Multi-Objective Economic Emission Dispatch using Backtracking Search Optimization Algorithm

V. Jaya Vaishnavi, A. Srinivasa Reddy

Abstract—To provide reliable and uninterrupted electrical supply to consumers, electrical utilities face many economic and technical problems in operation, planning and control of power systems. Most of the power system optimization problems like economic load dispatch include complex and non-linear characteristics with heavy equality and inequality constraints. Cost minimization of power generation is one of the most important power system problems. In this project, an attempt is made to minimize the cost for generation in a power system. The aim of this project is to find the optimum set of power to be generated for a given loading conditions. Equality constraint which is the relation between power generated, losses and power demand is taken into account. In this thesis, transmission losses have not been taken. Inequality constraints such as the maximum and minimum generation values for each of the generators are also considered along with valve point loading. This paper introduces backtracking search optimization algorithm (BSA), a new evolutionary algorithm (EA) for solving real-valued numerical optimization problems .EA's are popular stochastic search algorithms that are widely used to solve non-linear, non-differentiable and complex numerical optimization problems. Unlike many search algorithms, BSA has a single control parameter. BSA has a simple structure that is effective, fast and capable of solving multi modal problems and that enables it to easily adapt to different numerical optimization problems. BSA's strategy for generating a trail population includes two new crossover and mutation operators.BSA strategies for generating trail populations and controlling the amplitude of the search-direction matrix and search space boundaries give it very powerful exploration and exploitation capabilities. In particular BSA possesses a memory in which it stores a population from a randomly chosen previous generation for use in generating the search-direction matrix. Thus BSA's memory allows it to take advantage of experiences gained from previous generations when it generates a trail preparation. The proposed algorithm is applied to EED problem. The purpose of EED is to obtain the optimal amount of generated power for the generating unit in the system by simultaneously minimizing the fuel and emission costs. To demonstrate the effectiveness of this method BSA have been performed on 6-unit system with valve point loading effect to obtain lesser fuel and emission costs

Index Terms—Economic Dispatch, Emission Dispatch, Multi-objective optimization, Backtracking search optimization algorithm, Trade-off curve

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I. INTRODUCTION

Power system Economic Dispatch (ED) is the most efficient, reliable and low cost operation of power system dispatching generation among the available generating units such that the cost of operation is least, subject to load demand and other operational constraints. However, since 1980s due to implementation of several pollution control acts, finding out of minimum generation cost is not only the major concern of the power generating companies. These industries are bound to consider the effect of pollutants like NO_X, SO_X, CO_X, etc. that are present in the waste matter which come out from the stack of thermal power plant. Economic Emission Dispatch (EED) has come out to minimize the emission of pollutants like NO_X, SO_X, CO_X, particulate matters, etc. from the thermal power plant. Moreover, the objective of minimum cost of generation or the objective of minimum emission may not be a desirable criterion. Therefore, the concept of Economic Emission Load Dispatch (EED) has come into the picture to figure out both the objective of minimum cost of generation and as well as mini-mum emission level at the same time. In a sentence it can be said that the combination of Economic Load and Emission Dispatch problem is known as Economic Emission Load Dispatch (EED) and it seeks a balance between cost and emission. This problem of EED may be formulated as a multi-objective Economic Emission Load Dispatch (EED) problem or an Emission Constrained Economic Load Dispatch problem. Economic dispatch (ED) is one of the prime functions in power system operation, management and planning and its objective echoes to schedule the committed generating units' output so as to meet the load demand at minimum operating cost while satisfying all units and system operational constraints [1,2] . The generation of electricity from fossil fuel releases several contaminants such as sulfur dioxides, nitrogen oxides and carbon dioxide into the atmosphere. In the past few decades, environ- mental awareness led to impose rigid environmental policies such as ''US Clean air amendments of 1990'' on power utilities to minimize their emissions. A host of strategies are in vogue to reduce power plant emissions like installing post-combustion cleaning equipment, switching to low emission fuels and replacement of the aged fuel burners or dispatching with emission considerations. The latter option is preferred in many cases due to economical reasons and its immediate availability for short- term operation. However, the other alternatives are considered as a long term option as they incur additional capital cost [3]. Emission dispatch (ED) is similar to ED except that it extends to minimize the net emissions instead of fuel cost. Operating either at absolute minimum fuel cost or at lowest pollution

