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Economic Emission Load Dispatch by Modified Shuffled Frog Leaping Algorithm

A. Srinivasa Reddy
Department of Electrical and Electronics Engineering
Sir C. R. Reddy College of Engineering, Vatluru, Eluru-534007
Andhra Pradesh, INDIA

K. Vaisakh
Department of Electrical Engineering,
A.U. College of Engineering, Andhra University
Visakhapatnam-530003
Andhra Pradesh, INDIA

ABSTRACT
This paper presents a newly developed optimization approach involving a modified shuffled frog leaping algorithm (MSFLA) applied for the solution of the economic emission load dispatch (EELD) problem. The approach utilizes the local search strategies for searching global solution. MSFLA is developed on the same frame work of shuffled frog leaping algorithm (SFLA). In this proposed algorithm, a search-acceleration parameter is introduced. To obtain the best compromising solution a pareto–optimal decision making approach is applied to a standard IEEE 30-bus six generator test system. The results confirm the potential and effectiveness of the proposed algorithm compared to various methods performed. The quality and usefulness of the proposed algorithm are demonstrated through its application to a standard test system in comparison with the other existing techniques. The current proposal was found to be better than, or at least comparable to them considering the quality of the solutions obtained. The MSFLA algorithm appears to be a robust and reliable optimization algorithm for the solution of the power system problems.

Keywords
Economic emission load dispatch, modified shuffled frog leaping algorithm, memetic algorithm, multi-objective optimization.

1. INTRODUCTION

The economic emission load dispatch (EELD) is a nonlinear multi-objective optimization problem and is basically used to generate optimal amount of generating power from the fossil fuel based generating units. The objective of EELD problem is the minimization of the fuel cost and emission level simultaneously, by satisfying all unit and system constraints. The increased concern over environmental protection forced the utilities to operate the units for generation of electrical power not only at minimum generation cost but, also at minimum emission level [1-2]. The cost and emission objectives are non-commensurable and the minimization of cost of generation will not provide minimum pollution level and the minimization of emission does not provide minimum cost of generation.

Various techniques have been proposed to solve this multi-objective optimization problem emphasizing the reduction in the atmospheric emissions [1-2]. In past decades, the EELD problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [3-4]. The important aspect of this weighted sum method is that a set of pareto-optimal solutions can be obtained by varying the weight factor. This method can be applied to the problems having a convex pareto-optimal front. The ϵ-constraint method was presented in [5-6] for EELD problem. This method optimizes the most preferred objective and considers the other objectives as constraints bounded by some allowable levels ϵ. Unfortunately, this method is time-consuming and finds weakly non-dominated solutions.

The economic emission load dispatch (EELD) problem has been handled as a multi-objective optimization problem with non-commensurable and contradictory objectives. In [7] the formulation of the problem has been reduced to a single objective problem by treating the emission as a constraint. This formulation, however, has a severe difficulty in getting the trade-off relations between cost of generation and emission.

The goal-programming techniques and a classical technique based on coordination equations are used to minimize the total cost of generation and pollution control simultaneously with varying degrees of compromise in [8-9]. In [10] a linear programming approach in which the objectives are considered one at a time was presented with mathematical assumptions to simplify the problem.

Unfortunately, these conventional optimization methods that make use of derivatives and gradients, in general, are not able to identify the global optimum. Recently, the studies on evolutionary algorithms have shown that these methods can be efficiently used to EELD to provide better results [11–13].

An evolutionary algorithm based approach evaluating the economic impacts of environmental dispatching and fuel switching was presented in [14]. However, some non-dominated solutions may be lost during the search process while some dominated solutions may be misclassified as non-dominated ones due to the selection process adopted. A multi-objective stochastic search technique for the EELD problem was presented in [15]. However, the technique is computationally involved and time-consuming. In [16] differential evolution (DE) method is applied to solve economic and emission load dispatch by considering emissions either as constraints or as a second objective function of a multi-objective optimization problem.

A modified bacterial foraging algorithm (MBFA) applied for the solution of the economic and emission load dispatch (EELD) problem in [17]. This approach utilizes the natural selection of global optimum bacterium having successful foraging strategies in the fitness function. Fuzzy clustering based particle swarm optimization (FCPSO) method is applied on economic emission load dispatch problem in [18]. Various established techniques like PSO, external repository of elite particles, niching, fuzzy based clustering, self-adaptive mutation, and fuzzy decision making have been integrated by the authors in that paper.

