Fuzzified Coulomb's and Franklin's laws behaved optimization for economic dispatch in multi-area multi-fuel power system

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Abstract

Multi-Area Multi-Fuel Economic Dispatch (MAMFED) aims to allocate the best generation schedule in each area and to offer the best power transfers between different areas by minimizing the objective functions among the available fuel alternatives for each unit while satisfying various constraints in power systems. In this paper, Fuzzified Coulomb's and Franklin's Laws Behaved Optimization (FCFLBO) approach is proposed to solve the MAMFED problem. Coulomb's and Franklin's Laws Behaved Optimization (CFLBO) approach is developed from Coulomb's and Franklin's theories, which encompass fascination/aversion, ionization, and contact stages. The suggested approach considers the line losses, valve point loading impacts, multi-fuel alternatives, and tie-line limits of the power system. Because of the contradicting nature of fuel cost and pollutant emission objectives, weighted sum approach and price penalty factor are used to transfer the bi-objective function into single objective function. Furthermore, a fuzzy decision strategy is introduced to find one of the Pareto optimal fronts as the best comprised solution. The feasibility of the FCFLBO algorithm is tested on a three-area test system for both the single-area multi-fuel economic dispatch and MAMFED problems. The results of FCFLBO algorithm are compared with those of the krill herd algorithm, exchange market algorithm and other heuristic approaches surfaced in the literature. To show the effectiveness of FCFLBO algorithm, multi-objective performance indicators such as generational distance, spacing metric and ratio of non-dominated individuals are evaluated. The results divulge that the FCFLBO is a promising approach to solve the MAMFED problem as it furnishes better compromised solution in comparison with the other heuristic approaches.

Keywords Fuzzy set theory · Heuristic optimization · Multi-area economic dispatch · Pareto-optimal front · Tie-line constraint

Abbreviations

a_i, b_i, c_i	Cost coefficients of generator i for single area power system	a_0 and r_0	Initial values for positive and negative charges respectively
a_{ij}, b_{ij}, c_{ij}	Cost coefficients of generator i in area j for multi-area power system	B_{ij}	Line loss coefficients
a_{ijk}	Cost coefficients of generator i in area j for fuel type k in multi-area multi-fuel power system	d_i, e_i	Cost coefficients of the VPL effect of generator i in single area power system
a_{max} and r_{max}	Maximum number of positive and negative charges respectively	e_{ij}, f_{ij}	Cost coefficients of the VPL effect of generator i in area j for multi-area power system
		E_i	Emission of the generator i in single area power system

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F_i	Fuel cost of the generator i in single area power system
$F_{ij}(P_{ij})$	Fuel cost of the generator i in area j for multi-area power system
$F_j^{\max}$ and $F_j^{\min}$	Maximum and minimum values of j th objective function respectively
F_{bcs} and E_{bcs}	Cost and emission obtained by EED
F_{min} and E_{max}	Cost and emission obtained by ED minimization respectively
F_{max} and E_{min}	Cost and emission obtained by EmD minimization respectively
h	Price penalty factor in \$/h
IP	Improvement percentage
k	Number of fuel alternatives
m	Population size of each object
M_i	Number of participated generators in area i
M	Number of non-dominated solutions
n	Maximum number of objects
ng	Total number of generating units
P_D	Power demand
P_i	Real power generation of generator i in single area power system
P_{ij}	Real power generation of generator i in area j for multi-area power system
$P_{i,\min}$, $P_{i,\max}$	Minimum and maximum generation of unit i in single area power system
$P_{ij,\min}$, $P_{ij,\max}$	Minimum and maximum generation j in area i for multi-area power system
p_i	Ionization probabilistic constant
P_c	Contact phase probabilistic constant
T_{iz}	Tie line power stream from area i to area z
$T_{iz,\max}$	Maximum tie line power stream from area i to area z
$-T_{iz,\max}$	Maximum tie line power stream from area z to area i
w	Weight or compromise factor
x_{ij}	j^{th} elementary charge of the i^{th} point charge
$x_j^{\min}$ and $x_j^{\max}$	Minimum and maximum limits of variable j
θ_j^{new}	Current electric angle of j th elementary charge in radians
θ_j^{old}	Previous electric angle of j th elementary charge in radians
$\alpha_i, \beta_i, \gamma_i$	Emission coefficients of generator i

1 Introduction

The goal of MAMFED problem is to decide the power delivered by every generator in various areas and the power stream between the areas in order to lessen the total production cost and pollutants outflows of the interconnected power system considering multi-fuel alternatives of each generating unit. The total load power is appropriated equally among various areas to decrease the fuel cost as well as the pollutant emissions. The power scheduling between the zones must not disregard the power balance, generator and tie-line limits. Thus, the MAMFED problem is addressed as the large-scale highly non-linear multi-objective optimization problem. In recent years, the MAMFED problem has received considerable attention.

