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Pareto-based Multi-objective Firefly Algorithm with Hierarchical Clustering for Environmental-Economic Power Dispatch Problem

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ABSTRACT

This paper proposes a multi-objective firefly algorithm (MOFFA) to solve the environmental-economic power dispatch (EEPD) problem. Also, it presents a modified firefly algorithm (FFA) to solve the economic power dispatch (EPD) and the emission dispatch (ED) problems as single goals. The modifications proposed on the traditional FFA aim to improve its exploration and ensure the feasibility of the obtained solutions. The proposed MOFFA uses an external Pareto set to keep the non-dominated solutions, where a hierarchical clustering algorithm is used to get a representative and controlled set of Pareto-optimal solutions. The best compromise solution is also extracted from the Pareto set using an approach based on the fuzzy set theory. The constraints of EEPD, EPD, and ED problems are power balance constraint, generation limits constraint, and transmission power losses. To verify the effectiveness of the proposed algorithms, two methodologies are adopted and tested on the IEEE 30-bus test and the 10-unit test system with valve-point loading. In methodology 1, the EPD problem and the ED problem are solved separately using the modified FFA. In methodology 2, the EEPD is solved as a true multi-objective optimization problem using the proposed MOFFA. The simulation results and the statistical analysis ensure the high-quality solutions of the proposed algorithms and prove the ability of the MOFFA to produce well-distributed Pareto-optimal solutions.

Keywords: *Environmental-economic power dispatch; Firefly algorithm; Multi-objective optimization; Pareto-based dominance.*

1. Introduction

The main objective of the economic power dispatch problem (EPD) is to determine the output power from generation units to meet the system demand such that the fuel cost of fossil fuel power plants is minimized [1-2].

The generation of electric power from fossil fuel power stations pollutes the environment as it emits several harmful pollutants into the atmosphere. For a clean environment, these emissions should be minimized. The minimization of environmental emissions can be achieved by treating emission as an objective in the overall EPD, which turns the problem into a multi-objective optimization problem [3-5].

Multi-objective optimization problem [3-7] is a challenging problem due to the conflicting nature of the different objective functions, which have to be optimized simultaneously. Each objective function may have a different individual optimal solution. This produces a set of optimal solutions instead of one optimal solution. These optimal solutions are known as Pareto-optimal solutions [8, 22], and the main aim is to find the Pareto-optimal set, which contains all non-inferior solutions.

Mainly, two search directions have been applied to solve multi-objective optimization problems. The first search direction depends on the idea of converting the multi-objective problem into a single-objective problem by combining the different objectives linearly, e.g., the weighted sum method [9-10]. This approach is simple, but it needs to understand the problem to set the weighting factors probably. Otherwise, some objectives might dominate the others. Besides, several runs with different weighting factors are required to find the Pareto-optimal solutions. The second search direction uses evolutionary algorithms (EAs) where the multiple objectives are handled simultaneously as competing objectives. The EAs are able to overcome most difficulties of the classical methods, as they use a population of solutions in their search, so they can find many Pareto-optimal solutions in each run [8, 29].

The field of nature-inspired EAs has continuous growth. Recently, many algorithms are proposed and applied to solve the EPD problem, such as Squirrel Search Algorithm [6], Cuckoo Search [11], Crow

Search Algorithm [12], Whale Optimization Method [13], Antlion Optimization Algorithm [14], Moth Search Algorithm [15], etc.

Firefly Algorithm (FFA) is one of the EAs which initially proposed to solve single-objective continuous optimization problems [16]. Later, a hybrid discrete FFA is used to solve multi-objective flexible job-shop scheduling problems [17] and multi-objective hybrid flow-shop scheduling problems [18]. In [17] & [18], the solution of the multi-objective optimization problems proposed by FFA was based on converting the multi-objective problem into a single-objective problem by using the weighted sum approach. In [19], the FFA is used to solve the multi-objective continuous optimization problems and is applied to solve the design optimization benchmarks. To the best of the author's knowledge, fewer attempts are carried out to solve the multi-objective EEPD problem using FFA [20-21], and these attempts depend on converting the problem from a multi-objective problem into a single-objective problem.

In this paper, a modified FFA is proposed to improve the exploration capability of the basic FFA and to ensure the feasibility of the obtained solutions. Also, a Pareto-based MOFFA with a hierarchical clustering algorithm is proposed to solve the EEPD problem without converting the problem into a single-objective problem. The modified FFA is firstly used to find the optimum solution of each objective function as a single goal, and then the MOFFA is used to solve the EEPD as a true multi-objective problem. The other sections of the paper are organized as follows: The mathematical model of the EEPD problem is given in section 2. The details of the modified FFA and the Pareto-based MOFFA are proposed in section 3. The simulation results are discussed in section 4, and section 5 concludes the paper.