Shuffled frog leaping algorithm (SFLA), developed by Eusuff and Lansey in 2000, and is a population based heuristic for combinatorial optimization [19]. It attempts to balance between a wide scan of a large solution space and also a deep search of promising locations for a global optimum. In this algorithm evolution of memes is driven by exchange of information among the interactive individuals. The SFLA has been tested on several benchmark functions that present its efficiency to many global optimization problems. A modified shuffled frog-leaping algorithm (MSFLA) [20] with new search-acceleration parameter introduced for applications to project management and concluded that the MSFLA with an acceleration factor in the range of 1.3 to 2.1, on average, has the best chance of finding the global optimum with the least number of evolutionary iterations.

In this paper modified shuffled frog leaping algorithm has been employed to economic emission load dispatch problem. The proposed approach applied to a standard IEEE 30-bus six unit test system neglecting transmission losses. The potential of the proposed approach to handle the multi-objective problem is investigated. Simulation results of the proposed approach are compared with the results obtained by recent approaches like MBFA [17], FCPSO [18] and other methods in the literature.

2. PROBLEM FORMULATION

2.1 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 problems can be defined as the following optimization problem,

$$\text{Minimize} \quad FC(P_g) = \sum_{i=1}^{N} a_i + b_i P_{gi} + c_i P_{gi}^2 \qquad (1)$$

where, a_i, b_i and c_i are fuel cost coefficients of ith generating unit. N is the total number of committed online generators, P_{gi} is the real power output of ith generator, FC is the fuel cost in \$/h subject to the following constraints

$$\sum_{i=1}^{N} P_{gi} = P_D \qquad (2)$$

$$P_{gi,\min} \le P_{gi} \le P_{gi,\max} \qquad (3)$$

where P_D is load demand on the system, $P_{gi,\min}$, and $P_{gi,\max}$ are the minimum and maximum real power output of ith generator.

2.2 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 amount of pollutants from a fossil based generating units depend on the amount of power generated by that unit, the total pollution level $E(P_g)$ can be expressed as:

$$E(P_g) = \sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2) + \varsigma_i \exp(\lambda_i P_{gi})$$
$$\text{for } i = 1,2,....,N \qquad (4)$$

where $E(P_g)$ is the total emission release (ton/h) and α_i, β_i, γ_i, ς_i, and λ_i are the pollution coefficients of the ith generating unit subjected to demand constraint and generating capacity constraints, as stated above.

2.3 Economic Emission Load Dispatch (EELD)

The constrained multi-objective optimization problem consisting of competing objectives can be converted to a single objective optimization problem (EELD) as:

$$TC(P_g) = w * FC(P_g) + \delta * (1-w) * E(P_g) \qquad (5)$$

where TC is total cost in \$/h. and w is a compromise factor which is primarily a function of rand [0, 1]. When w is 1, the objective function becomes classical economic load dispatch. In this economic load dispatch option, units are optimally shared to minimize the total system production costs. When w is zero, the objective function becomes only emission dispatch problem. The price penalty factor δ is also called as scaling factor, multiplied with emission (ton/h) to get total cost. In this paper, the value of scaling factor δ = 3287 is used in (5). The multi-objective constrained nonlinear optimization problem can be mathematically formulated as:

$$\text{Minimize} \quad [\, f_1(P_g),\ f_2(P_g)\,] \qquad (6)$$

$$\text{Subject :} \quad g\,(P_g) = 0 \qquad (7)$$

$$h\,(P_g) \le 0 \qquad (8)$$

where g is the equality constraint representing the power balance, while h is the inequality constraint representing the generation capacity and power emission constraint.

3. MODIFIED SHUFFLED FROG LEAPING ALGORITHM

In this section, a modified shuffled frog leaping algorithm (MSFLA) is designed based on the same frame work of shuffled frog leaping algorithm (SFLA). MSFLA starts with an initial population of "*X*" frogs created randomly like other evolutionary algorithms. The whole population of frogs is then partitioned into subsets referred to as memeplexes. The different memeplexes are considered as different cultures of frogs that are located at different places in the solution space (i.e., global search). Each culture of frogs performs a deep local search. Within each memeplex, the individual frogs hold information that can be influenced by the information of their frogs within their memeplex, and evolve through a process of change of information among frogs from different memeplexes. After a defined number of evolutionary steps, information is passed among memeplexes in a shuffling process. The local search and the shuffling processes (global relocation) continue until a defined convergence criterion is satisfied.