Over the years, various classical multi-area power generation scheduling methods have been proposed. Shoults, et al. [1] applied an efficient approach for unit commitment and Economic Dispatch (ED) problems with area import/export constraints. The proposed approach has been tested on the Texas utilities and Texas municipal power pool systems. Quintana et al. [2] suggested the use of the Dantzig-Wolfe decomposition principle regarding the revised simplex method and a fast-decoupled power flow algorithm for constrained Multi-Area ED (MAED) of power systems. Ouyang and Shahidehpour [3] developed a model of large-scale multi-area power generation system and used a rule-based heuristic strategy to improve the generation schedule for every zone. Wang and Shahidehpour [4] suggested a decomposition approach which upgrades the scheduling process and accelerates the execution of a large-scale multi-area generation system in a real-time application. Streiffert [5] expressed the MAED problem as a capacitated nonlinear network flow problem and solved it through an Incremental Network Flow Programming (INFP) approach. The results showed that the INFP approach was fast, robust, and extendable to large-scale systems. Yalcinoz and Short [6] presented an Improved Hopfield Neural Network (IHNN) to solve MAED problems with transmission capacity constraints and showed that the IHNN achieved efficient and accurate solutions for two-area power systems. Thang [7] proposed a Hopfield Lagrange network for solving economic emission dispatch (EED) problem with multiple fuel alternatives (MFAs). Furthermore, the best compromise from the set of obtained solutions was found and compared with from Lambda-iteration method. These techniques are probably to come upon severe difficulty due to their heavy imposition of diverse constraints such as continuity, convexity and differentiability on the objective functions, and

high sensitivity to the initial values of involved optimized variables. Furthermore, their performances are progressively worsened by the dimension of the problem. Thus, these strategies do not offer reasonable possibilities for dealing with the MAED problem when prohibited operating zones (POZs), valve point loading (VPL), and MFAs are considered. To adapt to these challenges, numerous meta-heuristic methodologies have been used to take care of enhancement issues with complicated objectives [8]. The results obtained by evolutionary approaches for complex optimizing problems are good, which means these approaches offer a reasonable possibility for solving MAED problems.

In recent years, swarm intelligence algorithms have been broadly used to overcome the computational unpredictability issues in the MAED problem. Jayabarathi et al. [9] proposed a proficient technique for MAED problems using an Evolutionary Programming (EP) approach. The performance of the various evolutionary algorithms, for example the Real-Coded Genetic Algorithm (RCGA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and the Covariance Matrix Adapted Evolution Strategy (CMAES), on MAED problems with Karush–Kuhn–Tucker optimality conditions was examined [10]. The simulation results revealed that the CMAES algorithm offers the best results and the Nelder–Mead simplex method offers an optimal solution in the shortest time among the different algorithms considered. The performance of different DE strategies enhanced with time-varying mutation was investigated and analyzed to solve the reserve-constrained MAED problem [11]. The time varying DE approach was found to be capable of determining better solutions than PSO with time-varying acceleration coefficients. Also, the DE variant approaches were able to find the global best solutions for large-scale systems, while basic DE suffered from premature convergence.

Somasundaram and Jothi Swaroopan [12] introduced another computationally efficient fuzzified PSO algorithm to solve the security-constrained MAED problem of an interconnected power system. The inertia weight of the standard PSO was made adaptive by using fuzzy logic strategies to improve the convergence speed and avoid premature convergence. Basu proposed artificial bee colony (ABC) optimization [13] to solve a MAED problem with tie-line constraints, transmission losses, multiple fuels, and valve point effects. Evolutionary approaches such as DE, EP, and RCGA were applied to analyze the efficiency of the ABC approach. The simulation results showed that the ABC approach converged to a better solution than the approaches with which it was compared. Teaching learning-based optimization (TLBO) [14] has been applied to solve the MAED issue. The approach was tested on 3 different systems and the results revealed that the presented

approach had the ability to provide better solutions and exhibited greater robustness than DE, EP, and RCGA. The different MAED models were solved by employing Fast Convergence Evolutionary Programming (FCEP) [15]. FCEP used Gaussian and Cauchy mutations to improve the convergence speed and solution quality. Nguyen et al. [16] developed the Hybrid Cuckoo Search Algorithm (HCSA) to solve the MAED problem. The HCSA consolidates the cuckoo search algorithm and TLBO to improve the recital of cuckoo eggs. Ghasemi et al. [17] presented a hybrid DE-PSO technique to address the MAED, reserve-constrained MAELD, and reserve-constrained multi-area ecological/economic dispatch problems.

Sum Differential Evolution with Particle Swarm Optimizer (SDEPSO) was used along with the local (Pbest) optimal value in a DE crossover operator. The simulation results showed that the hybrid algorithm achieved a balance between global search ability and provision of better convergence and solution quality. Zhang et al. [18] introduced an Improved Grasshopper Optimization Algorithm (IGOA) to deal with the MAED problem. A chaos mechanism was adopted in the IGOA to handle the premature convergence of the grasshopper optimization algorithm. The simulation results demonstrated that the IGOA could converge better than the other approaches. Modiri-Delshad et al. [19] presented Backtracking Search Algorithm (BSA) for solving ED problems with considering VPL effects, POZs, and MFAs. Different variants of Krill Herd Algorithm (KHA) to small, medium and large-scale power systems for solving the ELD problems were applied by Mandal et al. [20]. Ghorbani and Babaei presented Exchange Market Algorithm (EMA) for solving the ELD problems. The EMA was employed by 2 searchers and absorbent operators which resulted in generation and organization of random numbers in the best way [21]. The MAED problem was solved by the hybridization of JAYA and TLBO approaches to simultaneously solve both non-smooth and non-convex characteristics [22]. A Parallel MAED (PMAED) was developed to maintain the independency and transfer the required power in each area [23]. The PMAED was solved with cost characteristics of different complexities. A Newton Method based Distributed Algorithm (NMDA) was employed to solve Single-Area Economic Dispatch (SAED) and MAED problems [24]. The virtual SAED formulation, backtracking line search algorithm, and average consensus theory were embedded in the NMDA approach. In [25] an improved fireworks algorithm (IFA) was used to solve the multi-area ELD problem considering the valve point loading (VPL) effects. The tie-line limit between different areas, generation limits, ramp rate limits, transmission losses, prohibited operating zone (POZ) and spinning reserve as the problem constraints. In the IFA, cross-generation

mutation mechanisms were employed to solve the multi-constrained the multi-area ELD problem. A novel swarm intelligence approach using salp swarm algorithm for the solution of multi-area generation scheduling with wind integration was presented [26]. These improved and hybrid forms of heuristic approaches involve complicated computation owing to the use of many control parameters. An efficient algorithm to solve MAED problems to ascertain the optimum dispatch solutions must be developed and proposed.

