each unit (P_{Gimax}) one at a time, starting from the smallest P_{fi} until $\sum P_{Gimax} \ge P_d$.
4. In this stage, P_{fi} associated with the last unit in the process is the price penalty factor of the given load P_f .

Once the value of P_f is known, then (6) can be rewritten in terms of known coefficients and the unknown output of the generators.

$$Min \ T(P_{Gi}) = \sum_{i=1}^{ng}(A_i P_{Gi}^2 + B_i P_{Gi} + C_i) \tag{8}$$

Where: $A_i = a_i + P_{fi}\alpha_i$, $B_i = b_i + P_{fi}\beta_i$, $C_i = c_i + P_{fi}\gamma_i$

2.5. Modified CEED problem formulation

The modified CEED problem formulation is based on its transformation into an unconstrained problem with (ng-1) variables [9]. In order to achieve the modified CEED problem, we apply two eliminations separately: Firstly, to eliminate the linear inequality constraints, new variable θ has to be introduced. The inequality constraints given by (4) can be formulated as

$$0 \le \frac{P_{Gi} - P_{Gi\,min}}{P_{Gi\,max} - P_{Gi\,min}} \le 1 \tag{9}$$

The function limited between 0 and 1 is the function $sin^2\theta$:

$$0 \le sin^2\theta \le 1 \tag{10}$$

Comparing equations (9) and (10)

$$P_{Gi} = P_{Gi\,min} + D_i\, sin^2\theta_i \tag{11}$$

Where $D_i = P_{Gi\,max} - P_{Gi\,min}$ and θ is an unconstrained variable.

Secondly, to eliminate the linear equality constraints, we express P_{Gng} as a function of P_{Gi}.

$$P_{Gng} = P_{ch} + P_L - \sum_{j=1}^{ng-1}(P_{Gj\,min} + D_j.sin^2\theta_j) \tag{12}$$

$$P_{Gng} = L - \sum_{j=1}^{ng-1} D_j.sin^2\theta_j \tag{13}$$

Where $L = P_{ch} + P_L - \sum_{j=1}^{ng-1} P_{Gj\,min}$.

Substitution of the expressions (11) and (13) in (8) gives:

$$Min\ G(\theta_j) = \sum_{j=1}^{ng-1}[A_j(P_{Gj\,min} + D_j\, sin^2\theta_j)^2 + B_j(P_{Gj\,min} + D_j\, sin^2\theta_j) + C_j] + A_{ng}(L - \sum_{j=1}^{ng-1} D_j\, sin^2\theta_j)^2$$
$$+ B_{ng}(L - \sum_{j=1}^{ng-1} D_j\, sin^2\theta_j) + C_{ng} \tag{14}$$

After development, equation (14) can be represented in the following general form:

$$Min\ G(\theta_j) = (sin^2\theta_j)^T M (sin^2\theta_j) + (sin^2\theta_j)^T V + K \tag{15}$$

M and V are (ng-1)-by-(ng-1) and (ng-1)-by-1 array of total cost coefficients and K is a constant total coefficient scalar.

The off-diagonal elements of matrix M are:

$$M_{ij} = D_i D_j A_{ng} \tag{16}$$

and the diagonal elements of matrix M are:

$$M_{jj} = D_j^2 (A_j + A_{ng}) \tag{17}$$

The elements of vector V are:

$$V_j = D_j(2A_j P_{Gj\,min} + B_j - 2LA_{ng} - B_{ng}) \tag{18}$$

The constant K is:

$$K = A_{ng}L^2 + B_{ng}L + C_{ng} + T_j(P_{Gj\,min}) \tag{19}$$

For modified economic dispatch $A_i = a_i$, $B_i = b_i$, $C_i = c_i$

For modified emission dispatch $A_i = \alpha_i$, $B_i = \beta_i$, $C_i = \gamma_i$

3. Galaxy-based search algorithm

Recently, Hamed Shah-Hosseini developed a new Galaxy-based Search meta-heuristic Algorithm that is an optimization technique inspired from nature. He applied GbSA to solve the principal components analysis problem [1] and multilevel image thresholding [2].