Within each memeplex, the frogs with the best and the worst fitness are identified as *Xb* and *Xw*, respectively. Also, the frog

with the global best fitness is identified as *Xg*. The position of the worst frog adjusts its position using frog leaping rule in each cycle.
The proposed algorithm is different from SFLA in two aspects in the memetic evolution step as follows

- A new acceleration factor is considered in the frog leaping rule of SFLA algorithm as
  $$D = C * rand() * (Xb - Xw) \qquad (9)$$
  where *C* is acceleration factor
- Censorship step of the SFLA i.e., creation of random frog in place of worst frog will be done after the maximum number of memetic evolutions are completed.

When the difference between the worst frog position i.e., the frog under evolution and the best frog becomes small, the change in frog position is small and thus algorithm may lead to premature convergence and this problem is called as stagnation. To avoid this, a large value of *C* in the equation (9) is assigned at the beginning of the evolution process, the global search area will be widening due to bigger change in frogs position. Then, as the evolution process continues, the acceleration factor will focus the process on a deeper local search as it allows the frogs to change its positions. Due to the shifting of censorship step, MSFLA attempts to balance between wide search (global search) of the solution space and a deep search (local search) of promising locations that are close to a local optimum. The flow chart of MSFLA is shown in Figure 1.

3.1 MSFL Algorithm for EELD Problem

In this section, a modified shuffled frog leaping algorithm (MSFLA) is described for solving the EELD problems. The search procedures of the MSFLA method were shown below.

Step 1: Specify the generator cost coefficients and emission coefficients, choose number of generator units (*N*), specify maximum and minimum capacity constraints of all generator as $X_{\min} = [x_{1,\min}, x_{2,\min} ..., x_{N,\min}]$ and $X_{\max} = [x_{1,\max}, x_{2,\max} ..., x_{N,\max}]$ respectively and load demand P_D.
In implementing the MSFLA, some parameters must be determined in advance like population size *P*, number of memeplexes *m*, number of frogs in each memeplex *n* such that *m* x *n*=*P*, maximum number of memetic evolutions (*IE*), maximum step size for each generator unit *Dmax*=[*D1,max, D2,max*,…., D_N,*max*].
In this problem, *Dmax* is taken as 100% i.e., *Xmax*. Also set the maximum number of shuffled iterations *SI*.

Step 2: An initial population of frogs $X = [X_1, X_2, ...X_P]$ is created randomly for an *N*-dimensional problem. A frog *i* is represented by *N* decision variables (number of units), such as $X_i = (x_{1,i}, x_{2,i}, x_{3,i}, ….., x_{N,i})$. Since the decision variables for the EELD problems are real power outputs of generation units, they are used to represent each element of a given population of virtual frogs. The element of the virtual frog's matrix (except the first one i.e., 2 to *N*) is initialized randomly within the effective real power operating limits as

[illegible] (10)

where $x_{i,j}$ is the power output i.e., *i*th population of *j*th generation unit. Each individual must be a feasible candidate solution that satisfies the inequality constraint in (3). The first element of virtual frog's matrix is taken as $P_D - \sum_{i=2}^{N} P_{gi}$. Each frog of the population matrix should satisfy equality constraint as in (2).

Step 3: Calculate the fitness value for each population set of the total population. Fitness value represents the total cost of the generators as in the equation (5) for a particular load demand.

Step 4: Sort the population in descending order of their fitness. Assign the first population (frog) as global frog, *Xg*. Partition the entire population into *m* memeplexes such that each containing *n* frogs. For example, *m*=3, frog ranking 1 goes to memeplex 1, frog ranking 2 goes to memeplex 2, frog ranking 3 goes to memeplex 3, frog ranking 4 goes to memeplex 1, and so on.

Step 5: In the memeplex evolution step, the group of frogs in each memeplex acts and evolves as an independent culture.

