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Modern Meta-Heuristic Algorithms for Solving Combined Economic and Emission Dispatch

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Abstract
The traditional economic dispatch (ED) inattention to the fossil fuels emission of thermal power plants no longer satisfies the environmental needs. As a result of the non-convex, non-smooth fuel cost functions in addition to the nonlinearity of the emission modelling. These make the combined economic and emission dispatch (CEED) a highly nonlinear optimization problem. Furthermore, different operation process constraints should be taken into account, such as loss in electrical networks and power balance of unit operation. These constraints increase the difficulty of obtaining the global optimal solution based on traditional methods. Recently, meta-heuristic population-based algorithms have successfully become a beneficial technique for solving nonlinear optimization problems. The major contribution in this work is presenting a recent meta-heuristic approach known as Mayfly algorithm (MA) for solving nonlinear and complex CEED problem. The numerical results are compared with results obtained from modern meta-heuristic algorithms like Jellyfish Search (JS) optimizer, Dwarf mongoose optimization (DMO), Tunicate swarm algorithm (TSA), Red deer algorithm (RDA), Tuna Swarm Optimization (TSO), Golden Eagle Optimizer (GEO) and Bald eagle search Optimization algorithm (BES). The standard IEEE 30-bus test system is used in this article. The simulation results are done using MATLAB environment. The results approve the reliability, stability, and consistency of the proposed approach. The proposed technique gives reliable, robust, and high-quality solution with faster computational time. Moreover, MA is more suitable for solving nonlinear CCED problem because it has a considerable convergence feature.

Keywords
Economic Emission Dispatch, Mayfly Algorithm, Meta-Heuristic.

I. Introduction

The economic dispatch problem has received clear attention, especially in operation, economic scheduling, and the security of the power systems. The essential objective of the combined economic and emission dispatch CEED is to minimize the generation cost of power plants. All units' constraints must be met while the committed generating unit's outputs are optimally adjusted. So, ED is an optimization problem with nonlinear large-scale limitations [1–4]. In classical ED, fossil fuel pollutant emissions are not considered in thermal plants. Due to the increasing attention paid to reducing environmental pollution, the classical ED that inattention to the fossil fuel emissions of thermal power plants no longer meets the environmental needs. When traditional ED constraints are combined with environmental conditions, it becomes a CEED problem. The multi-objective CEED problems consider minimizing two objective functions (OFs): fuel cost and thermal power plant emissions considering their constraints [5]. Because of the nonlinear characteristics of the emission modelling and non-convex, non-smooth fuel cost functions. These make the CEED problem a highly nonlinear, non-smooth, and non-convex optimization problem. Moreover, various process operation constraints must be considered, such as transmis-

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Nomenclature			
Abbreviation			
CEED	combined economic emission dispatch	$pbest_i$ & $gbest_i$	local & global best position of the i[th] mayfly
ED	economic dispatch	pz$i$	POZs No. of generator i
MA	mayfly algorithm	P^0_{Gi}	the preceding power output of the i[th] generator
OF	objective function	P^{min}_{Gi} & P^{max}_{Gij}	Min.& max. power of generator i (fuel type j)
PB	Power Balance	$P^l_{Gi,k}$& $P^u_{Gi,k}$	lower & upper limits of generator iPOZ
POZs	prohibited operating zones	r_1	random number in ∈ [-1,1]
TOL_ε	error tolerance value	r_g	cartesian distance between y_i&gbest
VPE	valve point effect	r_p	cartesian distance between y_i& $pbest_i$
Parameters		r_l	index of the slack generator
a_i ,b_i ,and c_i	i[th] generator coefficients	t	time instance
a_{ij} ,b_{ij} ,c_{ij},e_{ij}, and d_{ij}	generator i cost coefficients (fuel type j)	w	weight factor
DR_i ,and UR_i	down and up-ramp limit of generator i	w^{t+1}_i	female mayfly's velocity in dimension j
d_i ,and e_i	coefficients of fuel cost representing VPE	x	control variables vector
B_{ij},B_{0i},and B_{00}	coefficients of B-loss matrices	Y_i	corresponds to $pbest_i$ and gbest
emission(x,y)	Emission cost function	y	dependent variable
$F_{(cost)}(x,y)$	fuel cost function	y_{ij}	j[th] element of mayfly i
fl	random walk coefficient	y^t_{ij} and w^t_{ij}	position & velocity of i[th] mayfly in dimension j
i j	generator index and fuel type	z^t_i	the i[th] female mayfly's current position
NF	fuel type No. of individual generators	z^t_{ij}	i[th] female mayfly current position in dimension j
N_G	thermal generation units set	α_1, and α_2	positive attraction constants
NG	total generator's number	α_i, β_i, η_i, ζ_i, and λ_i	coefficients of the i[th] generator emission characteristics
NPZ	generator No, including POZs	β	fixed visibility constant
PG	Generator active power outputs	γ	scaling factor