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level is no longer acceptable owing to the fact that both of the objectives are conflicting in the sense that minimization of one causes the other to increase. This endears to the formation of combined Economic emission dispatch (EED) that focuses to simultaneously minimize both the fuel cost and emission levels by satisfying all unit and systems constraints. There is no single optimal solution to the bi-objective EED problem unless exact preference or weight of both the objectives is known. It gives rise to finding a set of compromise solutions known as Pareto optimal solutions, which show the trade- off between the two competing objectives.

II. Economic Emission Dispatch

A. Single Objective Optimization

When an optimization problem modeling a physical system involves only one objective function, the task of finding the optimal solution is called single objective optimization.

B. Multi Objective Optimization

The Multiobjective Optimization Problem (also called multi-criteria optimization, Multi performance or vector optimization problem) can then be defined (in words) as the problem of finding: A vector of decision variables which satisfies constraints and optimizes a vector function whose elements represent the objective functions. These functions from a mathematical description of performance criteria which are usually in conflict with each other. Hence, the terms optimize means finding such a solution which would give the values of all the objective functions acceptable to the decision maker. The mathematical definition of a MOP is important in providing a foundation of under-standing between the interdisciplinary nature of deriving possible solution techniques (deterministic, stochastic); i.e., search algorithms. The following discussions present generic MOP mathematical and formal symbolic definitions. The single objective formulation is extended to reflect the nature of multiobjective Problems where there is not one objective function to optimize, but many. Thus, there is not one unique solution but set of solutions. These sets of solutions are found through the use of Pareto Optimality Theory. Note that multiobjective problems require a decision marker to make a choice of x_i^* values. The selection is essentially a trade-off of one complete solution x over another in multiobjective space. More precisely, MOPs are those problems where the goal is to optimize k objective functions simultaneously. This may involve the maximization of all k functions, the Minimization of all k functions or a combination of maximization and minimization of these k functions.

A general MOP is defined as minimizing (or Maximizing)

F(x)= [f1(x) f2(x)…………fk(x)]

Subjected to

$g_i(x)\leq 0$, i={1,2,………m}

$h_j(x)\leq 0$, j={1,2,………p}

A MOP solution minimizes (or maximizes) the components of vector F(x)

Where x is an n dimensional decision variable vector

X = [x1 x2 x3……….xn].

It is noted that $g_i(x)\leq 0$, $h_j(x)\leq 0$ represent constraints that must be full filled while minimizing (or maximizes) F(x).

Thus a MOP consist of k objectives reflected in the k objective functions, m+p constraints on the objective functions and n decision variables. The k objective functions may be linear or nonlinear and continuous or discrete in nature.

C. Definition of Economic Dispatch

The economic load dispatch ELD can be defined as the process of allocating generation levels to generating units, so that the system load is supplied entirely and most economically. The ELD is used to define the production level of each plant, so that the total cost of generation and transmission for a prescribed schedule of load is minimum.

D. Necessity of generation scheduling

In a practical power system, the power plants are not located at the same distance from the centre of loads and there fuel costs are different. Also under normal operating, the generation capacity is more than the total load demand and losses [31]. Thus, there are many options for scheduling generation. In an interconnected power system, the objective is to find the real and reactive power scheduling of each power plant in such a way so as to minimize the operating cost. This means that the generators real and reactive powers are allowed to vary within certain limits so as to meet a particular load demand with minimum fuel cost. This is called the Economic load dispatch ELD problem. The objective functions, also known as cost functions may present economic cost system security or other objectives. The transmission loss formula can be derived and the economic load dispatch of generation based on the loss formula can also be obtained. The Loss coefficients are known as B-coefficients. A major challenge for all power utilities is not only to satisfy the consumer demand for power, but to do so at minimal cost. Any given power system can be comprised of multiple generating stations having number of generators and the cost of operating these generators does not usually correlate proportionally with their outputs; therefore the challenge for power utilities is to try to balance the total load among generators that are running as efficiently as possible. The economic load dispatch ELD problem assumes that the amount of power to be supplied by a given set of units is constants for a given interval of time and attempts to minimize cost of supplying this energy subject to constraints of the generating units[34]. Therefore, it is concerned with the minimization of total cost incurred in the system and constraints over the entire dispatch period. Therefore, the main aim in the economic load dispatch problem is to minimize the total cost of generating real power (production cost) at various stations while satisfying the loads and the losses in the transmission links.