The GbSA imitates the spiral arm of spiral galaxies to search its surrounding. This spiral movement is enhanced by chaos to escape from local optimums. A local search algorithm is also utilised to adjust the solution obtained by the spiral movement of the GbSA (*SpiralChaoticMove*). The pseudo-codes of the GbSA is:

```
Procedure GbSA
    SG ← GenerateInitialSolution
    SG ← LocalSearch(SG)
While (termination condition is not met) do
        Flag ← false
        SpiralChaoticMove (SG, Flag)
        If (Flag) then
        SG ← LocalSearch( SG )
        Endif
Endwhile
Return SG
Endprocedure
```

At first, the initial solution is created by the function *GenerateInitialSolution(SG)*. Following solution initialization, the local search component of the GbSA, *LocalSearch(SG)* , is activated with the initial solution in variable SG. The local search is a modified Hill-Climbing. Other components of the proposed GbSA are called in the "while" loop of the pseudo-code. *SpiralChaoticMove* is the first component in the loop which globally searches around the solution SG

3.1 Local search: modified Hill-Climbing

Hill Climbing is a mathematical optimization technique which belongs to the family of local search. It is an iterative algorithm that can be used to solve problems that have many solutions, some of which are better than others. It starts with a random (potentially poor) solution, and iteratively makes small changes to the solution, each time improving it a little [10, 11].

When the algorithm cannot see any improvement anymore, it terminates. Ideally, at that point the current solution is close to optimal, but it is not guaranteed that Hill Climbing will ever come close to the optimal solution [11].

The relative simplicity of the algorithm makes it a popular first choice amongst optimizing algorithms. It is used widely in artificial intelligence, for reaching a goal state from a starting node. Choice of next node and starting node can be varied to give a list of related algorithms. Although more advanced algorithms such as simulated annealing or Tabu search may give better results, in some situations hill climbing works just as well [12].

Pseudo-code of modified Hill-Climbing search algorithm is shown in table 1.

Table 1: The pseudo-code of the local search used in the GbSA

Procedure LocalSearch	
// **Input**	L is the number of components of candidate solutions. S is the current solution with L components such that Si denotes the component ith of solution S.
//**Output**	*SNext* is the output of the local search.
//**Parameters**	ΔS is the step size which is set by function NextChaos(). α is a dynamic parameter. Δ α is 0.5 k_{Max} denotes the maximum iteration that the local Search has to search around a component to find a better solution.
	$\text{Re}\ peat\ For\ i = 1\ to\ L$ $\alpha \leftarrow 1$ $k \leftarrow 0$ $while\quad k \prec k\max$ $SL_i \leftarrow S_i - \alpha.\Delta S; SU_i \leftarrow S_i + \alpha.\Delta S$ $if\ f(SL) \prec f(S)\ and\ f(S) \prec f(S)\ then$ $Goto\ Endrepeat$ $Endif$ $if\ f(SU) \succ f(S)\ then$ $S_i \leftarrow SU_i;\quad SL_i \leftarrow SU_i;\quad \alpha \leftarrow 1;\quad k \leftarrow 0$ $Endif$ $if\ f(SL) \succ f(S)\ then$ $S_i \leftarrow SL_i;\quad SU_i \leftarrow SL_i;\quad \alpha \leftarrow 1;\quad k \leftarrow 0$ $Endif$ $\alpha \leftarrow \alpha + \Delta\alpha.NextChaos();\quad k \leftarrow k+1$ $Endwhile$ $SL_i \leftarrow S_i$ $Endrepeat$ $SNext \leftarrow S$ Endprocedure

3.2 Spiral movement

The *SpiralChaoticMove* has the role of searching around the current solution denoted by SG. When the *SpiralChaoticMove* finds an improved solution better than the SG, it updates the SG with the improved solution, and the variable Flag is set to true. When Flag is true, the *LocalSearch* component of the GbSA is activated to search locally around the updated solution SG.

The *SpiralChaoticMove* is iterated maximally for Maxrep number of times. However, whenever it finds a solution better than the current solution, the *SpiralChaoticMove* is terminated. If *SpiralChaotic* Move finds a better solution, Flag is set to true and Local Search is called to search locally around the newly-updated solution SG. The whole process above is repeated until a stopping condition is satisfied [2].The *SpiralChaoticMove* searches the space around the current best solution using a spiral movement enhanced by a chaotic variable generated by *NextChaos*(). The pseudo-code of *SpiralChaoticMove* is shown in table 2.