sion system losses and the power balance of unit operation. These constraints increase the difficulty of finding the global optimum using traditional mathematical methods. The CEED problem is an extremely nonlinear multimodal optimization problem because of the nonlinear properties of the emission model in addition to non-convex and non-smooth fuel costs when considering valve-point effects [1]. Multiple Objective Meta-heuristic algorithms have recently been confirmed to be superior and convenient for solving several optimization problems [6–17]. Recently, several optimization strategies have been utilized to solve the CEED problem. Previously, many traditional methods were used for solving ED problems, like linear and nonlinear programming (LP and NLP), gradient methods (GM), dynamic programming (DP), goal programming (GP), Lagrangian relaxation (LR), etc. [18]. These conventional techniques are unsuitable for solving ED due to fuel-emission objectives' nonlinear and non-convex characteristics. It is critical to the starting point and commonly converges to a local optimal. The conventional techniques fail to find the problem solutions with significant computational time, so they are unsuitable for solving medium or large-scale CEED [19]. Thus, to address these issues, meta-heuristic population-based algorithms are proposed in this study for solving combined CEED problems with complex constraints. Various agents-based metaheuristic strategies have been utilized recently to solve complex constrained optimization problems. Numerous population-based methods were used for solving the nonlinear multi-objective CEED. Different techniques like a flash algorithm (LFA) [20], Modified Harmony Search (MHS) Algorithm [21], Bat Algorithm (BA) [22], Harmony search (HS) [23], Kho-Kho optimization (KKO) algorithm [24], Grasshopper Optimization Algorithm (GOA) [25], Squirrel Search Algorithm (SSA) [26]Moth Swarm Algorithm, Competitive Swarm Optimization [27], Modified Marine Predators Algorithm (MMPA) [28], Grasshopper Optimization Algorithm [29], Whale Optimization Algorithm (WOA) [30], Modified Artificial Bee Colony Algorithm [31], were proposed to solve various CEED problems.

MA is discovered by Zervoudakis and Tsafarakis in 2020 [32]. MA is used for solving various optimization problems such as optimizing maximum power point tracking (mppt) for photovoltaic systems [33], designing of uzzy PD-(1+I) controller for fully-renewable interconnected microgrid [34], optimal sizing and sitting of EVCS in the distribution system [35], a multi-stage PD(1+PI) controller design for DC–DC buck converter [36], performance analysis of various voltage stability indices in a stochastic OPF [37], design of PSS and SSSC-POD controllers in power system [38], OPF solution to deregulated electricity power market [39].

The essential contribution of this manuscript is suggesting MA approach for solving nonlinear and complex CEED problem. This strategy has various advantages, such as fast convergence, lower computational time, satisfactory exploration and exploitation performance, avoiding premature convergence, less complexity, and obtaining the optimal solution without trapping in global optima. This work is based on MATLAB environment. The proposed approach is established on the IEEE 30-bus benchmark. The numerical results are compared with results achieved from modern approaches, like the Jellyfish Search (JS) optimizer [40], Dwarf mongoose optimization (DMO) [41], Tunicate swarm algorithm (TSA) [42], Red deer algorithm (RDA) [43], Tuna Swarm Optimization (TSO) [44], Golden Eagle Optimizer (GEO) [45] and Bald eagle search Optimization algorithm (BES) [46].