E. Generator operating cost

The total cost of operation includes the fuel cost, cost of labour, supplies and maintenance. Generally, cost of labour, supplies and maintenance are fixed percentages of incoming fuel costs. The power output of fossil plants is increased sequentially by opening a set of valves to its steam turbine at the inlet. The throttling losses are large when a valve is just opened and small when it is fully opened.

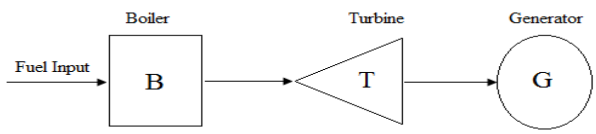

Figure (a) Simple model of a fossil plant

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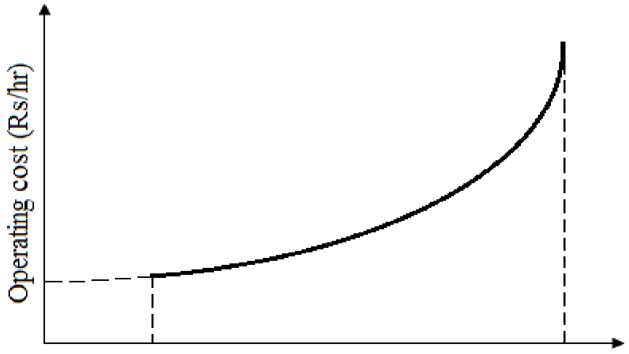
Figure (a) shows the simple model of a fossil plant dispatching purposes. The cost is usually approximated by one or more quadratic segments. The operating cost of the plant has the form shown in Figure (b). For dispatching purposes, this cost is usually approximated by one or more quadratic segments. So, the fuel cost curve in the active power generation, takes up a quadratic form, given in equation (1).



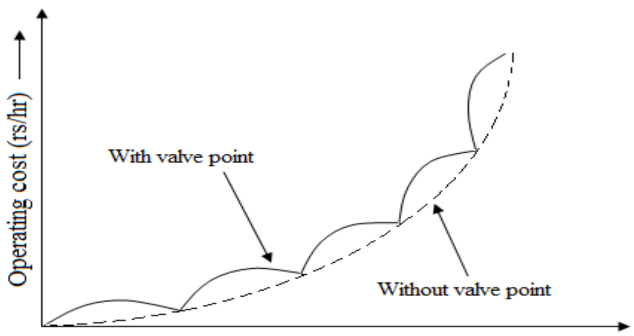
Output Power (MW)

Figure (b) Operating costs of a fossil fired generator

The fuel cost curve may have a number of discontinuities. The discontinuities occur when the output power is extended by using additional boilers, steam condensers, or other equipment. They may also appear if the cost represents the operation of an entire power station, and hence cost has discontinuities on paralleling of generators. Within the continuity range the incremental fuel cost may be expressed by a number of short line segments or piece-wise linearization.

F. Economic load dispatch with valve point loading effect

Economic load dispatch ELD is considered one of the key functions in electric power system operation. The economic load dispatch problem is commonly formulated as an optimization problem, with the aim of minimizing the total generation cost of power system but still satisfying specified constrains[32,33]. The input-output characteristics (or cost functions) of a generator are approximated using quadratic or piecewise quadratic function, under the assumption that the incremental cost curves of the units are monotonically increasing piecewise linear functions. However, real input-output characteristics display higher-order nonlinearities and discontinuities due to valve-point loading in fossil fuel burning plant. The valve-point loading effect has been modeled in as a recurring rectified sinusoidal function, such as the one show in figure (c).