2. Problem Formulation

In this section, the objective functions and the constraints of the EEPD problem are discussed as follows:

2.1 Objective Functions

1) <u>Minimization of fuel cost:</u> The total fuel cost $F(P_G)$ in (\$/hr) of NG fossil-fueled thermal generating units can be found as follows [1]:

$$F\left(P_G\right) = \sum_{m=1}^{NG} (a_m + b_m P_{Gm} + c_m P_{Gm}^2) \tag{1}$$

where P_{Gm} is the real power output of m^{th} generator, and a_m, b_m and c_m are the cost coefficients of the m^{th} generator.

In case of considering the valve point loading effects, the total fuel cost can be calculated as [12]:

$$F\left(P_G\right) = \sum_{m=1}^{NG} (a_m + b_m P_{Gm} + c_m P_{Gm}^2 + \left| d_m \sin\left\{ e_m \left(P_{Gm}^{min} - P_{Gm} \right) \right\} \right|) \tag{2}$$

Where P_{Gm}^{min} is the minimum power output of m^{th} generator, and d_m, and e_m are the cost coefficients of the m^{th} generator.

2) <u>Minimization of emission:</u> The total emission $E(P_G)$ of nitrogen oxides (NO_x) and sulfur oxides (SO_x) pollutions emitted by generation units in ton/h can be expressed as [3]:

$$E\left(P_G\right) = \sum_{m=1}^{NG} (\alpha_m + \beta_m P_{Gm} + \gamma_{im} P_{Gm}^2 + \varepsilon_m \exp(\lambda_m P_{Gm})) \tag{3}$$

where α_m, β_m, γ_m, ζ_m, and λ_m are the m^{th} generator emission coefficients.

2.2 System Constraints

1) Power balance constraint: The total generated power must satisfy the total load demand (P_D) and the real power losses in transmission lines ($Ploss$) as follows [2]:

$$\sum_{m=1}^{NG} P_{Gm} = P_D + Ploss \tag{4}$$

The $Ploss$ can be computed from the Kron's loss formula (B-coefficient) as follows [2]:

$$Ploss = \sum_{m=1}^{NG} \sum_{n=1}^{NG} P_m B_{mn} P_n + \sum_{m=1}^{NG} P_m B_{om} + B_{oo} \tag{5}$$

2) Generation limits constraint: The output power from each generator must be within its minimum and maximum limits as follows [2]:

$$P_{Gm}^{min} \le P_{Gm} \le P_{Gm}^{max} \qquad m = 1{:}\,NG \tag{6}$$

3.Multi-objective Firefly Algorithm

In this section, the details of the modified firefly algorithm (FFA) and the proposed Pareto-based multi-objective firefly algorithm (MOFFA) are given.

3.1 Modified Firefly Algorithm

FFA is a natural-inspired population-based optimization algorithm initially introduced by Xin-She Yang in 2008 [16]. FFA simulates the fireflies' behavior and how they are attracted to light [21]. It has more similarity to the optimization algorithms employing swarm intelligence, but FFA is much simpler in implementation and concept. It uses real random numbers. Firstly, the important parameters of the basic FFA proposed in [16] & [21] are summarized as follows:

1. Light intensity: To find the light intensity I_i or brightness of each firefly i, the firefly is evaluated using the objective function and assign a scalar value called fitness.
$$I_i = Fitness(x_i) \tag{7}$$
2. Attractiveness: The attractiveness (β) between the fireflies can be found as follows:
$$\beta(r_{ij}) = \beta_0 exp(-\gamma r_{ij}^2) \tag{8}$$
where $r_{i,j}$ is the distance between any two fireflies i and j, β_0 is the attractiveness at r=0, and γ is the light absorption coefficient.
3. Distance: The distance between any two fireflies i and j at positions x_i and x_j can be calculated using the Cartesian Distance method as follows:
$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \tag{9}$$
where d is the number of optimized parameters.
4. Position update: In each iterative step, the position of the firefly i is updated as follows:
$$x_i^{n+1} = x_i^n + \beta(x_j^n - x_i^n) + \alpha(rand - 0.5) \tag{10}$$
where α is the randomness parameter. For most cases, $\alpha \in (0, 1)$, β_0=1 and γ varies from 0.1 to 10.