II. Problem Formulation

Recently, numerous of studies have tried to model the power dispatch problem with planned generation units considering optimal economic-emission dispatch. The key target to solve the CEED problem is combining the weighted sum method and the minimized objective function taking into consideration the system constraints. The problem OF is defined as follows:

$$\min_x F(x,y) = \min_x \{w \sum_{n\in N_G} F_{\cos t}(x,y) + (1-w)\gamma \sum_{n\in N_G} Emission(x,y)\} \tag{1}$$

$$x = [P_{G1} ... P_{GNG-1}] \tag{2}$$

$$y = P_{Gsl} \tag{3}$$

A. Fuel Cost Objective

Individual generators have an essential fuel cost function that is depicted as a quadratic function of actual power.

$$F_{cost}(P_{Gi}) = a_i + b_i P_{Gi} + c_i {P_{Gi}}^2 \tag{4}$$

The sequential opening of a series of steam admission valves controls the output power of large generators driven by a steam turbine. The progressive rate of heat between the points of opening of every two valves decreases as the unit loading, input, and output all rise. Yet, the losses of throttling and the progressive rate of heating greatly rise when a valve is first opened. This phenomenon, called the "valve point effect (VPE)," results in non-convex and non-smooth input-output characteristics. Generally, a recurrent rectified sinusoid is collected to the fundamental quadratic cost objective to mimic the VPE. Practically, VPE is considered in the generator's cost function. As a result of the wire drawing effect, the losses are subject to a sharp increase. This occurs because the individual steam admission valve starts to open, causing a nonlinear rippled input-output curve [2, 3], as shown in Fig. 1. Considering the rippled curve, the OF represents a more accurate model:

$$F_{cost}(P_{Gi}) = a_i + b_i P_{Gi} + c_i {P_{Gi}}^2 + |d_i sin(e_i({P_{Gi}}^{\min} - P_{Gi}))| \tag{5}$$

Practically, various generating units in a power system are provided with multiple fuel types, like coal, oil, or natural gas. The ED problem becomes more complex and non-smooth when modelling the multifuel effect. This quadratic function is superimposed to form the unit cost function using several fuels as [48]:

$$\left\{ \begin{array}{c} F_{\cos t\; i}(P_{Gi}) = a_{ij} + b_{ij} P_{Gi} + c_{ij} {P_{Gi}}^2 + |d_{ij} sin(e_{ij}({P_{Gi}}^{\min} - P_{Gi}))| \\ if\ {P_{Gij}}^{\min} \le P_{Gi} \le {P_{Gij}}^{\max}, \text{ j=1,...,NF} \end{array} \right\} \tag{6}$$

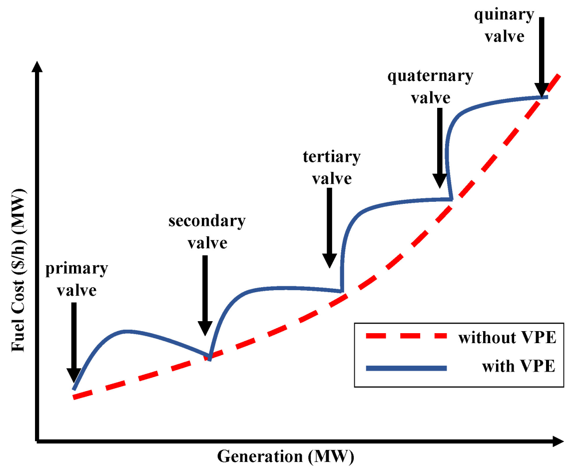

Fig. 1. Valve Point Effect [47]

B. Emission Objective

One of the most significant challenges that are facing humans is environmental pollution generated by thermal plants. These units emit particles and gases like sulfur dioxide (SO_2), carbon dioxide (CO_2), and nitrogen oxide (NO_x) into the atmosphere due to fossil fuels. Various OFs were suggested to denote the thermal unit emission. In this work, the addition of quadratic and exponential OFs is suggested. to define the thermal-units emission [49]:

$$Emission(P_{Gi}) = \alpha_i + \beta_i P_{Gi} + \eta_i {P_{Gi}}^2 + \xi_i e^{(\lambda_i P_{Gi})} \quad (7)$$

C. Constraints

Throughout the process of minimization, certain equality and inequality constraints should be fulfilled. An equality constraint in this process is referred to as a Power Balance (PB), while an inequality constraint is a generating capacity constraint.