A new swarm intelligence approach, Squirrel Search Algorithm (SSA) was developed to solve the ELD of thermal units by addressing VPL and MFO for single area power system [27]. Recently, Sakthivel et al. [28] applied SSA and Coulomb's and Franklin's Laws Based Optimizer (CFLBO) [29] to solve the economic environmental dispatch of single area power system. In these research works; the multiple fuel options and multi-area power systems were not considered for the solution of economic environmental dispatch problem.

In 2018, a new physics-motivated approach, CFLBO was introduced by Ghasemi et al. [30]. This approach is a populace-based methodology propelled by Coulomb's and Franklin's speculations. The powers of fascination and repugnance between the point charges, ionization and contact stages are contemplated. CFLBO is beneficially used in ED issues with different complexities and is superior to other approaches surfaced in the literature. The special features of the CFLBO algorithm are as follows:

- i. The attraction/repulsion stage is used to increase the learning ability of the population and to enhance the global search ability of the algorithm.
- ii. The probabilistic ionization and contact stages are used to increase the population diversity and to avoid premature convergence of the algorithm.

Due to the above characteristics, the CFLBO approach is able to provide solutions of better quality than the existing heuristic approaches.

The main contributions of this paper are briefly summarized as follows:

- This paper aims to first introduce the FCFLBO algorithm to solve the MAMFED problem. The proposed algo-

rithm involves the CFLBO algorithm, weighted sum approach and fuzzy decision strategy.

- The FCFLBO algorithm successfully solves the Single Area Multi-Fuel ED (SAMFED) such that the fuel costs and pollutant emissions are simultaneously minimized while fulfilling the power balance and generation limits. Furthermore, the suggested algorithm is successfully applied to solve the MFMAED such that the total fuel cost is minimized while fulfilling the system and area constraints.
- The suggested FCFLBO, KHA and EMA are applied on a three-area 10-units system in order to demonstrate its effectiveness in solving the SAMFED and MAMFED problems. The obtained results are compared with different state-of-the-art heuristic approaches surfaced in the literature.

The structure of this paper is as follows. [Section 2](#) presents the details of the SAMFED and MAMFED models. The recommended FCFLBO is presented in [Sect. 3](#). The implementation of the FCFLBO approach for the MAMFED problem is discussed in [Sect. 4](#). In [Sect. 5](#), the numerical results are discussed and the adequacy of the proposed FCFLBO approach is additionally demonstrated. Finally, [Sect. 6](#) concludes the paper.

2 Problem formulation of multi-fuel economic dispatch

2.1 SAMFED

2.1.1 Fuel cost objective function

The goal of the ED problem is to limit the all-out expense of thermal units as follows:

$$\text{Minimize } F = \sum_{i=1}^{ng} F_i(P_i) \quad (1)$$

In the ED problem, the fuel cost of each generating unit is communicated as a quadratic function of its capacity yield. As the generating units utilize different fuel choices to create power and the valve point impacts considered, the fuel cost function is expressed as

$$F_i(P_i) = \begin{cases} \text{Fuel type 1 ; } a_{i1} + b_{i1}P_i + c_{i1}P_i^2 + |e_{i1} \times \sin(f_{i1} \times (P_{i,\min} - P_i))| ; & P_{i,\min} \leq P_i \leq P_{i1} \\ \text{Fuel type 2 ; } a_{i2} + b_{i2}P_i + c_{i2}P_i^2 + |e_{i2} \times \sin(f_{i2} \times (P_{i,\min} - P_i))| ; & P_{i1} < P_i \leq P_{i2} \\ \dots & \\ \text{Fuel type } k ; & a_{ik} + b_{ik}P_i + c_{ik}P_i^2 + |e_{ik} \times \sin(f_{ik} \times (P_{i,\min} - P_i))| ; & P_{ik-1} < P_i \leq P_{i,\max} \end{cases} \quad (2)$$

Fig. 1 Multi-fuel cost curve

The multi-fuel cost curve with and without VPL impacts is shown in Fig. 1.