Some modifications are proposed in this paper to improve the FFA exploration capability and guarantee the feasibility of the solutions, which are:

- If two parameters of the objective function have different possible value ranges, a fixed range of random numbers will cause different relative randomness for each dimension. To solve this issue, the random numbers generated can be multiplied by the scale of the dimension to produce a vector of scaling values S. Hence, the position update defined by Eq. (10) is modified to:
$$x_i^{n+1} = x_i^n + \beta(x_j^n - x_i^n) + \alpha S(rand - 0.5) \tag{11}$$
Where β is calculated as follows:
$$\beta = (\beta_0 - \beta_{min}) * exp(-\gamma r_{i,j}^2) + \beta_{min} \tag{12}$$
where $\beta_{\min}$ is the minimum value of β. The attraction between the fireflies is changed due to the value of β_{min}. Increasing the value of β_{min} increases the desire of the firefly to move towards brighter fireflies. Thus a global solution is obtained.
- After updating the fireflies' positions according to Eq. (11), the boundary limits of the variables should be checked. If the limits are violated, the firefly position is reset to its maximum value or its minimum value as follows:
$$\begin{aligned} &if\ x_k < x_k(min) \\ &\quad x_k = x_k(min) \\ &else\ if\ x_k > x_k(max) \\ &\quad x_k = x_k(max) \end{aligned} \tag{13}$$

The procedure for solving the EPD problem using the modified FFA is shown in pseudo-code in Figure (1).

```
Define α (randomness parameter), β0 (initial attractiveness), βmin
(min attractiveness), n (number of fireflies ), and γ (light
absorption coefficient)
Define P^min , P^max , and cost coefficients of each generation unit
Define objective function  f(x)  (Eq.1 or Eq. 2)
Initialize a population of fireflies
Determine the Light intensity Ii   (Eq.7)
while (t <MaxGen (maximum number of iterations))
    for i=1: n all n fireflies
        for j=1: i all n fireflies
            if (Ij>Ii)
                Calculate the distance ri,j  (Eq. 9)
                Calculate the attractiveness β (Eq.12)
                Move firefly i towards firefly j in all d dimensions and
                update positions   (Eq. 11)
                Check the boundary limits of each variable   (Eq. 13)
            end if
          Calculate fitness values for new solutions by substituting
in Eq.1 or Eq.2 if valve-point effects are considered
          Update light intensity
        end for j
    end for i
Rank the fireflies and find the current best
end while
Find the optimal solution  (power output from each generation
unit at min. cost and corresponding fuel cost)
End of the algorithm
```

Figure 1- Pseudo-code of modified FFA applied to EPD problem

3.2 Proposed Multi-objective Firefly Algorithm

In a multi-objective optimization problem, if there are two solutions x^1 and x^2. Solution x^1 will be better than solution x^2 *if* and *only if* it's better in at least one objective and not worse in any of the other objectives. In this case, it is said that x^1 dominates x^2, and x^1 is called the non-dominated solution [8]. It is referred to this concept as Pareto-based dominance and to the solutions that are non-dominated within the entire search space as Pareto-optimal solutions, which compose the Pareto-optimal set.

The proposed MOFFA is developed by extending the basic ideas of the modified FFA and joining them with the Pareto-based dominance. Hence, the light intensity is redefined as a vector of objective functions, e.g., fuel cost and emission, and the comparison of light intensities of fireflies i and j are modified according to Pareto-based dominance. The main features of the proposed algorithm are discussed as follows:

3.2.1 External Pareto-optimal set update: Initially, an empty external Pareto-optimal set is created. To update the external Pareto-optimal set, the non-dominated solutions in the population are found and copied to the external Pareto-optimal set. Then, the external Pareto-optimal set is searched for the non-dominated solutions, and all dominated solutions are taken off. The size of the external Pareto-optimal set is firstly set to a certain value. If the number of solutions externally stored in this set exceeds the predefined number, the clustering algorithm will be used to obtain a representative and controlled Pareto-optimal set within the predefined size [8, 22].

3.2.2 Clustering algorithm: This algorithm is based on joining the adjacent clusters iteratively until the specified number of groups is reached. The complete details of the algorithm are given in [8, 22].

3.2.3 Best compromise solution extraction: It is required to introduce only one solution to the decision-maker from the Pareto-optimal set of non-dominated solutions. This solution is known as the best compromise solution. In this paper, the best compromise solution will be found based on the Fuzzy approach as follows [8, 22-23]:

Firstly, the objective function F_i is represented by a membership function μ_i defined as:

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{min} \\ \frac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} < F_i < F_i^{max} \\ 0 & F_i \ge F_i^{max} \end{cases} \quad (14)$$

where F_i^{min} and F_i^{max} are the minimum and maximum values of the objective function F_i among all non-dominated solutions, respectively. The range of μ_i is from 0 to 1. After computing μ_i, the normalized membership function μ^k for each non-dominated solution k is calculated as:

$$\mu^k = \frac{\sum_{i=1}^{No} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{No} \mu_i^k} \quad (15)$$

where M is the number of non-dominated solutions.

The best compromise solution is the solution, which has the maximum value of μ^k.