Power output (p_i)

Figure (c) Operating cost characteristics with valve point loading

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost functions. The valve-point effects introduce ripples in the heat rate curves. Mathematically, economic load dispatch problem considering valve point loading is defined as:

$$F_i(P_i) = \sum_{i=1}^{n} a_i P_i^2 + b_i P_i + C_i + \left| e_i \sin\left(f_i\left(P_{min,i} - P_i\right)\right)\right|$$

a_i, b_i, c_i, e_i, and f_i are the coefficients of the i[th] generating unit.

G. Economic Load Dispatch

The economic load dispatch (ELD) problem may be expressed by minimizing the fuel cost of generating units under equality and inequality constraints. The ELD problem can be defined as the following optimization problem.

Minimize $F_i = \sum_{i=1}^{n} a_i P_i^2 + b_i P_i + C_i$ (Rs/hr) …….(1)

Where P_i is the real power output in MW

a_i, b_i, and c_i are the coefficients of the i[th] generating unit.

F_i is the fuel cost in Rs/hr

Subjected to the following constraints.

$\sum_{i=1}^{n} P_i = P_D$

$P_{i,min} \leq P_i \leq P_{i,max}$

Where

$P_{i,min}$ is the minimum real power output of i[th] generator

$P_{i,max}$ is the maximum real power output of i[th] generator

P_D is the load demand on the system in MW.

H. System constraints

1) Equality constraint:

$\sum_{i=1}^{n} P_i = P_D + P_L$

If the system is lossless, the total power generation must be equal to the load demand. Thus

$\sum_{i=1}^{n} P_i = P_D$

2) Inequality constraint:

$P_{i,min} \leq P_i \leq P_{i,max}$

Where

$P_{i,min}$ is the minimum real power output of i[th] generator

$P_{i,max}$ is the maximum real power output of i[th] generator

P_D is the load demand on the system in MW.

I. Emission Dispatch

The objective of emission dispatch is to minimize the total pollutant emission due to the burning of fuels for production of power to meet the load demand. The total pollution level can be defined as the following,

$E_i = \sum_{i=1}^{n} \alpha_i P_i^2 + \beta_i P_i + \gamma_i$ (kg/hr)

Where

P_i is the output power in MW

α_i, β_i, and γ_i are the emission coefficients of the i[th] generating unit.

1) Emission:

The emission control cost results from the requirement for power utilities to reduce their pollutant levels below the annual emission allowances assigned for the effected fossil units. The total emission is expressed in 2.4.

To carry out the EED these emissions must be modeled through functions that relate emissions with power production for each unit.

J. Economic emission dispatch (EED)

In this formulation both fuel cost objective and emission level objective are combined to form a single objective with the introduction of a factor called price penalty factor.

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Price penalty factor = h_m (Rs/kg)
$Ft= \sum_{i=1}^{n} a_i P_i^2 + b_i P_i + C_i + h_m (\sum_{i=1}^{n} \alpha_i P_i^2 + \beta_i P_i + \gamma_i)$
F_t is the total cost of generation in Rs/hr
$Ft= w*Fi + h_m*(1-w)*E_i$
Fi is the fuel cost function
Et is the emission cost function
w is the weighing function
w is the function of rand whose value is in between [0,1]. When w is 1, the objective function becomes economic load dispatch. In this economic load dispatch, units are optimally shared to minimize the total system production costs. When w is zero, the objective function becomes emission dispatch problem.

1) Procedure for computing h_m parameter:

- Evaluate the ratio between fuel cost and emissions corresponding to $P_{i,max}$ for each generator i

$ratio_i = \frac{F_t(P_{i,max})}{E_i(P_{i,max})}$ (Rs/hr) ------------------

Where i=1,2,3……n

- Arrange the ratios in the ascending order
- Arrange the maximum capacity of each generator ($P_{i,max}$) one at a time, starting from the smallest ratio until $\sum_{i=1}^{n} P_i \geq P_D$
- At this stage $ratio_i$ is associated with the last unit is the penalty factor h_m for the given power demand P_D.