2.1.2 Emission objective function

The objective of the emission dispatch (EmD) problem is to lessen the hazardous emissions as follows:

$$\text{Minimize } E = \sum_{i=1}^{ng} E_i(P_i) \quad (3)$$

The emission objective function is truly like the fuel cost function while it deals with all discharge types discharged by generation units. The scientific model for emanation function with MFA is introduced as

$$E_i(P_i) = \begin{cases} \text{Fuel type 1 ; } \alpha_{i1} + \beta_{i1}P_i + \gamma_{i1}P_i^2 & ; P_{i,\min} \leq P_i \leq P_{i1} \\ \text{Fuel type 2 ; } \alpha_{i2} + \beta_{i2}P_i + \gamma_{i2}P_i^2 & ; P_{i1} < P_i \leq P_{i2} \\ \dots & \\ \text{Fuel type k ; } \alpha_{ik} + \beta_{ik}P_i + \gamma_{ik}P_i^2 & ; P_{i,k-1} < P_i \leq P_{i,\max} \end{cases} \quad (4)$$

$$F_{ij}(P_{ij}) = \begin{cases} \text{Fuel type 1 ; } a_{ij1} + b_{ij1}P_{ij} + c_{ij1}P_{ij}^2 + |e_{ij1} \times \sin(f_{ij1} \times (P_{ij,\min} - P_{ij}))| & ; P_{ij,\min} \leq P_{ij} \leq P_{ij1} \\ \text{Fuel type 2 ; } a_{ij2} + b_{ij2}P_{ij} + c_{ij2}P_{ij}^2 + |e_{ij2} \times \sin(f_{ij2} \times (P_{ij,\min} - P_{ij}))| & ; P_{ij1} < P_{ij} \leq P_{ij2} \\ \dots & \\ \text{Fuel type k ; } a_{ijk} + b_{ijk}P_{ij} + c_{ijk}P_{ij}^2 + |e_{ijk} \times \sin(f_{ijk} \times (P_{ij,\min} - P_{ij}))| & ; P_{ij,k-1} < P_{ij} \leq P_{ij,\max} \end{cases} \quad (8)$$

2.1.3 Economic and emission dispatch (EED) function

The EED problem can be figured as bi-target work in which fuel cost and discharge as equalling objectives. This bi-target function can be moved to a solitary target function as follows:

$$\text{Minimize } F_{EED} = w \times F + h \times (1 - w) \times E \quad (5)$$

The above condition becomes ED target function when $w=1$ and becomes EmD target work when $w=0$. w is a primary function of $\text{rand}[0,1]$ which bargains the fuel cost and emanation objectives.

2.1.4 Power balance constraint

The total power generated from a set of committed units must fulfil the total load demand.

$$\sum_{i=1}^{ng} P_i = P_D \quad (6)$$

2.1.5 Generator capacity limits

The real output power of thermal units ought to be in their range between minimum and maximum limits:

$$P_{i,\min} \leq P_i \leq P_{i,\max} \quad (7)$$

2.2 MAMFED

2.2.1 Fuel cost objective function

The aim of the MAMFED problem is to find the amount of power that can be efficiently generated in one area and transferred to another area, and to determine the economic fuel choice for each unit. Since generators are provided with multi-fuel sources, every generator ought to be defined with a few piecewise quadratic capacities superimposed by sine terms mirroring the impact of changes in the type of fuel and the generator must determine the most conservative fuel to consume. The MAED problem with VPL and MFA impacts [13] can be modeled as

The objective function for the MAMFED problem is defined as:

$$\text{Minimize } F = \sum_{j=1}^{Mi} \sum_{i=1}^{ng} F_{ij}(P_{ij}) \quad (9)$$

2.2.2 Power balance constraint

The total power generated by a set of accessible units must satisfy the total load demand, tie-line power flow, and transmission losses [8] and is given by.

$$\sum_{j=1}^{M_i} P_{ij} = P_{Di} + P_{Li} + \sum_{z, z \neq i} T_{iz} \quad i \in n_g, j \in M_i \quad (10)$$

where P_{Di} is the load demand in area j ; P_{Li} represents the transmission line losses in area i ; T_{iz} is the tie-line power flow from area i to area z .

The transmission loss P_{Lj} of area j can be defined by utilizing B-coefficients as

$$P_{Li} = \sum_{l=1}^{M_i} \sum_{j=1}^{M_i} P_{ij} B_{ijl} P_{il} + \sum_{j=1}^{M_i} B_{0ij} P_{ij} + B_{00i} \quad (11)$$

2.2.3 Generator capacity limits.

The real output power of the thermal units should be in the range between minimum and maximum limits [9]:

$$P_{ij,\min} \leq P_{ij} \leq P_{ij,\max} \quad (12)$$

2.2.4 Tie-line limit.

Because of the security basis, power shifted between various lines must not surpass their cutoff points [11]. The power transfer requirement between two unique regions is characterized by

$$-T_{iz,\max} \leq T_{iz} \leq T_{iz,\max} \quad (13)$$

3 Brief overview of the FCFLBO Approach

3.1 CFLBO algorithm

CFLBO is a heuristic algorithm, developed by Ghasemi et al. [30]. This methodology impersonates Coulomb's and Franklin's speculations. The accompanying ideas are related with CFLBO approach.

Coulomb's Law The association between two distinctive point charges is constrained by the extent of electrostatic intensity of fascination (or) repugnance.

Franklin's Law Every object involves equivalent positive and negative charges.

The CFLBO approach utilizes different objects of point charges (X) which turn around different regions in a researched space to locate the global arrangement. The underlying items are framed by various gatherings of point charges which are self-assertively produced in the pursuit space. Each point charge includes D quantized charges and each point charge is contrasted with a solution of the issue. The paradigm of CFLBO is a monotonous procedure, which contains initiation, fascination/aversion, ionization and contact stages.