The pseudo-code of the proposed MOFFA algorithm is shown in Figure (2).

Define α, β_0, n and γ
Define decision variables, constraints and objective functions $f_1(x_i)$......, $f_{No}(x_i)$ *with* $x_i=(x_1,..............,x_d)^T$ in domain d
Initialize a population of fireflies x_i ($i=1,2,........,n$)
and create the empty external Pareto-optimal set.
Determine the Light intensity I_i at x_i by [$f_1(x_i)$, $f_2(x_i)$......, $f_{No}(x_i)$]
while (t <MaxGen)
  for i=1:n all n fireflies
    for j=1:i all n fireflies
      if (*firefly j dominate firefly i*)
        Calculate distance $r_{i,j}$ (Eq. 9)
        Calculate attractiveness β (Eq.12)
        Move firefly i towards firefly j in all d dimensions and update positions using Eq. (11)
        Check the boundary limits of each variable (Eq. 13)
      else
        Move firefly i randomly
      end if
      Calculate fitness values for new solutions
      Update light intensity
    end for *j*
  end for *i*
  Updated external Pareto-optimal set as given in section 3.2.1
end while
Select the best compromise solution using fuzzy set theory as given in section 3.2.3
End of the algorithm

Figure 2- Pseudo-code of the proposed MOFFA

To solve the EEPD problem, two methodologies are carried out to demonstrate the efficiency and the high performance of the proposed algorithm:

Methodology 1*:* A pure economic dispatch and pure emission dispatch are carried out separately using the modified FFA to obtain the optimal values of fuel cost and emission.

Methodology 2**:** The EEPD problem was handled as a multi-objective problem where fuel cost and emission are optimized simultaneously with the proposed Pareto-based MOFFA.

4. Optimization Results and Discussion

In this section, the effectiveness of the modified FFA in solving EPD and ED problems, and the proposed MOFFA in solving the EEPD problem is investigated. The proposed algorithms are applied to two widely-used test systems. The first system is the IEEE 30-bus test system with 6 generating units and 283.4 MW load demand [8], and the second system is the 10-unit test system with 2000 MW load demand and valve-point loading effects [31]. The problems are solved with and without power losses. The proposed algorithms are implemented using MATLAB R2010a. The developed codes are run on a personal computer with an Intel Core I5, 4 GB RAM, and Windows 8.1 operating system.

4.1 Setting of FFA Control Parameters

Modified FFA has a set of control parameters, which are β_{min}, α, γ, n, βo, and MaxGen (max number of generations). These parameters affect the quality of the optimal solution. So, the best values of these parameters should be found to achieve the optimal solution to the considered problem. In our problem, the values of MaxGen and βo are set to 200 and 1, respectively. Several experiments are run by varying the values of the other control parameters as follows:

α is changed from 0 to 1 with a step 0.05, β_{min} is changed from 0 to 1 with a step 0.05, γ is changed from 0.1 to 10 with a step 0.1 till 1 and then with a step 1, and n is changed from 50 to 250 with step 5.

For each combination, the optimization problem was solved, and the statistical indices of the objective functions are calculated. The optimal settings of control parameters for the modified FFA and the proposed MOFFA are given in Table (1).

Table 1- Optimal parameters for the modified FFA and the proposed MOFFA

	Case 1: IEEE 30-bus test system				Case 2: 10-unit test system			
	Methodology 1 (FFA)		Methodology 2 (MOFFA)		Methodology 1 (FFA)		Methodology 2 (MOFFA)	
	Without losses	With losses	Without losses	With losses	Without losses	With losses	Without losses	With losses
n	50	50	150	150	150	100	100	100
α	0.1	0.1	0.1	0.1	0.1	0.1	0.4	0.1
β_0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
β_{min}	0.5	0.8	0.9	0.9	0.9	0.8	0.9	0.8
γ	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0

4.2 Test Case 1: IEEE 30-bus test system

Methodology 1: The best results for fuel cost and emission when optimized individually along with output power from each generation unit and the corresponding statistical indices with and without power losses are listed in Table (2). The best value of fuel cost obtained by FFA is 600.1127 $/hr without power losses and 605.439 $/hr with power losses. While the best value of emission is 0.1942 ton/hr. A comparison between the results of the modified FFA and other reported algorithms is listed in Table (3). It is clear that the proposed FFA gives the best results compared to the other algorithms. For checking the robustness of FFA, 20 individual runs are considered. The corresponding statistical indices are listed in Table (4). The statistical results show that the proposed algorithm produces high-quality solutions. Also, it is clear that FFA is superior to PHOA [24], MSCO [25], and MOBSA [26] as it gives better values of the statistical results, i.e., mean, best, worst, and standard deviation.