Different steps of memeplex evolution are given bellow

Step 5.1: Set *im*=0 (memeplex counter)
Step 5.2: Increment memeplex counter i.e., *im*=*im*+1;
Step 5.3: Set *ie*=0 (internal evolution counter)
Step 5.4: Increment internal evolution counter i.e., *ie*=*ie*+1;
Step 5.5: Find best and worst frog and worst frog fit, i.e., *Xb* and *Xw* and *mwfit*. Save the fitness of worst frog in different location, i,e, *owfit*=*mwfit*
Step 5.6: Apply frog leaping rule for the improvement of worst frog position using (9)
Step 5.7: Evaluate the fitness of new position of *Xw* i.e., *nwfit* If fitness improves replace the old frogs by new one and *mwfit*=*nwfit* and go to step 5.10
Step 5.8: Improvement of worst frog position using the Equation (12) by replacing *Xb* by Xg
Step 5.9: Evaluate the fitness of new position of *Xw*. If fitness improves replace the old frogs by new one and *mwfit*=*nwfit* and go to step 5.10
Step 5.10: Check number of internal evolution, i.e., if $ie \le IE$ go to step 5.4
Step 5.11: If *mwfit*>*owfit* go to step 5.13
Step 5.12 The frogs new position is not better than the old position after maximum number internal evolutions using both criteria, the spread of defective meme is stopped by randomly generating a new frog to replace *Xw*, whose new position was not favorable to progress towards an optimal value.

$$x_{ji} = x_{j,\min} + rand()(x_{j,\max} - x_{j,\min}) \qquad (11)$$

Step 5.13: Check number memeplexes, i.e., if $im \le m$ go to step 5.2. Otherwise go to shuffling operation to form new memeplex sets