3.1.1 Initiation stage

Let an object is generated by a populace of m charges with variables D . The objects, populaces and each individual are indicated as follows [29]:

$$O = [O_1, O_2, \dots, O_n]$$

$$X = [X_1, X_2, \dots, X_q]$$

$$X_{ij} = [x_{i1}, x_{i2}, \dots, x_{iD}]$$

The underlying populaces of point charges are created as [29]:

$$x_{ij} = U(x_j^{\min}, x_j^{\max}) \quad \text{for } i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, D \quad (14)$$

where U is a vector of consistently disseminated arbitrary numbers from $x_j^{\min}$ to $x_j^{\max}$.

At that point, the underlying populace is organized and scattered into a couple of objects ($O_1, \dots, O_n$).

3.1.2 Fascination/Aversion stage

The migration of point charge is affected by fascination and aversion powers following up on them. The net force following upon a point charge (X_i) is equivalent to its worth (F_i). The CFLBO approach is utilized to restrict the net power following upon them. The point charges of each object are refreshed as [29]:

$$x_j^{new} = x_{ij}^{old} + \left| \cos \theta_j^{new} \right|^2 \times (x_j^{best} - x_j^{Worst}) + \left| \sin \theta_j^{new} \right|^2 \times \left(\text{mean} \left(\sum_{n=1}^{a_{\max}} x_{jn} \right) - \text{mean} \left(\sum_{n=1}^{r_{\max}} x_{jn} \right) \right) \quad (15)$$

According to this equation, if the objective value of the new location $f(x_j^{new})$ is preferable or less over that of the old position $f(x_{ij}^{old})$, x_j^{new} is set as the new location of x_j ; or else, x_j sustains its past position x_{ij}^{old} . The negative point charges with respect to x_j , which repulse x_j , seem with negative sign in the Eq. 15 to rise the separation between the charges. where, $\theta_j^{initial} = U(0, 2\pi)$

$$\theta_j^{new} = \theta_j^{old} + U\left(0, \frac{3}{2}\pi\right)$$

The $a_{\max}$ and $r_{\max}$ are defined as:

$$a_{\max} = a_0 \times (1 + \cos \theta) \quad (16)$$

$$r_{\max} = r_0 \times (1 - \cos \theta) \quad (17)$$

3.1.3 Probabilistic ionization stage

Because of the impact of probabilistic ionization energy, there is a chance of removal of the position of the rudimentary charge x_j . It can be expressed by the accompanying condition [29].

$$x_j^{new} = x_j^{Best} + x_j^{Worst} - x_j^{old} \text{ if } \text{rand}(i) \leq p_i \quad (18)$$

The parameter ' j ' is selected as follows.

$$j = \text{round}(\text{unifrnd}(1, D)) \quad (19)$$

where $\text{rand}(i)$ is the i th point charge of a randomly generated number between zero and one.

If P_i for j th member (x_j) is higher than $\text{rand}(i)$, the variable $x_{j,k}$ is randomly chosen by Eq. 19 and the k th control variable is updated using Eq. 18.

3.1.4 Probabilistic contact stage

In the event that the objects are engaging with one another, at that point each object elapses its best and worst charges for its neighborhood. The contact stage is communicated as [29]:

If $\text{rand}_c \leq p_c$, then

$$x_j^{Best_{Obj1}} = x_j^{Best_{Objn}}, \dots, x_j^{Best_{Objn}} = x_j^{Best_{Objn-1}} \quad (20)$$

$$x_j^{Worst_{Obj1}} = x_j^{Worst_{Objn}}, \dots, x_j^{Worst_{Objn}} = x_j^{Worst_{Objn-1}}$$

where rand_c is a randomly generated number between zero and one.

If the factor P_c is higher than rand_c , then each object elapses its greatest and lowest cost values of charges for its neighborhood using Eq. (20).

4 Fuzzy decision strategy

Fuzzy set hypothesis is used to proficiently determine the best compromised solution (BCS) from a Pareto optimal fronts (POF) set. Generally, a membership function (MF) for every objective function is expressed by the expertness and instinctive information. A basic straight MF is used for every objective function. It can be expressed as [29]:

$$\mu(F_j) = \begin{cases} 1 & \text{if } F_j \leq F_j^{\min} \\ \frac{F_j^{\max} - F_j}{F_j^{\max} - F_j^{\min}} & \text{if } F_j^{\min} \leq F_j \leq F_j^{\max} \\ 0 & \text{if } F_j \geq F_j^{\max} \end{cases} \quad (21)$$

The standardized MF μ_D^k for each POF is determined as [29]:

$$\mu_D^k = \frac{\sum_{i=1}^2 \mu(F_i^k)}{\sum_{k=1}^M \sum_{i=1}^2 \mu(F_i^k)} \quad (22)$$

The solution which acquires a maximum μ_D^k value is the BCS of the MAMFED problem.

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While  $\sum_{i=1}^{n_g} \sum_{j=1}^{M_i} P_{ij} - \left( P_{Di} + P_{Li} + \sum_{z,z \neq i} T_{iz} \right) = 0$ 
  Randomly select a generator  $i$  of an individual
  Find  $\Delta P_{ij} = \left| \sum_{i=1}^{n_g} \sum_{j=1}^{M_i} P_{ij} - \left( P_{Di} + P_{Li} + \sum_{z,z \neq i} T_{iz} \right) \right|$ 
  If  $\sum_{i=1}^{n_g} \sum_{j=1}^{M_i} P_{ij} - \left( P_{Di} + P_{Li} + \sum_{z,z \neq i} T_{iz} \right) \neq 0$ 
    Update  $P_{ij} = \min(P_{ij} + \Delta P_{ij}, P_{ij, \max})$ 
  Else
    Update  $P_{ij} = \max(P_{ij} - \Delta P_{ij}, P_{ij, \min})$ 
  End if
End while
    