Methodology 2**:** The optimal settings of MOFFA control parameters are given in Table (1). The Pareto-optimal set has 20 non-dominated solutions. Out of them, two solutions represent the best cost and the best emission. If the number of solutions is more than 20, the clustering algorithm is applied. The values of the best cost, the best emission, and the best compromise solutions obtained for this case with and without power losses are given in Table (5). The diversity of the Pareto-optimal set over the trade-off surface is shown in Figure (3) in case of neglecting losses and Figure (4) in case of considering losses. It can be seen that the proposed MOFFA provides a well-distributed Pareto front. The results of the proposed MOFFA are compared to some of the reported algorithms to evaluate the performance of the proposed MOFFA regarding Pareto optimal solutions. The comparative results are listed in Table (6). It can be seen that the proposed MOFFA gives good results compared to other algorithms.

4.3 Test Case 2: 10-unit test system with valve-point loading effects

Methodology 1**:** The best solutions for fuel cost and emission objective functions when optimized individually with and without power losses are listed in Table (7). The proposed FFA reaches minimum values of 106170 $/hr and 3651.1 ton/hr for fuel cost and emission, respectively, in case of neglecting power losses, and it gives a minimum value of 111140.0 $/hr for fuel cost and 3915.7 ton/hr for emission when the power losses is considered. For checking the robustness of FFA, 50 individual runs are considered. The corresponding statistical indices are listed in Table (8). The statistical results show that the proposed FFA produces high-quality solutions. A comparison between the proposed FFA and some of the reported algorithms in case of considering power losses is given in Table (9). Tables (8) and (9) clear that the proposed FFA gives the minimum values of cost and emission compared to the other methods, which confirm its high performance.

Methodology 2**:** For this methodology, the Pareto-optimal set has 30 non-dominated solutions. Figure (5) shows the diversity of the Pareto-optimal set over the trade-off surface in case of neglecting power losses, and Figure (6) shows the non-dominated solutions in case of considering power losses. It is obvious that the solutions are well distributed on the Pareto-front. The non-dominated solutions for the best cost, best emission, and best compromise solutions are listed in Table (10). The comparative results are listed in Table (11) in case of neglecting power losses and Table (12) in case of considering power losses. As clear, the proposed MOFFA outperforms PHOA [24] as it gives better values for the best cost and best emission. From Table (12), the range of fuel cost for the comparative algorithms is from 112807 $/hr to 113539 $/hr, and the range of emission is from 4109 ton/hr to 4188 ton/hr. While the best cost provided by MOFFA is 112570 $/hr and the best emission is 4199 ton/hr.

Table 2- Best solutions for the IEEE 30-bus test system obtained by the modified FFA

Outputs	Without losses		With losses	
	Best cost	Best emission	Best cost	Best emission
P_1 (MW)	11.1961	41.0717	11.1204	41.2779
P_2 (MW)	29.9399	46.1656	28.8625	44.9044
P_3 (MW)	52.6840	53.5317	58.6937	55.0540
P_4 (MW)	101.4161	39.4782	98.5998	40.0340
P_5 (MW)	52.1623	53.6311	52.7615	54.4915
P_6 (MW)	36.0016	49.5218	35.6601	51.2467
Fuel cost ($/hr)	600.1127	637.332	605.438	643.155
Emission(ton/h)	0.2219	0.1942	0.2206	0.1942
Losses(MW)	-	-	2.2980	3.6085

Table 3- Comparison of the best solution for fuel cost minimization and emission minimization for Case 1

Objective	Without losses			With losses		
	Method	Fuel cost ($/hr)	Emission (ton/h)	Method	Fuel cost ($/hr)	Emission (ton/h)
Best Fuel Cost	FFA	600.1127	0.2219	FFA	605.4390	0.2206
	PHOA[24]	600.1321	0.2٢١٨	MODE [8]	608.0658	0.2193
	MSCO[25]	600.5800	0.2243	MOPSO[29]	607.7900	0.2193
	θ-PSO[27]	601.1260	0.2223	MBFA [30]	606.1700	-
	FSBF [28]	600.1141	0.2220	MODE [31]	606.4160	-
	NSBF [28]	600.2704	0.2198			
Best Emission	FFA	643.1549	0.1942	FFA	643.1549	0.1942
	PHOA[24]	639.3130	0.1942	MODE [8]	645.0850	0.1942
	MSCO[25]	650.3365	0.19427	MOPSO[29]	644.74	0.1942
	θ-PSO[27]	638.3410	0.19421	MBFA [30]	-	0.1942
	FSBF [28]	638.2835	0.1942	MODE [31]	-	0.1942
	NSBF [28]	642.1336	0.1944			