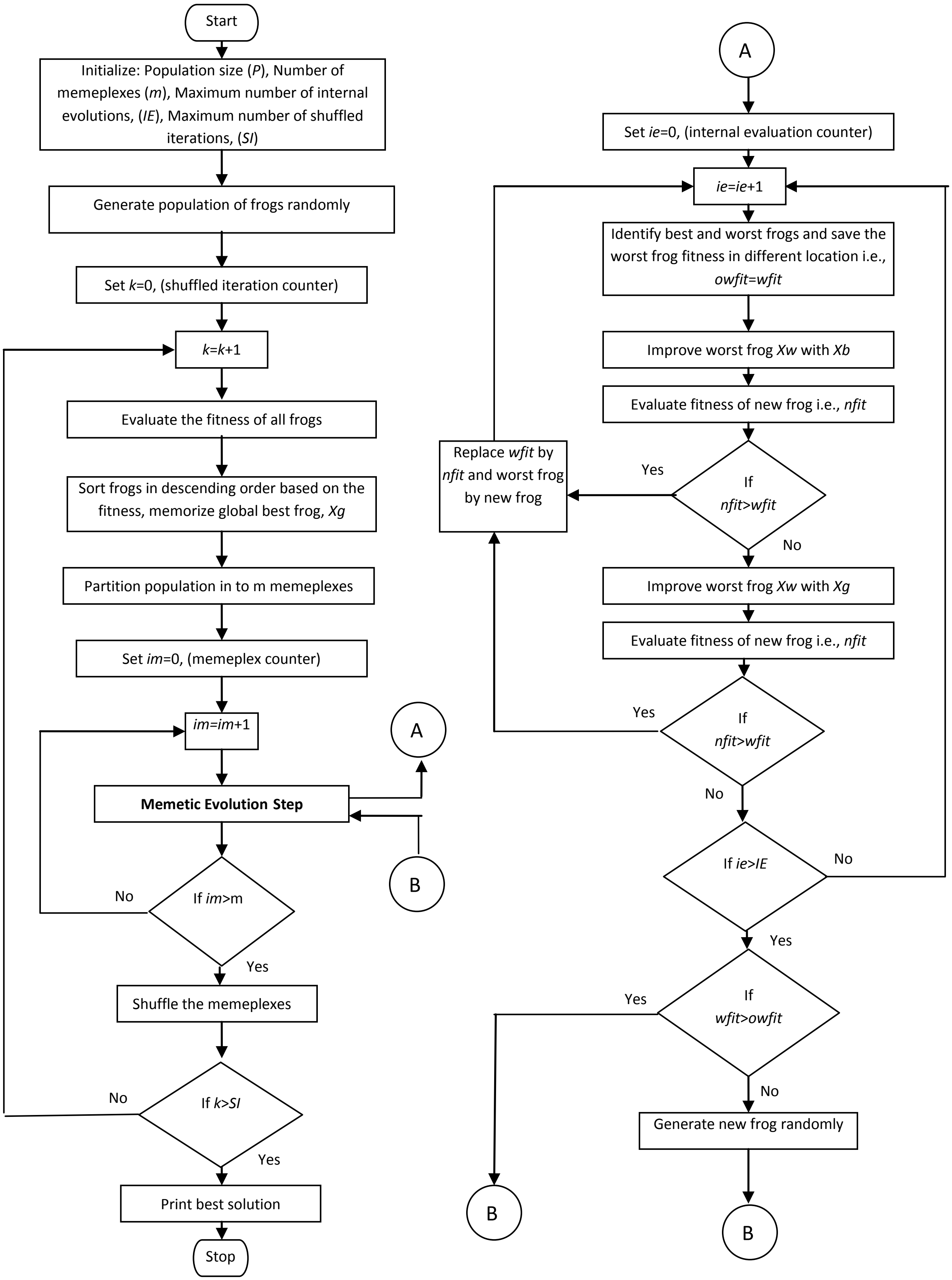

Fig.1. Flow chart of Modified Shuffled Frog Leaping Algorithm

Step 6: After *IE* number of internal evolution within each memeplex the population is shuffled. Periodic shuffling strategy promotes a global exchange of information among the frogs. The shuffling property helps to concentrate the search direction in a most promising region identified by individual memeplexes.

Step 7: Maximum number of shuffled iterations is reached, the algorithm is terminated. Otherwise, go to the Steps 4.

4. SIMULATION RESULTS AND DISCUSSION

In order to validate the feasibility of the proposed MSFLA method for the EELD problem, the method is applied on a 6-unit test system. The proposed method was implemented in MATLAB 7.4 running on Pentium IV 2.66 GHz, 512 MB RAM Personnel Computer. The economic dispatch with emissions was simulated using the standard IEEE 30-bus six generator test system. The values of fuel cost and emission coefficients of this system are adopted from [13].

After testing and evaluating different parameter combinations, parameters of the MSFLA used for the system is listed in Table 1 for clarity. Initially, the fuel cost objective and emission objective are optimized individually by taking the weighting factor 'w' as 1 and 0 in (5), respectively to explore the extreme points of trade-off curve of this case. The proposed algorithm has been applied to the problem and both objectives were treated simultaneously as competing objectives.

Table 1. Simulation parameters of MSFL Algorithm

MSFLA Parameters	Value
Population size (*P*)	20
Max. no. of generations (*SI*)	150
Number of memeplexes (*m*)	4
Number of frogs per memeplex (*n*)	5
Maximum iterations per memeplex (*IE*)	2
Acceleration factor (*C*)	2

The best cost, the best emission, best compromise solutions of system obtained out of twenty runs with the proposed algorithm are given in Tables 2. The minimum cost and minimum emission by the proposed MSFLA algorithm are found to be 600.111410 $/h and 0.1942029 ton/h, respectively.

The proposed algorithm also provides a solution of minimum cost of 600.111410 $/h with emission of 0.2221473 ton/h. The generation scheduling is given in Table 2. The convergence characteristics of cost and emission for the cost objective are shown in Figure 2 and Figure 3 respectively.

Table 2. Simulation results of MSFL algorithm

Unit	Cost Objective	Emission Objective	Best Compromise Solution
1	10.97254	40.60054	26.03437
2	29.97002	45.89237	37.51399
3	52.43866	53.77669	53.94821
4	101.61961	38.32125	68.76503
5	52.43683	53.81174	53.94641
6	35.96234	50.99741	43.19198
Cost ($/h)	600.111410	638.242536	610.078288
Emission (Ton/h)	0.2221473	0.1942029	0.2005852