```

Fig. 2 Equality constraint handling mechanism

$$\text{Max } \{ \mu_D^k : k = 1, 2, \dots, M \}$$

(23) 5 Implementation of FCFLBO algorithm for MAMFED problem

The main steps involved in the FCFLBO algorithm for solving the MAMFED problem are as follows.

Step 1: initial feasible solutions are randomly generated. The fuel cost and emission objectives are

Fig. 3 Flow chart of FCFLBO algorithm for solving the MAMFED problem

transferred into single objective function by Eq. 5 and their values are determined.

Step 2: The position of the generation of each unit is varied by implementing fascination/repugnance, probabilistic ionization and contact stages using Eqs. 15, 16, 17, 18, 19 and 20.

Step 3: The power generation and tie-line constraints are satisfied by Eqs. 12 and 13 respectively. For satisfying the power balance constraints (Eq. 11), an equality constraint handling strategy which is described in Fig. 2 is applied.

Step 4: The objective values of all the point charges are evaluated. Steps 2 to 3 are repeated until the stopping criterion is met.

Step 5: Finally, the fuzzy decision strategy is employed to acquire the BCS from the POF set.

The detailed step-by step procedure of FCFLBO based MAMFED problem is explained in Fig. 3.

6 Numerical results and discussion

To demonstrate the effectiveness of the suggested FCFLBO approach, it is applied to a three-area, 10-unit power system for the SAMFED and MAMFED problems. The power demand of the test system is chosen as 2700 MW. The coefficients of multi-fuel cost and emissions, generation limits of generating unit, and tie-line capacity limits are given in "Appendix". The suggested FCFLBO approach is executed in Matlab 7.1 and executed on an Intel core i3 processor with 4 GB RAM PC. In order to compare the performance of the FCFLBO algorithm, the SAMFED and MAMFED problems are also solved using KHA and EMA approaches. The FCFLBO, KHA and EMA approaches are executed for 50 autonomous trials to assess the solution quality and convergence behavior. The accompanying four scenarios are researched and the results of the suggested FCFLBO approach are compared with KHA, EMA and other state-of-art heuristic approaches surfaced in the literature.

Table 1 Optimal FCFLBO parameters

Parameter	Value
Maximum number of objects (n)	5
Population size of each object (q)	20
Maximum number of iterations ($iter_{max}$)	200
Ionization probabilistic constant (p_i)	0.1
Contact phase probabilistic constant (P_c)	0.5

Scenerio 1: Minimization of the total fuel cost in the SAMFED problem,

Scenerio 2: Minimization of the total pollutant emissions in the SAMFED problem,

Scenerio 3: Minimization of both the total fuel cost and the total emission level simultaneously in the SAMFED problem, and

Scenerio 4: Minimization of the total fuel cost in the MAMFED problem

6.1 Parameter selection

In the FCFLBO approach, 5 main parameters that have to be predetermined are the number of objects, population size of each object, maximum number of iterations, probabilistic ionization, and contact constants. These parameters can be easily fixed depending on the complexity and scale of the considered SAMFED and MAMFED problems. The population size and maximum number of generations are fixed by trial and error method. The optimization procedure is terminated when there is no change in the result for 50 consecutive iterations or when 200 iterations are reached, whichever occurs first. The parameters selected for the suggested FCFLBO approach are given in Table 1. The accuracy or tolerance limit of the computation conducted using

Table 2 Optimal solution acquired by the suggested approach for scenario 1

Unit	Fuel Types	FCFLBO
1	2	218.2496
2	1	211.6654
3	1	280.9792
4	3	239.8704
5	1	278.7599
6	3	239.3943
7	1	288.5493
8	3	239.3835
9	3	428.2963
10	1	274.4732
Minimum cost (\$/h)		623.8613
Emission (kg/h)		6460.9222

Table 3 Performance comparison of the FCFLBO algorithm with other techniques for scenario 1

Approach	Fuel cost (\$/h)
BSA	623.9016
KHA	623.9545
EMA	623.9389
FCFLBO	623.8613

Table 4 Optimal solution acquired by the FCFLBO algorithm for scenario 2

Unit	Fuel Types	FCFLBO
1	2	199.7561
2	1	212.9532
3	1	298.5494
4	3	255.6735
5	1	287.3095
6	1	169.7462
7	2	366.8659
8	3	256.3758
9	3	440
10	1	212.7704
Fuel cost (\$/h)		668.6195
Minimum Emission (kg/h)		6044.4789

Table 5 Performance comparison of the FCFLBO algorithm with other techniques for scenario 2

Approach	Emission (kg/h)
KHA	6051.8174
EMA	6054.5773
FCFLBO	6044.4789

Table 6 Non-dominated solutions for various weighting values acquired by the suggested FCFLBO approach

W_1	W_2	Fuel cost (\$/h)	Emission (kg/h)	Membership value (μ_D)
1	0	623.8613	6460.9222	0.077760
0.9	0.1	627.1618	6394.3657	0.085477
0.8	0.2	630.0796	6327.4648	0.092783
0.7	0.3	633.9257	6251.7609	0.100097
0.6	0.4	637.4385	6198.1572	0.103891
0.5	0.5	642.4138	6161.9721	0.101887
0.4	0.6	647.8515	6140.8452	0.096277
0.3	0.7	652.3607	6117.9579	0.092621
0.2	0.8	657.7984	6088.0282	0.088645
0.1	0.9	663.3687	6066.9014	0.082802
0	1	668.6193	6044.4789	0.077760

Bold instances indicate the BCS from a POF set

Eqs. 6 and 10 for obtaining the optimal solutions is 0.0001.

6.2 Scenario 1

Table 2 presents the optimal generation schedule acquired by the fuel cost minimization of the SAMFED using the suggested FCFLBO approach. In this scenario, the suggested approach is compared with the known approaches