2) Fitness function:

Minimization problems are usually transferred into maximization problems' using some suitable transformations. Fitness value f (x) is derived from the objective function and is used in successive genetic operations. The fitness function for maximization problem can be used the same as objective function f(X). Fitness function for the maximization problem is, $f(x)=F_t$. For minimization problems, the fitness function is an equivalent maximization problem chosen such that the optimum point remains unchanged. The following fitness function is often used in minimization problems.
$f(x)= 1/(1+F_t)$
where, f(x) = fitness function
F_t= objective function

3) Problem formulation:

The basic objective of EED of electrical power generation is to obtain the optimal amount of the generated power for the generating unit so as to meet the load demand at minimum operating fuel cost, satisfying all unit and system constraints. Thus the EED problem can be formulated as a multi-objective optimization problem in which the emission, in addition to the fuel cost objective, is to be minimized.

Objective of the work:

- To find the solution of EED problem so that the total fuel cost is minimized while satisfying the power generation limits.
- Use the BSA technique to find the optimal settings.
- Investigate the effectiveness of this method for EED problem with and without considering transmission losses.

K. Purpose of EED

The purpose of EED is to minimize both the operating fuel cost and emission level simultaneously while satisfying load demand and operational constraints. The multiobjective EED problem is converted into a single objective function using a modified price penalty factor approach.

III. APPLICATION OF BSA ALGORITHM TO MULTIOBJECTIVE EED PROBLEM

In this section, a backtracking search optimization algorithm (BSA) is described for solving the EELD problems. The search procedures for the BSA method were shown below.

Step 1:

Specify the generator cost coefficients and emission coefficients, choose the number of generator units (n), specify maximum and minimum capacity of constraints for all the generators as
$L_1= [l_1,l_2,\ldots\ldots\ldots l_n]$ and
$U_1= [u_1,u_2,\ldots\ldots\ldots u_n]$ respectively and load demand (xt). In implementing the BSA, some parameters must be determined in advance like population size(pop), number of generations (g_n). For this pop=60, g_n = 200, dim=6, dimrate=0.5 and dimrate=0.8

Step 2:

Initialize population that is created randomly for the N-dimension problem. A population is represented by N decision variable such as
$X_i= [x_1\ x_2\ x_3 \ldots\ldots\ldots\ldots x_{Ni}]$
Since decision variables for the EED problems are the real power outputs of generation units, they are used to represent each element of the given population.

$$X = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nN} \end{bmatrix}$$

Where Xi is the position of the first particle for the set of power generations (set of solutions).
N is the number of generator units.
n is number of particles(population size).
x11 must be randomly generated in between the minimum and the maximum loading limits as shown in (3.1) means the solution that satisfies the inequality constraint in (2.3), and each population matrix should satisfy the equality constraint in (2.2).

Step 3:

Calculate the fitness value for each set of the total population. Fitness value represents the total cost of generators as in (2.6) for a particular load demand. The bi-objective EED problem is represented as a single objective optimization problem by assigning different weights for each objective.
$F_t = w * F_i + h_m * (1 - w) * E_i$
The price penalty factor h_m is called scaling factor, is multiplied with emission function to get an equivalent cost curve in $/hr. The value of w indicates relative significance between the two objectives. When w is 1, the problem becomes economic dispatch (EcD) that minimizes only the fuel cost. The fuel cost increases and emission cost decreases when w is reduced in steps from1 to 0.The problem becomes emission dispatch (EmD) that minimizes only the emissions when w equals 0. The constrained optimization problem of $F_t = w * F_i + h_m * (1 - w) * E_i$ along with power balance constraint of (2.3) and generation limit constraints can be solved for optimal generations for a chosen value of w. Though the Pareto front based on the non-dominated

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solutions can be obtained by solving the problem several times with different w values, it may not yield the best compromise solution, which may be defined as the one with equal percent deviations from the optimal solutions corresponding to economic dispatch (EcD) and emission dispatch (EmD) besides lying nearer to both of the best solutions. The best compromise solution can be obtained simply by setting w as 0.5, if the chosen h_m parameter does make fuel cost and emission cost components to the same level in the objective function but the methods available in the literature provide approximate h_m parameter values. If the fuel cost component of equation $F_t = w * F_i + h_m * (1 - w) * E_i$ is larger than the equivalent emission cost, then the optimization process attempts to give more importance to fuel cost than emission cost and vice versa.