Table 2: The pseudo-code of the *SpiralChaoticMove* used in the GbSA

Procedure SpiralChaoticMove	
// **Input**	*S* is the current best solution with *L* components such that *S*i denotes the *i*th component of solution *S*.
// **Output**	*SNext* is the output, which is found first that is better than the given solution *S*. *Flag* is set to *true* to indicate that a better solution has been found.
// **Parameters**	Each θ*i* is initialised by (–1 + 2 *NextChaos*()). Δθ is a parameter. Here, 0.01. *r* is 0.001. Δ*r* is set by the value *NextChaos*() in each procedure call. *Max*re *p* is the maximum iteration that the *SpiralChaoticMove* searches.

	Repeat
	$for\ i=1\ to\ L$
	$\theta_i \leftarrow (-1+2.NextChaos()).\pi;$
	Endrepeat
	$while\quad rep \prec Maxrep$
	Repeat $for\ i=1\ to\ L$
	$SNext_i \leftarrow S_i + NextChaos\ ().r.\cos(\theta_i);$
	Endrepeat
	$if\ (SNext) \geq f(S)\ then$
	$Flag \leftarrow true;\quad GotoEndpro\ cedure;$
	Endif
	Repeat $for\ i=1\ to\ L$
	$SNext_i \leftarrow S_i - NextChaos\ ().r.\cos(\theta_i);$
	Endrepeat
	$if\ (SNest) \geq f(S)\ then$
	$Flag \leftarrow true;\quad GotoEndpro\ cedure;$
	Endif
	$r \leftarrow r+\Delta r;$
	Repeat $i=1\ to\ L$
	$\theta_i \leftarrow \theta_i + \Delta\theta;$
	$if\ \ (\theta_i \succ \pi)\ then\ \theta_i \leftarrow -\pi;$
	Endif
	Endrepeat
	$rep \leftarrow rep+1;$
	Endwhile
	Endprocedure.

The chaotic sequence is generated by the logistic map:

$$x_{n+1} = \lambda.x_n.(1-x_n) \qquad n=0,1,2,... \tag{20}$$

The initial value x_0 should be chosen from [0, 1]. λ is the control parameter, and x_n denotes the variable at discrete time *n*. The logistic map exhibits chaotic dynamics when λ = 4 and $x_0 \in [0,1]$ {0, 0.25, 0.5, 0.75, 1}.

4. Simulation results

GbSA has been tested on IEEE 30-bus six-generator and eleven generator sample systems. These test systems are widely used as benchmarks in the power system field for solving the CEED problem and have been used by many other research groups around the world for similar purposes. The results obtained from the GbSA are compared with other population-based optimization techniques, which have already been tested and reported by earlier authors.

The GbSA parameters are taken as follows:

$\lambda = 4, x_0 = 0.25, \Delta\alpha = 0.5, \Delta\theta = 0.01, r = 0.001, K_{max} = 100, Maxrep = 500.$

The simulations were run for three different cases:

Case 1: Minimize total fuel cost (Economic Dispatch).

Case 2: Minimize total emission (Emission Dispatch).

Case 3: Minimize fuel cost and emission simultaneously (CEED).

4.1 Test System I

The detailed data of this system are given in [6].This power system which is considered as lossless, is interconnected by 41 transmission lines and the total system demand for the 21 load buses is 283.40 MW. Operating limits, Fuel cost and emission coefficients for this system are illustrated in table 3 [13].

Table 3: Generation limits, fuel cost and emission coefficients of six-generator system

Generator	$P_{Gi\,min}$	$P_{Gi\,max}$	$F(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i$ (\$/h)			$E(P_{Gi}) = (\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i).10^{-2}$ (ton/h)		
			a_i (\$/MW²h)	b_i (\$/MWh)	c_i (\$/h)	α_i (ton/MW²h)	β_i (ton/MWh)	γ_i (ton/h)
1	0.05	0.5	100	200	10	6.490	-5.554	4.091
2	0.05	0.6	120	150	10	5.638	-6.047	2.543
3	0.05	1	40	180	20	4.586	-5.094	4.258
4	0.05	1.2	60	100	10	3.380	-3.550	5.426
5	0.05	1	40	180	20	4.586	-5.094	4.258
6	0.05	0.6	100	150	10	5.151	-5.555	6.131

The price penalty factor is evaluated to 1336.26 ton/h.

The optimal values of the generated powers, fuel cost and NO_x emission for case1, 2 and 3 are reported in table 4.

Table 4: GbSA solution of Economic Dispatch, Emission Dispatch and CEED for test system I.