Table 7 BCS acquired by the FCFLBO approach for scenario 3

Unit	Fuel Types	FCFLBO
1	2	209.3864
2	1	212.9548
3	1	294.2932
4	3	252.7033
5	1	285.8751
6	1	195.8957
7	2	300.7344
8	3	245.6157
9	3	425.6682
10	1	276.8732
Fuel cost (\$/h)		637.4385
Emission (kg/h)		6198.1572

such as EMA, KHA, and BSA [19] in Table 3. As can be seen from the results presented in Table 3, the FCFLBO approach outflanks the aforementioned approaches as far as the total fuel cost.

6.3 Scenario 2

The optimal values of generating units obtained by the FCFLBO for emission minimization are given in Table 4. The minimum emission value incurred from the FCFLBO algorithm is 6044.4789 kg/h. In order to demonstrate the effectiveness of the FCFLBO algorithm, the same problem is also solved using the KHA and EMA approaches. In Table 5, the pollutant emissions obtained from the suggested FCFLBO algorithm are compared with the KHA and EMA approaches. The results of this comparison demonstrate that the suggested approach is better than those of the KHA and EMA approaches. The FCFLBO algorithm obtains lesser emission level of 7.34 kg/h and 10.1 kg/h than those obtained using the KHA and EMA respectively.

6.4 Scenario 3

For this scenario, the total fuel cost and emission objectives of the SAMFED are simultaneously minimized. The objective function of the EED which is given in Eq. 5 is minimized. In order to provide the best trade-off, the weights w_1 and w_2 are varied in the range 0 to 1 in step of 0.1 so that their sum is one. The non-dominated solutions set acquired by the FCFLBO approach are depicted in Table 6. The solution corresponding to the maximum membership value estimation is chosen as the BCS. It may be seen that the BCS are determined at $w_1 = 0.6$ and $w_2 = 0.4$ corresponding to $\mu_D = 0.103891$. For the FCFLBO algorithm, the total fuel cost is 637.4385 \$/h and the total pollutant emissions of 6198.1572 kg/h. Table 7 presents the optimal

Fig. 4 Performance comparison of the FCFLBO algorithm with other techniques for scenario 3

Fig. 5 POF curve of the proposed FCFLBO algorithm scenario 3

Fig. 6 Schematic diagram of three-area system

generation schedule of the SAMFED problem by minimizing both the total fuel cost and emissions.

Table 8 Best dispatch solution incurred by the suggested FCFLBO algorithm for scenario 4

Unit	$P_{ij,min}$ (MW)	$P_{ij,max}$ (MW)	Fuel types	Power generation (MW)
$P_{1,1}$	196	250	2	224.4524
$P_{1,2}$	157	230	1	212.1998
$P_{1,3}$	388	500	2	490.1287
$P_{1,4}$	200	265	3	240.5451
$P_{2,1}$	190	338	1	252.9731
$P_{2,2}$	200	265	3	234.5827
$P_{2,3}$	200	331	1	265.6763
$P_{3,1}$	200	265	3	234.9516
$P_{3,2}$	213	370	1	329.1937
$P_{3,3}$	200	362	1	251.0647
T_{21}	100	P_{L1}	17.2541	
T_{31}	99.9281	P_{L2}	9.8343	
T_{32}	31.6022	P_{L3}	8.6804	
Fuel cost (\$/h)			653.8601	

Table 9 Comparison of generation costs incurred by various approaches for scenario 4

Approach	Fuel cost (\$/h)
RCGA [13]	657.3
EP [13]	655.2
DE [13]	654
ABC [13]	654
TLBO [14]	653.99
KHA	654.72
EMA	654.6
FCFLBO	653.86

The performance indices of EED problem such as fuel cost performance index (FCPI) and emission cost performance index (ECPI) are additionally performed. The FCPI and ECPI can be expressed as follows [28]:

$$FCPI = \frac{F_{bcs} - F_{min}}{F_{max} - F_{min}} \times 100 \quad (24)$$

$$ECPI = \frac{E_{bcs} - E_{min}}{E_{max} - E_{min}} \times 100 \quad (25)$$

The performance indices of the FCFLBO algorithm are compared with the results obtained using the KHA and EMA approaches, as shown in Fig. 4. It is evident that the performance indices acquired using the FCFLBO approach is superior to the aforementioned approaches as far as divergence. Figure 5 shows the Pareto optimal fronts (POF) curve of the suggested FCFLBO approach. It is seen that the POF curve of the suggested FCFLBO algorithm remains nearer to the axes, which implies that the FCFLBO approach offers better results.

Fig. 7 Boxplots of multi-objective performance measures

6.5 Scenario 4

In this scenario, the fuel cost minimization of MAMFED is addressed. Three areas, a 10-unit test system with transmission losses, and VPL and MFA impacts are taken into consideration. Areas 1, 2, and 3 comprise four, three and three generating units, respectively as displayed in Fig. 6. The power demand of this system is 2700 MW. The power demand shares of areas 1, 2, and 3 are 50, 25, and 25% of total load demand respectively. The power stream from one area to another is restricted to 100 MW. Table 8 presents the simulation results obtained by the proposed FCFLBO approach. It can be easily seen that the optimal generation cost obtained by the FCFLBO approach is 653.8601 \$/h, which is the lowest among the compared approaches. Area 1 imports power from areas 2 and 3, and area 3 exports power to area 2. The comparison of the results of FCFLBO approach with those of EMA, KHA, RCGA [13], EP [13], DE [13], TLBO [14] and ABC [13] approaches is tabulated in Table 9. The results show that the proposed strategy outperforms the other strategies considered with regard to finding the best generation schedule.

6.6 Statistical analysis of the FCFLBO algorithm

6.6.1 Multi-objective performance indicators