Table 4- Statistical results of the EPD and ED problems for 20 runs obtained by the modified FFA for Case 1

Objective	Statistical indices	Without losses			With Losses	
		FFA	PHOA [24]	MSCO [25]	FFA	MOBSA [26]
EPD	Min (cost)	600.1127	600.1138	600.5800	605.4380	605.9984
	Mean (cost)	600.1321	600.1321	601.9624	605.4878	605.9984
	Max (cost)	600.1658	600.8281	602.9957	605.7656	605.9985
	SD	0.0113	0.0738	0.5924	0.0793	1.52E-05
ED	Min (emission)	0.1942	0.1942	0.1942	0.1942	0.194179
	Mean (emission)	0.1942	0.1943	0.1945	0.1942	0.194179
	Max (emission)	0.1942	0.1956	0.1949	0.1942	0.194179
	SD	6.1829E-6	1.4697E-4	0.0002	1.3183e-005	2.83E-09

Table 5- Best solutions of the multi-objective EEPD problem provided by MOFFA for Case 1

Outputs	Without losses			With Losses		
	Best cost	Best emission	Best compromise	Best cost	Best emission	Best compromise
P_1 (MW)	10.560	39.06	10.56	8.5690	41.8703	27.7721
P_2 (MW)	30.250	44.02	36.90	28.6899	44.5998	35.3812
P_3 (MW)	51.070	52.74	52.21	62.7773	53.3107	52.6529
P_4 (MW)	101.39	42.55	71.26	97.0809	43.6135	70.2097
P_5 (MW)	55.660	54.86	60.72	51.8414	54.2257	57.7703
P_6 (MW)	34.460	50.17	40.47	36.6625	49.2894	42.2010
Fuel cost ($/hr)	600.18	633.35	607.87	605.6763	641.9913	615.4485
Emission (ton/hr)	0.2224	0.1943	0.2028	0.2209	0.1943	0.2011
Losses (MW)	-	-	-	2.2210	3.5094	2.5872

Table 6- Comparison of the best fuel cost and the best emission provided by different algorithms for Case 1

	Without losses			With losses		
	Method	Fuel cost ($/hr)	Emission (ton/h)	Method	Fuel cost ($/hr)	Emission (ton/h)
Best Fuel Cost	MOFFA	600.18	0.2224	MOFFA	605.6763	0.2209
	MNSGA-II-MPVDE [3]	607.13	0.2031	MNSGA-II-MPVDE [3]	614.2687	0.2009
	SPEA [23]	600.22	0.2206	-	-	-
	NPGA [23]	600.31	0.2238	-	-	-
	NSGA [23]	600.34	0.2241	-	-	-
	FCPSO [32]	600.13	0.2222	FCPSO [32]	607.786	0.2201
	SPEA2 [32]	600.11	0.2221	SPEA2 [32]	605.548	0.2208
Best Emission	MOFFA	633.350	0.1942	MOFFA	641.9913	0.1942
	MNSGA-II-MPVDE [3]	637.872	0.1942	MNSGA-II-MPVDE [3]	640.2599	0.1942
	SPEA [23]	640.420	0.1942	-	-	-
	NPGA [23]	636.040	0.1943	-	-	-
	NSGA [23]	633.830	0.1946	-	-	-
	FCPSO [32]	638.358	0.1942	FCPSO [32]	642.896	0.1942
	SPEA2 [32]	644.112	0.19418	SPEA2 [32]	646.190	0.1942