1) Constraint of PB

The overall amount of power generated should meet the power loss P_{loss} and the overall power load demand P_{load}. Hence, the constraint of PB is denoted as:

$$\sum_{i\in NG} P_{Gi} - P_{load} - P_{loss} = 0 \quad (8)$$

Loss coefficients (B_{nj}) are used to represent system transmission losses which are known as B-loss matrices. These matrices denote the losses as a quadratic function of the generator's active power. So,

$$P_{loss} = \sum_{i\in NG}\sum_{j\in NG} P_{Gi}B_{ij}P_j + \sum_{i\in NG} B_{oi}P_{Gi} + B_{oo} \quad (9)$$

2) Generation Capacity Constraint

Individual generator active power is constrained by P_{Gi}^{min} and P_{Gi}^{max} output- power restrictions for stable operation and formulated as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le {P_{Gi}}^{\max}, \text{ i=1,...,NG} \quad (10)$$

Insertion of a rate limit of ramp function. The associated ramp rate constraints constrain all online units' actual operational ranges. The following conditions can be used to express the ramp-up and ramp-down:

$$\left\{ \begin{array}{l} P_{Gi} - {P_{Gi}}^o \le UR_i \\ {P_{Gi}}^o - P_{Gi} \le DR_i \end{array} \right\} \quad (11)$$

(10) should be modified owing to ramp rate limits as follows:

$$\max\{{P_{Gi}}^{\min}, {P_{Gi}}^0 - DR_i\} \le P_{Gi} \le min\{{P_{Gi}}^{\max}, {P_{Gi}}^0 + UR_i\} \quad (12)$$

Typically, ramp rate constraints are considered while dealing with a dynamic ED/CEED situation. With a time horizon schedule made up of consecutive time intervals (T). Traditional ED/CEED is solved for the individual time interval from the temporal T-horizon. They are considering the limits of prohibited operating zones (POZs). Sometimes physical operation restrictions prevent a generator from operating within its entire operating range. POZs may exist in a thermal-generating unit due to the shaft-bearing vibration. This vibration is caused due to steam valves, machines issues, and auxiliary equipment (boilers and feeding pumps). Such occurrences might cause instability in particular generator power output ranges. As a result, there are extra restrictions on the operating range for units with POZs as follows [50]:

$$P_{Gi} \in \left\{ \begin{array}{l} P_{Gi}^{\min} \le P_{Gi} \le P_{Gi,1}^{l} \\ P_{Gi,k-1}^{u} \le P_{Gi} \le P_{Gi,k}^{l}., k = 2,3,\ldots,pz_i; i = 1,2,\ldots,NPZ \\ P_{Gi,pz_i}^{u} \le P_{Gi} \le P_{Gi}^{\max} \end{array} \right. \quad (13)$$

D. Calculations of Slack Generator

A slack generator is a dependent generator that should be chosen to impose the power balancing constraint stated in (8). When the initial power loss value is zero ($P_{loss}^{old} = P_{loss}^{first} = 0$), the value of the slack generator's generation power, P_{Gsl}^{old}, is calculated using (14).

$$P_{Gsl}^{old} = P_{load} - \sum_{\substack{i=1 \\ i \neq sl}}^{NG} P_{Gi} \tag{14}$$

P_{Gsl}^{old} is obtained, after which P_{loss}^{new} is calculated from (9). According to this, the following equation is used to calculate P_{Gsl}^{new}.

$$P_{Gsl}^{new} = P_{load} + P_{loss}^{new} - \sum_{\substack{i=1 \\ i \neq sl}}^{NG} P_{Gi} \tag{15}$$

Equation (15) is controlled in (16). Power balance constraints are satisfied through this equation if the error (ε) value is less than the error tolerance value, $TOL_{\varepsilon}(TOL_{\varepsilon} = 10^{-6})$

$$\varepsilon = \left| P_{\text{loss}}^{\text{new}} - P_{\text{loss}}^{\text{old}} \right|, \varepsilon \leq TOL_{\varepsilon} \tag{16}$$