Step 4:

Sort the population in the descending order of their fitness. Assign the first population as the global best (G_{best}).

Step 5:

Start the iteration count, and generate the historical population (oldp), means the historical population should be randomly generated by using the above equation which is given by

$$oldp = L_1 + (U_1 - L_1) * rand \qquad (3.1)$$

And then after the generation of historical population the order of the each individual is changed. And then similarly in the same way the fitness is calculated by using the new position values and if the evaluation of each particle is better than the previous P_{best} the current value is said to be P_{best},if the P_{best} is better than the G_{best}, the P_{best} is said to be G_{best}.
Where,
P_{best} is said to be local best.
G_{best} is said to be global best.

Step 6:

Obtain the crossover strategy. And in this strategy we will consider the binary-integer valued matrix (map).and in the same way the population was also updated .And similarly the binary-integer valued matrix (map) consists only 0's and 1's

$$F = 3 * rand \qquad (3.2)$$

Step 7:

The next step is recombination. In this process the recombination of the mutation and the crossover takes place. In this the generation of the offspring's is calculated
Offspring's is nothing but mutant.

$$mutant = p + (F * map) * (oldp - p)$$

Where F is given in (3.2)
F controls the amplitude of the search direction matrix. Because the historical population is used in the calculation of the search direction matrix

Step 8:

Calculate the fitness value and similarly update the value of the global best ($\boldsymbol{G_{best}}$).

Step 9:

If number of iterations reaches maximum then print the value of the global best ($\boldsymbol{G_{best}}$) otherwise go to step 5.

A. Introduction

In this chapter, the proposed method BSA is applied to six unit test systems with varying degree of complexity for studying its performance

IV. SIMULATION RESULTS

A. Six unit test system

The characteristics of the six thermal units are given in Table 4.1. This test system contains six thermal units. The load demand is 2.834 p.u. This system is considered as a lossless system. Therefore, the problem constraints are the generation capacity constraint and the power balance constraint Without Ploss. Initially, the fuel cost objective and emission objective are optimized individually by taking the weighting factor 'w' as 1 and 0 in equation (6), respectively to explore the extreme points of trade-off curve in all cases. The proposed algorithms have been applied to the problem and both objectives were treated simultaneously as competing objectives. The optimal parameter setting the BSA for 6-unit system is given in Table 4.2

Table 1 Cost coefficients and emission coefficients for 6-unit system

P_{min}	P_{max}	a_i	b_i	c_i	a_e	b_e	c_e	d_e	e_e
0.05	0.5	100	200	10	6.49	-5.55	4.091	2e-4	2.857
0.05	0.6	120	150	10	5.638	-6.04	2.543	5e-4	3.333
0.05	1.0	40	180	20	4.586	-5.09	4.258	1e-6	8.000
0.05	1.2	60	100	10	3.380	-3.55	5.326	2e-3	2.000
0.05	1.0	40	180	20	4.586	-5.09	4.258	1e-6	8.000
0.05	0.6	100	150	10	5.151	-5.55	6.131	1e-5	6.667

Table 2 Optimal parameters setting

Parameter	Description	Value
Pop	Population of size	60
Dim	Dimension of the search space	6
Dimrate	Dimension rate	0.8
Gn	Maximum number of generations	200

The best cost and the best emission solutions of 6-unit test System obtained out of ten runs with the proposed algorithm are given in Tables 4.3 and Table 4.4 respectively. From Tables 4.3 and Table 4.4, it can be observed that the proposed BSA method gives best solution compare to multi-objective stochastic search technique (MOSST) [1] and linear programming (LP) [2], modified bacterial foraging optimization algorithm (MBFA) [3], Non-dominated sorting genetic algorithm (NSGA) [4], and differential evolution (DE) [5].