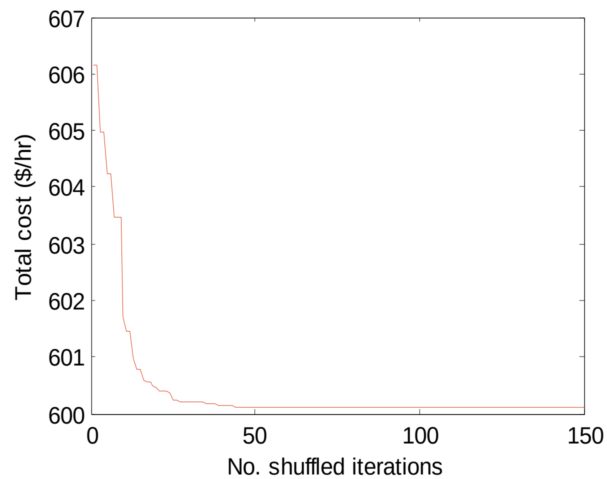

Fig. 2 Convergence characteristics of cost with cost objective

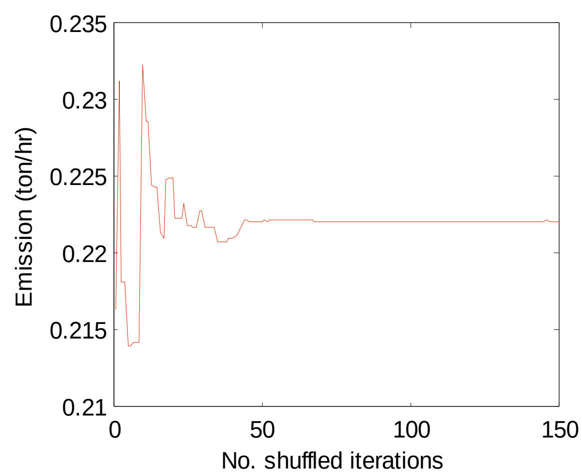

Fig. 3 Convergence characteristics of emission with cost objective

Table 3. Comparison of different methods for the best cost

Method	Cost ($/h)	Emission (Ton/h)
LP [10]	606.3100	0.2230
MOSST [15]	605.8900	0.2220
NSGA [13]	600.3400	0.2241
NPGA [13]	600.3100	0.2238
SPEA [13]	600.2200	0.2206
MBFA [17]	600.1700	0.2200
FCPSO [18]	600.1300	0.2223
MSFLA	**600.111410**	0.2221473

The comparisons of best solution for cost of system by the proposed method with various methods are provided in Table 3. Table 3 shows that MSFLA gives the best cost compared to those reported in LP [10], MOSST [15], NSGA [13], NPGA [13], SPEA [13], MBFA [17], and Fuzzy clustering based PSO [18]. From this, it is clear that the MSFLA gives slightly better cost with reduced emission level when compared with those of methods reported in the literature.

MSFLA provides a solution of minimum emission of 0.1942029 ton/h. with cost of 638.242536 $/h. The generation scheduling is given in Table 2. The convergence characteristics of emission and cost for the emission objective are shown in Figure 4 and Figure 5 respectively.

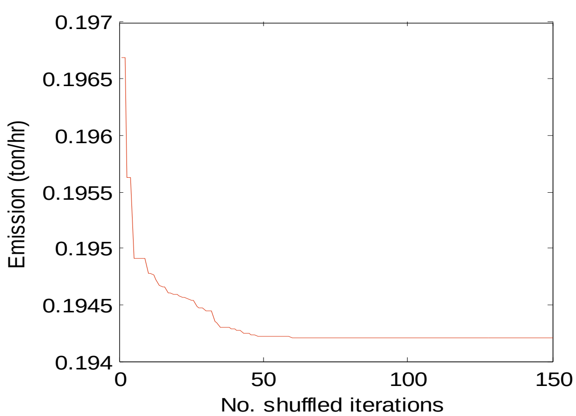

Fig. 4 Convergence characteristics of emission with emission objective

The comparisons of best solution for emission of system by the proposed method with various methods are provided in Table 4. It is clear that the proposed MSFLA gives minimum emission of 0.1942029 ton/h which is equal to the emission level obtained from DE [16], SPEA [13], FCPSO [18], MOSST [15] and LP [10] methods. MSFLA gives better reduction of emission level when compared NPGA [13] method, i.e., 0.1943 ton/h, NSGA [13] method, i.e., 0.1946 ton/h, and MBFA [17] method, i.e., 0.1946 ton/h. The MSFLA algorithm takes 1.02 s on an average to arrive at a solution. The best compromise solution for this system is obtained as the cost of 610.078288 $/h and the emission of 0.2005852 ton/h.