Generator	Case 1		Case2		Case 3	
	θ_{opt} (rd)	P_{Gopt} (pu)	θ_{opt} (rd)	P_{Gopt} (pu)	θ_{opt} (rd)	P_{Gopt} (pu)
1	16.08123	0.10984	8.36982	0.39051	-8.50064	0.33663
2	-10.16412	0.29970	19.96387	0.49313	-17.83684	0.44576
3	-10.20933	0.52420	-5.52171	0.50228	-3.90717	0.50617
4	1.15975	1.01640	-0.63403	0.45358	3.88546	0.57729
5	-21.20670	0.52410	30.65429	0.50244	18.08408	0.50608
P_{G6opt} (pu)	0.35976		0.49206		0.46206	
Fuel cost (\$/h)	**600.111**		633.265		**620.450**	
Emission (ton/h)	0.20501		**0.18613**		**0.18701**	

According to table 4, the fuel cost in case 1 is 5.24% and 3.28% lower than that found by considering cases 2 and 3, respectively. In addition, the emission level in case 1 is 10.14% and 9.65% higher than that found in cases 2 and 3, respectively. We can see that the fuel cost and emissions are reduced by considering the CEED.

Convergence characteristics of fuel cost (case 1), NO_x emission (case 2) and total cost (case 3) are shown in figures 1 and 2 respectively.

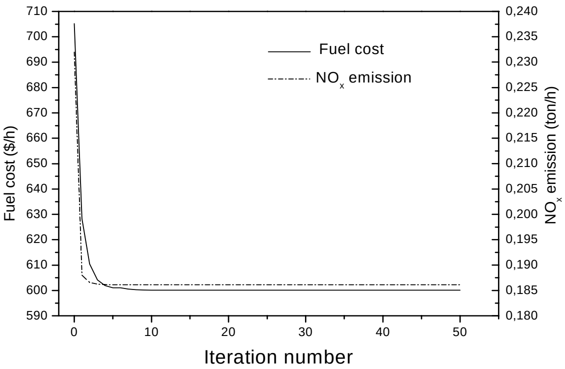

Figure 1. Convergence of fuel cost (case1) and NO_x emission (case 2)

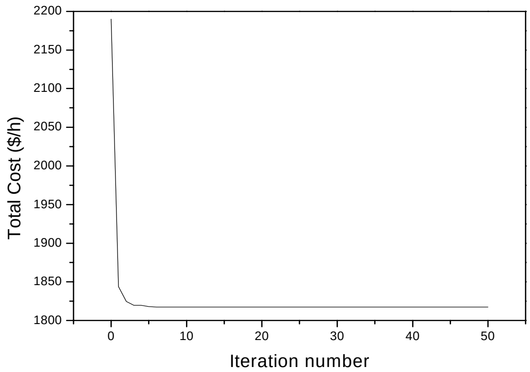

Figure 2. Convergence of total cost (case 3)

These graphs indicate that GbSA converges rapidly to the optimal solution.

In order to demonstrate the performance of the GbSA, its results are compared to those obtained using Non-dominated Sorting Genetic Algorithm (NSGA) [13]. The comparison results are given in table 5.

Table 5: Comparison of fuel cost and emission for test system I.

Case	Case 1		Case2		Case3	
Algorithm	GbSA	NSGA	GbSA	NSGA	GbSA	NSGA*
P_{G1} (pu)	0.10984	0.10954	0.39051	0.40584	0.33663	0.2571
P_{G2} (pu)	0.29970	0.29967	0.49313	0.45915	0.44576	0.3774
P_{G3} (pu)	0.52420	0.52447	0.50228	0.53797	0.50617	0.5381
P_{G4} (pu)	1.01640	1.01601	0.45358	0.38300	0.57729	0.6872
P_{G5} (pu)	0.52410	0.52469	0.50244	0.53791	0.50608	0.5404
P_{G6} (pu)	0.35976	0.35963	0.49206	0.51012	0.46206	0.4337
Fuel cost ($/h)	**600.111**	**600.114**	633.265	638.260	**620.450**	**610.067**
Emission (ton/h)	0.20501	0.22214	**0.18613**	**0.19420**	**0.18701**	**0.20060**
NSGA*: Best compromise solutions.						

From the above table, it is noted that the fuel cost (case 1) obtained by GbSA is comparable to that obtained using NSGA. Moreover, the NO_x emission (case 2) obtained by GbSA is better than that obtained using NSGA.