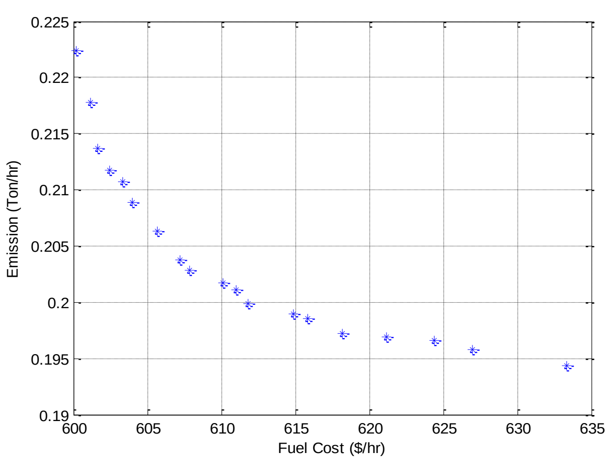

Figure 3-Pareto-optimal front of Case1 without losses

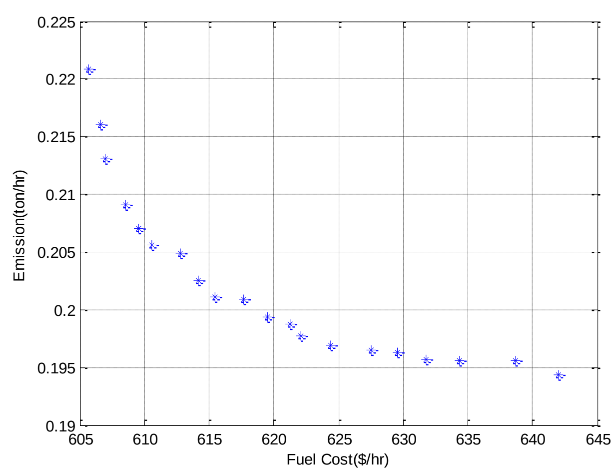

Figure 4- Pareto-optimal front of Case1 with losses

Table 7- Best solutions for fuel cost minimization and emission minimization obtained by the modified FFA for Case 2

Outputs	Without power losses		With power losses	
	Best cost($/hr)	Best emission (ton/hr)	Best cost($/hr)	Best emission(ton/hr)
P_1 (MW)	55.0000	55.0000	54.9357	54.9537
P_2 (MW)	80.0000	80.0000	80.0000	79.5000
P_3 (MW)	86.0299	76.2499	104.7861	81.0900
P_4 (MW)	82.5017	78.2748	97.8150	82.4353
P_5 (MW)	67.6984	160.0000	83.4184	160.0000
P_6 (MW)	70.0000	240.0000	80.5115	240.0000
P_7 (MW)	289.2816	273.7016	300.0000	296.7648
P_8 (MW)	329.8361	275.8853	340.0000	292.4923
P_9 (MW)	470.0000	378.9602	470.0000	391.3080
P_{10} (MW)	469.6522	381.9281	470.0000	398.2312
Fuel cost($/hr)	106170	111840	111140.0	116160
Emission(ton/hr)	4273.5	3651.1	4544	3915.7
Losses(MW)	-	-	81.5	76.8

Table 8- Statistical results of the EPD and ED problems for 50 runs of the modified FFA for Case 2

Objective	Statistical indices	Without power losses			With power losses
		Proposed FFA	PHOA [24]	MSCO [25]	Proposed FFA
EPD	Min (cost)	1.0617E5	1.0621E5	1.06198E5	1.1114E5
	Mean (cost)	1.0618E5	1.0621E5	1.0632E5	1.1115E5
	Max (cost)	1.0622E5	1.0621E5	1.0645E5	1.1118E5
	SD	6.0580	1.782E-11	6E-4	6.5921
	Emission at Min. cost	4.2735E3	4.28547E3	4.2747E3	3915.7
ED	Min (emission)	3651.1000	3661.8815	3660.7106	3916.6
	Mean (emission)	3651.1000	3661.8815	3660.7106	3918.7
	Max (emission)	3651.1000	3661.8815	3660.7106	0.7631
	SD	0.0000	0.0000	0.0000	1.1114E5
	Cost at Min. emission	1.1184E5	1.1182E5	1.1202E5	1.1115E5

Table 9- Comparison of the best solution for fuel cost minimization and emission minimization for Case 2 with power losses

	Method	Fuel Cost ($/hr)	Emission (ton/hr)
Best Fuel Cost	FFA	111140.0	4544.0
	PHOA [24]	112130.0	4520.0
	BSA[26]	111498.0	4572.0
	TLBO[33]	111500.0	4563.3
	QOTLBO [33]	111498.0	4568.7
Best Emission	FFA	116130.0	3915.7
	PHOA [24]	114130.0	3889.0
	BSA[26]	116412.0	3932.0
	TLBO[33]	116412.0	3932.2
	QOTLBO [33]	116412.0	3932.2

Table 10- Best solutions of the multi-objective EEPD problem provided by MOFFA for Case 2

Outputs	Without power losses			With power losses		
	Best cost	Best emission	Best compromise	Best cost	Best emission	Best compromise
P_1 (MW)	45.6986	53.5470	55.0000	44.6722	53.0690	51.5264
P_2 (MW)	76.5589	76.4696	69.8971	78.9384	80.0000	72.1358
P_3 (MW)	96.5634	87.3736	66.4447	109.5644	84.1992	79.7071
P_4 (MW)	96.2679	63.8510	91.1972	105.9777	88.4993	84.0658
P_5 (MW)	67.8787	157.1030	125.0540	83.2215	145.8445	116.9398
P_6 (MW)	70.0000	240.0000	144.4259	106.6654	236.6008	163.8571
P_7 (MW)	300.0000	289.7540	287.2129	300.0000	290.2082	279.4257
P_8 (MW)	340.0000	246.8066	308.9380	332.8129	248.0537	328.1406
P_9 (MW)	444.0589	392.8178	440.0804	461.6090	443.2627	443.7745
P_{10}(MW)	462.9736	392.2773	462.9736	457.1223	407.7897	459.9927
Fuel cost ($/hr)	106380	111430	107930	111470	115590	112570
Emission(ton/hr)	4294.9	3682.8	3901.3	4506.1	3990.9	4199.3
Losses (MW)	-	-	-	80.6	77.5	79.6