To determine if the obtained P_{Gsl} meets the constraint specified in (10). So, the definition of the P_{Gsl}^{lim} is

$$P_{Gsl}^{\text{lim}} = \begin{cases} P_{Gsl}^{\max} \text{ if } P_{Gsl} > P_{Gsl}^{\max} \\ P_{Gsl}^{\min} \text{ if } P_{Gsl} < P_{Gsl}^{\min} \\ P_{Gsl} \text{ if } P_{Gsl}^{\min} \leq P_{Gsl} \leq P_{Gsl}^{\max} \end{cases} \tag{17}$$

The quadratic penalty term can be obtained by adding the dependent variable's inequality constraint (P_{Gsl}) to the objective function. Assuming that λ_P is the penalty factor, the new objective function is,

$$F_p = F + \lambda_P (P_{Gsl} - P_{Gsl}^{\text{lim}})^2 \tag{18}$$

III. Research Methodology

The inspiration and mathematical model of Mayfly algorithm (MA) are first explained. Then, the algorithm stages are illustrated with complete expression of the mathematical model of MA.

IV. Inspiration of Mayfly Algorithm

2020 Zervoudakis and Tsafarakis discovered MA [32], inspired by adult mayflies' mating and flying behaviours. MA are aquatic insects. It is known as up-winged flies or fishflies. There are approximately 42 families and about 3500 species of mayflies worldwide. Their sizes range from tiny to medium; they are members of the Ephemeroptera family and belong to the Atalophlebia genus [51]. Their name is derived because they appear mainly in the UK during May [32]. MA algorithm is inspired by the movements and behaviour of female and male mayflies, also the mating behaviour of mayflies [51]. MA algorithm consists of three stages, i.e., initialization, movement, and mating

A. Initialization

In the initial stage, two populations are generated randomly. These random populations are, i.e., male mayflies and female mayflies.

B. Male and Female Mayflies Movement

After the initial stage, each mayfly updates its position in the search space to improve its fitness. The male's and female's behaviours are different during the mating process. The position, velocity of i^{th} mayfly male, and the cartesian distances are formulated as,

$$y_{ij}^{(t+1)} = y_{ij}^{t} + w_{ij}^{(t+1)} \tag{19}$$

$$w_{ij}^{(t+1)} = w_{ij}^{t} + \alpha_1 e^{-\beta r_p^2} * (pbest_{ij} - y_{ij}^{t}) + \alpha_2 e^{-\beta r_g^2} * (gbest_{ij} - y_{ij}^{t}) \tag{20}$$

$$\|y_i - Y_i\| = \sqrt{\sum_{j=1}^{n} (y_{ij} - Y_{ij})^2} \tag{21}$$

The velocity update of best mayfly is calculated as:

$$w_{ij}{}^{(t+1)} = w_{ij}^{t} + d_n * r_1 \tag{22}$$

Female mayflies do not group. They don't update their velocities while updating their movement. The survival duration range for mayflies' females is [1 day -1 week]. During this period, females mayfly fly attractive to males for mating and reproduction of new generations [51]. The current position and velocity of ith mayfly female are,

$$z_i^{(t+1)} = z_i^{t} + w_i^{(t+1)} \tag{23}$$

$$w_i^{(t+1)} = \begin{cases} {w_{ij}}^t + \alpha_2 e^{-\beta r_{mf}^2} * (y_{ij}^t - z_{ij}^t) \text{ if } f(z_i) > f(y_i) \\ {w_{ij}}^t + fl * r_1 \text{ if } f(z_i) > f(y_i) \end{cases} \tag{24}$$

C. Mating Process

In this stage, all the fittest half-female mayflies would be mated with the fittest half-male mayflies and the other best female with the other best male. The resulting offspring pair with l as a random number $\in [-1,1]$, are formulated in (25) and (26). The mayfly optimization algorithm is illustrated in the flowchart shown in Fig.2.