The fuel cost obtained by GbSA in case 3 is higher than that obtained by NSGA*. Moreover, NO_x emission obtained in the same case by GbSA, is better than that obtained using NSGA*.

4.2 Test System II

This system consists of eleven generating units, having quadratic cost and emission functions. The input data for the 11-generator system are taken from [14, 15, 16] and the total demand is set as 2500 MW. For this system, transmission losses are neglected. Operating limits, Fuel cost and emission coefficients are given in table 6.
For comparison of results with recent reports, coefficients for the modified CEED are taken as follows: $A_i = a_i + P_{fi}\alpha_i$, $B_i = b_i + P_{fi}\beta_i$, $C_i = c_i + P_{fi}\gamma_i$

P_{fi} is the price penalty factor of each generator.

Table 6: Generation limits, fuel cost and emission coefficients of eleven-generator system

Generator	$P_{Gi\,min}$ (MW)	$P_{Gi\,max}$ (MW)	$F(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i$ ($/h)			$E(P_{Gi}) = (\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i)$ (Kg/h)		
			a_i ($/MW²h)	b_i ($/MWh)	c_i ($/h)	α_i (Kg/MW²h)	β_i (Kg/MWh)	γ_i (Kg/h)
1	20	250	0.00762	1.92699	387.85	0.00419	-0.67767	33.93
2	20	210	0.00838	2.11969	441.62	0.00461	-0.69044	24.62
3	20	250	0.00523	2.19196	422.57	0.00419	-0.67767	33.93
4	60	300	0.00140	2.01983	552.50	0.00683	-0.54551	27.14
5	20	210	0.00154	2.22181	557.75	0.00751	-0.40060	24.15
6	60	300	0.00177	1.91528	562.18	0.00683	-0.54551	27.14
7	20	215	0.00195	2.10681	568.39	0.00751	-0.40006	24.15
8	100	455	0.00106	1.99138	682.93	0.00355	-0.51116	30.45
9	100	455	0.00117	1.99802	741.22	0.00417	-0.56228	25.59
10	110	460	0.00089	2.12352	617.83	0.00355	-0.41116	30.45
11	110	465	0.00098	2.10487	674.61	0.00417	-0.56228	25.59

The optimal values of the generated powers, fuel cost and NO_x emission for case1, 2 and 3 are given in table 7.

Table 7: GbSA solution of Economic Dispatch, Emission Dispatch and CEED for test system II.

Bus	Case 1		Case2		Case 3	
	θ_{opt} (rd)	P_{Gopt} (MW)	θ_{opt} (rd)	P_{Gopt} (MW)	θ_{opt} (rd)	P_{Gopt} (MW)
1	-12.9797	57.1155	1.5707	250.0000	-14.9023	139.6504
2	-0.3339	40.4065	-4.7124	210.0000	-10.1979	112.6706
3	-5.8655	57.8494	-1.5707	250.0000	19.6819	145.7959
4	-5.0215	277.7904	-8.6927	167.2304	-5.3212	221.4886
5	13.7807	186.8629	13.4977	142.3451	8.5235	136.8058
6	-24.0398	249.2444	0.7314	167.0680	-16.6572	218.6314
7	-20.8774	177.0252	-5.3693	142.2783	-33.6542	140.2709
8	-10.5185	380.1425	29.1707	316.5621	-2.1610	345.0302
9	-13.5364	341.5759	2.3603	276.0231	11.6320	329.5759
10	-16.7759	378.7072	0.8362	302.7439	-26.1511	363.6264
P_{G11opt} (MW)	353.2797		275.7488		346.4535	
Fuel cost ($/h)	**12274.40**		13046.66		**12424.76**	
Emission (Kg/h)	2540.694		**1659.262**		**2003.543**	

Convergence characteristics of fuel cost (case 1), NO_x emission (case 2) and total cost (case 3) are shown in figures 3 and 4 respectively.