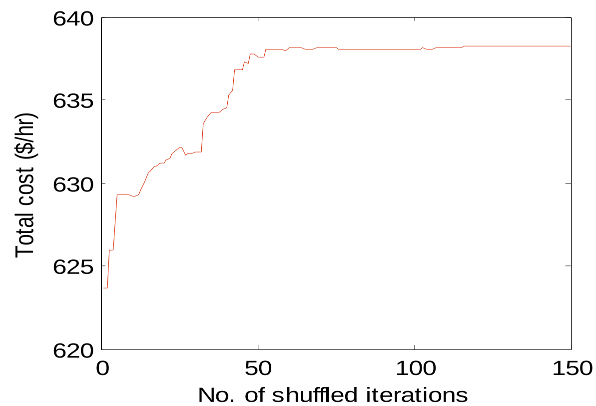

Fig. 5 Convergence characteristics of cost with emission objective

Table 4. Comparison of different methods for the best emission

Method	Cost ($/h)	Emission (Ton/h)
DE [16]	638.2700	0.1952
MBFA [17]	629.6500	0.1946
NSGA [13]	633.8300	0.1946
NPGA [13]	636.0400	0.1943
MOSST [15]	644.1100	0.1942
LP [10]	639.6000	0.1942
FCPSO [18]	638.3577	0.1942
SPEA [13]	640.4200	0.1942
MSFLA	638.242536	**0.1942029**

The results of this method for the best compromise solution are compared with the other methods reported in literature in Table 5. Though the fuel cost is less for NSGA [13] and NPGA [13] compare to MSFLA, the emission levels are high. The results confirm the potential of the proposed MSFLA approach to solve highly nonlinear constrained real-world multi-objective problems. The emission-cost trade off curve of this method is shown in Figure 6.

Table 5. Comparison of different methods for the best compromise solution

Method	Cost ($/h)	Emission (Ton/h)
MBFA [17]	610.9060	0.2000
SPEA [13]	610.3000	0.2004
NSGA [13]	606.03	0.2041
NPGA [13]	608.90	0.2015
MSFLA	610.078288	0.2005852

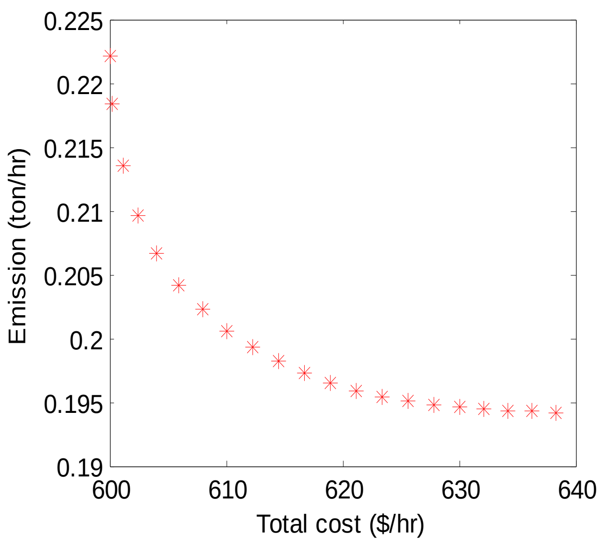

Fig. 6 Pareto-optimal fronts: Emission-cost trade-off curve

5. CONCLUSIONS

This paper has employed a novel optimization method modified shuffled frog leaping algorithm (MSFLA) on the constrained economic emission load dispatch (EELD) problem. The results obtained by the proposed method are better than the earlier best reported results with cost objective applied to IEEE- 30 bus six unit system. The algorithm provides better optimal solutions than those obtained from other complicated algorithms with emission objective. The best compromise solution of the proposed approach show that this method is efficient for solving multi-objective optimization problem. Hence, the solution of the economic emission load dispatch for the best compromise solution out of many optimal solutions over the trade-off curve is assessed and helps the power system operator to adjust the generation levels effectively and efficiently. It can be concluded that MSFLA method appears to be a robust and reliable optimization algorithm for solution of different multi-objective power system optimization problems compared to the other methods.

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