Table 3 Comparison of cost/emission obtained by different methods with cost objective for 6-unit system

Methods Unit	MOSST [26]	LP [27]	BSA
1	0.1130	0.1500	0.0835
2	0.3020	0.3000	0.2683
3	0.5310	0.5500	0.5308
4	1.0210	1.0500	1.0438
5	0.5310	0.4600	0.5366
6	0.3630	0.3500	0.3710
Cost ($/hr)	605.8900	606.3100	600.3654
Emission (ton/hr)	0.2220	0.2230	0.2256

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The minimum cost and emission obtained by the proposed BSA algorithm with cost objective is 600.3654 $/h and 0.2256 ton/h, respectively. The proposed algorithm also provides a solution of minimum emission of 0.1945 ton/h with cost of 643.1197 $/hr., with emission objective. These are extreme points of the emission-cost trade off curve of BSA shown in Fig. 4.1. From this, it is clear that the BSA gives slightly better cost with reduced emission level when compared with those of methods reported in the literature.

Table 4 Comparison of cost/emission obtained by different methods with emission objective for 6-unit system

Methods Units	MBFA [28]	NSGA [29]	DE [30]	BSA
1	0.3693	0.4072	0.4060	0.4095
2	0.4326	0.4536	0.4590	0.4620
3	0.5556	0.4888	0.5380	0.5861
4	0.4503	0.4302	0.3830	0.3227
5	0.5478	0.5836	0.5380	0.5599
6	0.4784	0.4707	0.5100	0.4940
Cost ($/hr)	629.6500	633.8300	638.2700	643.1197
Emission (ton/hr)	0.1946	0.1946	0.1952	0.1945

The comparison of best compromise solution for multi-objective function without valve point loading effects and without loss for 6-unit test system by the BSA with various methods is provided in Table 4.5. It is clear that the proposed BSA gives minimum cost and minimum emission of 609.442$/hr., 0.2040 ton/hr., respectively.

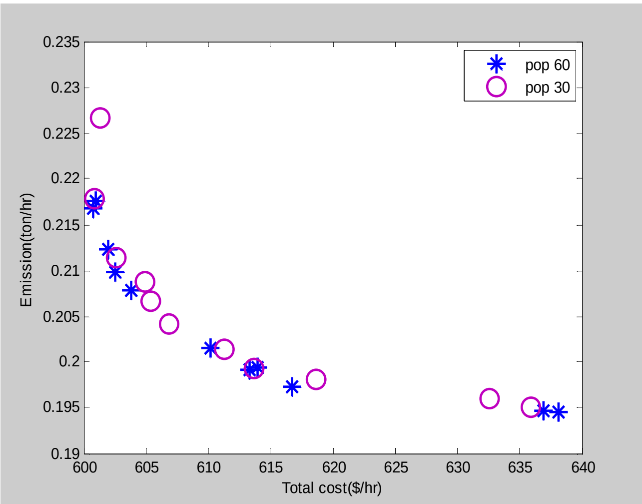


Fig. (a) Emission-cost trade-off curve for 6-unit test system

Table 5 Comparison of best compromise solution for 6unit test system

Methods Units	MBFA [28]	SPEA [29]	NSGA [29]	NPGA [29]	BSA
1	0.2661	0.2623	0.2252	0.2663	0.1849
2	0.3792	0.3765	0.3622	0.3700	0.3271
3	0.5387	0.5428	0.5222	0.5222	0.4804
4	0.6750	0.6838	0.7660	0.7202	0.7183
5	0.5383	0.5381	0.5397	0.5256	0.5869
6	0.4366	0.4305	0.4187	0.4296	0.5363
Cost ($/hr)	610.9060	610.3000	606.03	608.90	609.4442
Emission(Ton/h)	0.2000	0.2004	0.2041	0.2015	0.2040

Table 6 Variation of emission/cost with dimrate

Dimrate	Minimum cost	Minimum emission
0.1	650.6138	0.1950
0.2	634.0976	0.1948
0.3	638.4872	0.1948
0.4	644.6708	0.1947
0.5	633.4503	0.1945
0.6	640.1814	0.1945
0.7	639.5004	0.1943
0.8	640.2422	0.1943