Table 11- Comparison of the best fuel cost and best emission provided by MOFFA for Case 2 without power losses

	Method	Fuel Cost ($/hr)	Emission (ton/hr)
Best Fuel Cost	MOFFA	106380	4294.9
	PHOA [24]	106720	4102.5
Best Emission	MOFFA	111780	3682.8
	PHOA[24]	111700	3699.3

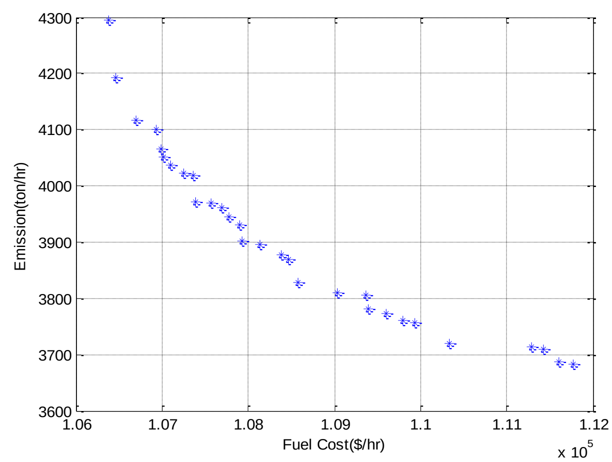

Figure 5- Pareto-optimal front of Case 2 without losses

Table 12- Comparison of the best compromise solution provided by different algorithms for Case 2 with power losses

Method	Fuel Cost ($/hr)	Emission (ton/hr)	Losses (MW)
MOFFA	112570	4199.30	79.60
MOBSA[26]	112807	4188.09	84.504
MODE [34]	113484	4124.9	84.33
NSGAII [34]	113539	4130.2	84.25
PDE [34]	113510	4111.4	83.9
SPEA-2 [34]	113520	4109.1	84.1
GSA [35]	113490	4111.4	83.987
ABC-PSO [36]	113420	4120.1	84.174
EMOCA [37]	113445	4113.98	83.56

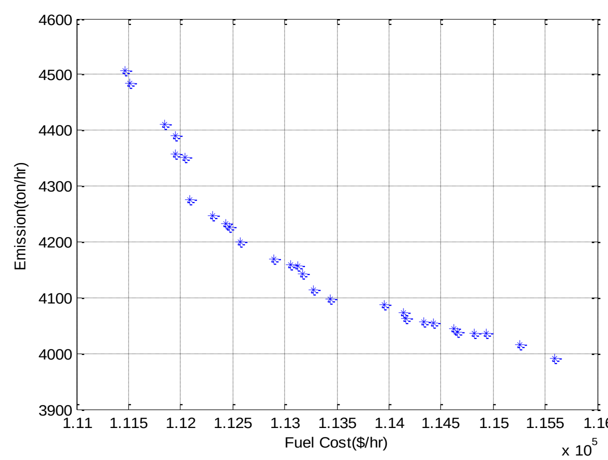

Figure 6- Pareto-optimal front of Case 2 with losses

5. Conclusions

In this paper, a Pareto-based MOFFA is proposed and successfully applied to solve the EEPD problem. The problem is formulated as a true nonlinear constrained multi-objective optimization problem with two competing objectives, which are fuel cost and emission. The concept of FFA for single-objective optimization is extended to solve multi-objective optimization. A hierarchical clustering algorithm is successfully applied to obtain a representative and controlled Pareto-optimal set. The best compromise solution is found using an approach based on fuzzy set theory. Also, a modified firefly algorithm (FFA) is proposed to solve the economic power dispatch (EPD) and the emission dispatch (ED) problems as single goals. The proposed algorithms are applied and tested on the IEEE 30-bus test system and the 10-unit test system with valve point loading effects to demonstrate their effectiveness. Two different methodologies have been efficiently carried out. The results prove the ability of the modified FFA and proposed MOFFA to solve the single and multi-objective optimization, respectively while generating well-distributed Pareto-optimal solutions with satisfactory diversity characteristics. Also, the results of the best cost and best emission obtained by the algorithms for both single and multi-objective problems are close, which indicates that the search of the proposed MOFFA span over the entire trade-off surface. The comparison with the reported results clears the high efficiency of the proposed algorithms as they outperform the other reported algorithms and confirm their potential to solve the single and multi-objective EEPD optimization problem.

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