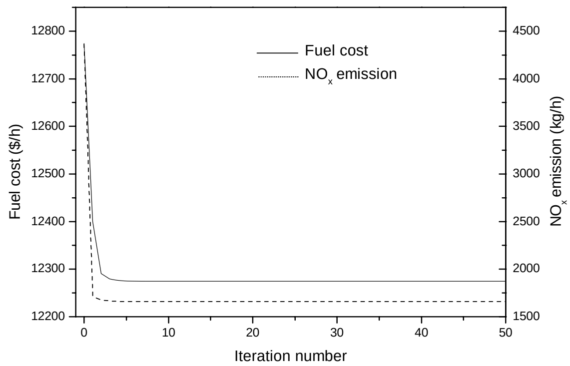

Figure 3. Convergence of fuel cost (case1) and NO_x emission (case 2)

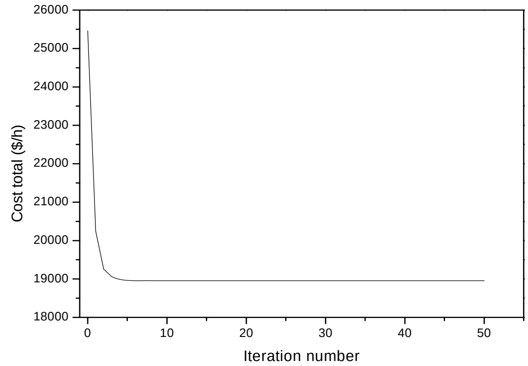

Figure 4. Convergence of total cost (case 3)

These graphs clearly indicate that GbSA converges rapidly to the optimal solution.

From the results, it is inferred that, the fuel cost and emission are conflicting objectives. Emission has maximum value when cost is minimized.

The fuel cost in case 1 is found to be better than other cases. The maximum difference between cases 1 and 2 is 772 $/h. But the emission level in this case is not the best. The best emission is found in case 2.

In order to demonstrate the efficiency of GbSA, the results obtained for eleven-generator sample system using λ-iteration method, Recursive method, Particle Swarm Optimization (PSO), Differential Evolution (DE), Simplified recursive method, Genetic Algorithm based on Similarity Crossover (GAbSC), Gravitational Search Algorithm (GSA) and GbSA are shown in table 8 and figure 5.

Table 8: Comparison of fuel cost and emission for test system II.

Method	Fuel cost ($/h)	Emission (Kg/h)
λ –iteration [14, 15, 16]	12424.94	2003.301
Recursive [14, 15, 16]	12424.94	2003.300
PSO [14, 15, 16]	12428.63	2003.720
DE [14, 15, 16]	12425.06	2003.350
Simplified Recursive [14, 15, 16]	12424.94	2003.300
GAbSC [14 , 16]	12423.77	2003.030
GSA [14]	12422.66	2002.950
GbSA	**12424.76**	**2003.543**

It appears in table 8 that GbSA has similar performance when comparing other population-based optimization algorithms in the literature. The PSO produced the highest cost and emission.

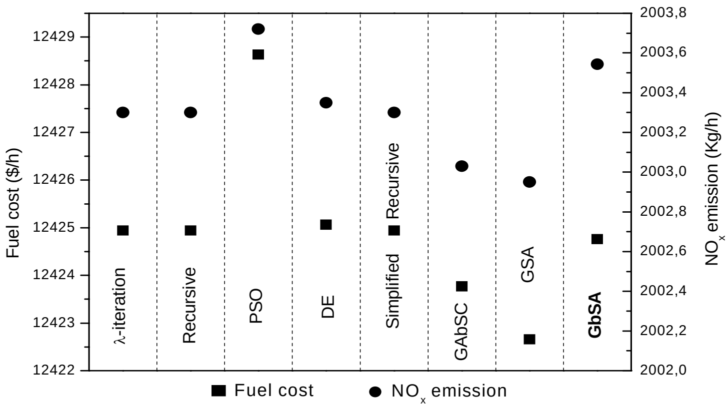

Figure 5. Comparison of the results.

5. Conclusion

In this paper, economic and emission dispatch problems are combined and converted into a single objective function. The converted objective function is solved by a newly introduced metaheuristic GbSA to minimize the fuel cost and NO_x emission for a given load. The GbSA imitates the arms of spiral galaxies to look for optimal solutions and also utilizes a local search algorithm for fine-tuning of the solutions obtained by the spiral arm.

Test results have shown that GbSA can provide identical solutions to others methods. The computing time of GbSA is insignificant since the number of iterations needed by the process to stop is very low. As a result, GbSA is acceptable and applicable for CEED problem solution.

Further extensions of GbSA should be explored to include more objective functions or constraints with regard to more realistic problems, as well as other data sets and standard test problems.

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