Table 7 Variation of cost/emission with dimrate

Dimrate	Minimum cost ($/hr)	Minimum emission (ton/hr)
0.1	600.3681	0.2239
0.2	600.2482	0.2223
0.3	600.5292	0.2220
0.4	600.6069	0.2247
0.5	600.3338	0.2200
0.6	600.5227	0.2268
0.7	600.5924	0.2237
0.8	600.6507	0.2241

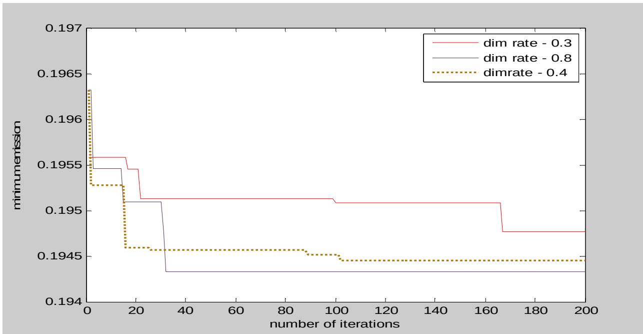
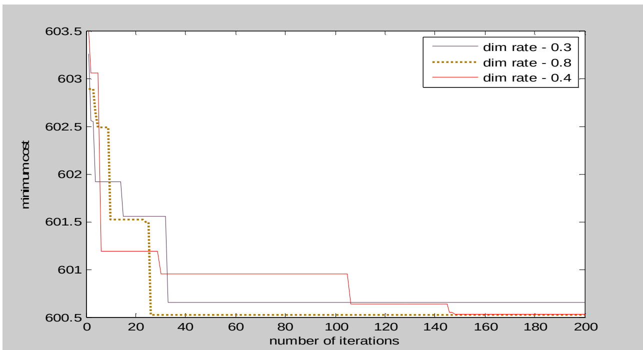


Fig. (b) Convergence of emission with emission objective for different dimrates



Fig(c) Convergence of cost with cost objective for different dimrate

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Table 8 Fuel cost/emission obtained by BSA for 6-unit system by varying w for population 60

Weight Factor (w)	Fuel cost ($/hr)	Emission (ton/hr)
0	638.1512	0.1946
0.1	636.9222	0.1947
0.2	616.7334	0.1973
0.3	614.0086	0.1994
0.4	613.3008	0.1991
0.5	610.1564	0.2015
0.6	603.8146	0.2078
0.7	602.5698	0.2098
0.8	602.0148	0.2123
0.9	600.9323	0.2175
1.0	600.7627	0.2168

The variation of emission and fuel cost with dimrate for the emission objective is given in Table 6. Similarly, the variation of emission and fuel cost with dimrate for the cost objective is given in Table 7. The convergence characteristics of the proposed algorithms with different objective functions are shown in Fig(b) to Fig(c). It was observed that the best values of minimum fuel cost and minimum emission values are obtained within 180 iterations for different dimrates. For dimrate 0.8, the minimum fuel cost and minimum emission values are obtained as shown in Fig(b) and Fig(c) compared to the other values. The variation of emission and fuel cost with different populations 60 and 30 are given in Table 8 and Table 9 respectively with dimrate 0.8.

Table 9 Fuel cost/emission obtained by BSA for 6-unit system by varying w for population 30

Weight Factor (w)	Fuel cost ($/hr)	Emission (ton/hr)
0	635.8751	0.1951
0.1	632.5514	0.1960
0.2	618.6714	0.1981
0.3	613.7130	0.1993
0.4	615.7824	0.1979
0.5	609.4442	0.2040
0.6	605.4143	0.2067
0.7	604.8932	0.2088
0.8	602.5941	0.2114
0.9	600.8887	0.2178
1.0	601.3195	0.2266

V. CONCLUSION

In the fourth chapter, realistic EED Problem has been considered with quadratic cost function, which always exists in the power systems. The proposed algorithm BSA has been successfully applied to solve this EED problem. These strategies improve the global searching ability but also prevent the solution from trapping in a local optimum point. The Proposed algorithm found the better solution for the 6-unit system than MBFA, SPEA.The result clearly show that the proposed method can be used as an efficient optimizer providing satisfactory solutions for realistic EED problems.

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