The multi-objective performance indicators such as, generational distance (GD), spacing metric (SM) and ratio of non-dominated individuals (RNI) are used to examine the performance of the suggested approach for Scenario 3. The smaller estimations of GD and SM demonstrate that better union to the POF curve, and better conveyance and assorted variety of the non-dominated solutions respectively. A closer estimation of one for RNI index demonstrates that the greatest number arrangements in a populace are non-dominated. The GD, SM, and RNI measures obtained by the proposed FCFLBO approach in 50 autonomous trials are shown as box and whisker plots

Fig. 8 Comparison of IP obtained by various approaches for scenario 4**Table 10** Comparison of function evaluation adopted by various scenarios

Approach	Scenario 1	Scenario 2	Scenario 3	Scenario 4
KHA	268	272	436	452
EMA	259	258	424	443
FCFLBO	250	246	397	423

Table 11 Comparison of CPU time adopted by various scenarios

Approach	Average CPU time (s)			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4
KHA	7.99	8.31	12.97	13.71
EMA	7.32	7.35	11.48	12.52
FCFLBO	6.08	6.13	9.72	10.23

in Fig. 7. It tends to be seen from them that the FCFLBO algorithm has estimated the smaller values regarding GD and SM indices, and more like one as for RNI indicator.

Fig. 9 Convergence comparison of the FCFLBO and EMA approaches

6.6.2 Fuel cost improvement percentage

Fuel cost improvement percentage (IP) is the ratio of fuel cost difference obtained between two approaches to the higher value of fuel cost obtained, expressed as a percentage, and is defined as follows:

$$IP = \frac{\text{fuel cost of the compared approach} - \text{fuel cost of the suggested approach}}{\text{fuel cost of the compared approach}} \times 100 \quad (26)$$

The IPs obtained by the FCFLBO approach in comparison with the existing heuristic approaches for the case studies are shown in Fig. 8. The fuel cost IP of the FCFLBO approach compared to other approaches ranges from 0.113 to 0.5234% for scenario 4. It is noteworthy that the IP of the FCFLBO approach is high for MAMFED with VPL impacts. Thus, the suggested FCFLBO approach provides better results than the other compared approaches.

6.6.3 Computational Efficiency

Tables 3, 4, 7, and 8 show that the minimum fuel costs achieved by the FCFLBO approach are 623.8613, 668.6195, 637.4385, and 653.8601 \$/h for scenarios 1, 2, 3 and 4 respectively. These costs are lower than the ones presented in recent literature. The FCFLBO approach is, likewise, definitely effective. Tables 10 and 11 bestow the number of function evaluation and average CPU time adopted by the FCFLBO and EMA strategies for the various scenarios. It is significant that the number of function evaluation and CPU time are lesser than those of other referenced techniques. So, in general, it tends to be noted that the FCFLBO technique is more computationally effective than the EMA strategy.

6.6.4 Convergence graph

The convergence comparison of the EMA and FCFLBO approaches is shown in Fig. 9. It can well be construed that the FCFLBO approach requires a smaller number of iterations to converge to the globally optimal solution.

7 Conclusion

The MAMFED problem as an imperative issue in the modern power system analysis is solved in this paper. The optimal generation schedule of all committed units and power transfer between the areas through tie-lines are determined. The FCFLBO algorithm is used to solve the SAMFED and the MAMFED problems. The transmission line losses, VPL impacts, and tie-line limits of the power system are addressed. The bi-objective function is transferred into single objective function by weighted sum approach. Moreover, a fuzzy decision strategy is introduced to find one of the Pareto optimal fronts as the best comprised solution. In order to demonstrate the effectiveness of the FCFLBO algorithm in terms of solution quality, computational efficiency and convergence speed, it is solved to the MFED problems with three different scenarios and compared with the other state-of-the- approaches. In this research article, the merits are summarized hereunder.

- To the best of authors' knowledge, this research article is the first research work of applying FCFLBO approach for solving the SAMFED and the MAMFED problems.
- The FCFLBO algorithm validates the superior performance to provide the best POF for economic and emission dispatch problems with MFO.
- The difference between FCPI and ECPI obtained from FCFLBO is lesser than those obtained from the other compared approaches, indicating the superiority of FCFLBO in obtaining the BCS. Thus, it can be concluded that the FCFLBO algorithm is an efficient method of solving the MFMAED problem.

This research work not only offers an optimizer that provides an amazing advance for the MFMAED problem but also additionally advances the use of the evolutionary approaches in the energy optimization domain. For future work, it will be intriguing to implement this compelling approach to solve other economic operation problems of hybrid thermal wind-solar thermal power systems.

Compliance with ethical standards

Conflict of interest On behalf of coauthor, the corresponding author states that there is no conflict of interest.

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