$$offspring1 = L * Male + (1-L) * Female \tag{25}$$

$$offspring2 = L * Female + (1-L) * Male \tag{26}$$

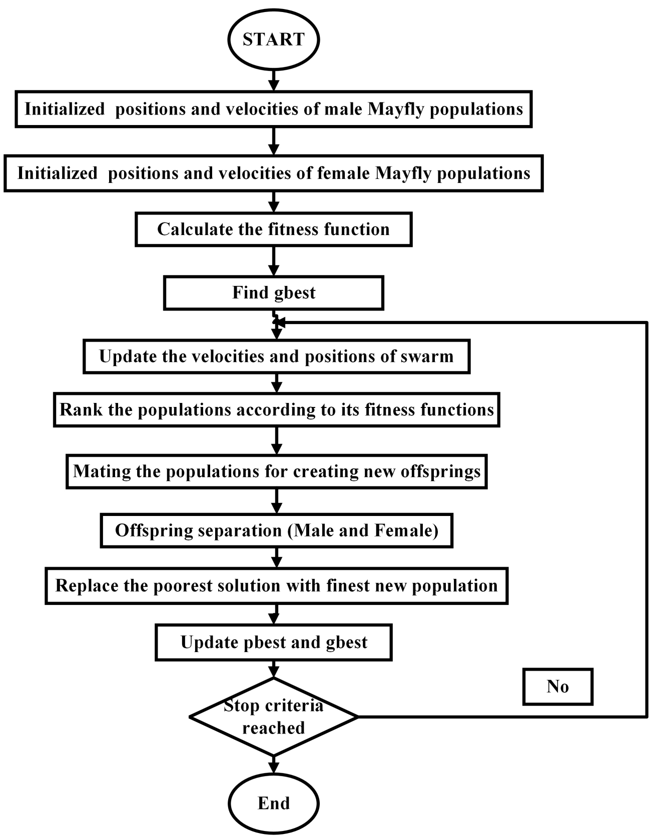

Fig. 2. Schematic Flowchart of MA.

V. Simulation and Results

This work proposes various metaheuristic optimization algorithms for solving CEED to examine its efficiencies. The IEEE 30-bus system is utilized to explore the applicability of the proposed algorithms. The total power demand of the test system is 283.4 MW. Table I. includes the fuel cost, NO_x emissions, and generation limit constants. The error tolerance value and the scaling factor are assumed $TOL_\varepsilon = 10^{-6}MW$ and $\gamma_{NOx} = 1,000(\$/t)$, respectively. The values of the B-loss matrix are illustrated in Table II. This study compares two cases: Case A considers P_{loss}, while Case B neglects P_{loss}. Three approaches are considered in this work. The first approach considered the fuel cost as an objective function with a weight factor of w=1. The second approach deals with NO_x emission as an objective function with a weight factor w=0. In the third approach, emission and fuel costs are treated as objective functions together in solving CEED problems with a weight factor of w=0.5. The identical system data, control variable limitations, and constraints were used to obtain the simulation results based on all proposed algorithms.

All proposed optimization algorithms are based on the same population size ($POP_{size} = 30$) and iteration number ($Max_{Iter} = 100$) for comparison purposes. The parameters of MA algorithms used in this work are $\alpha_1 = 0.9, \alpha_2 = 0.9$, $\beta = 0.5$, $\rho = 0.2$, *and* $fl = 1.5$.The optimum simulation results based on the proposed algorithms are recorded in Table III. All generating units share the loads optimally, considering reducing the fuel cost ($/h) and NO_x emission cost (ton/h) individually and collectively while maintaining all system constraints, taking into account P_{loss} (Case A) and neglecting P_{loss} (Case B). Table IV. shows the obtained comparison results for Case A with all considered approaches based on all proposed algorithms. In contrast, Table V. shows the obtained comparison results for Case B with all considered techniques based on all proposed algorithms. From the results, it's clear that all proposed algorithms have suitable characteristics for optimizing CEED problems for all considered cases and approaches. Some algorithms showed comparable results, but the MA algorithm performs better than other proposed techniques for solving CEED problems. MA has approximately the fastest convergence rate for all considered cases and approaches. MA shows advanced features for solving single-objective and multi-objective problems due to its ability to balance exploring and exploiting phases when discovering the search space during the optimization procedure. The algorithm's convergence curves for all considered cases and objectives are shown from Fig.3 to Fig. 8. The convergence curves show the fastest algorithms for attaining the optimal solution and the required iteration numbers of algorithms. It is clear that some algorithms have comparable features, but MA shows the fastest convergence rate with a lower iteration

TABLE I. Fuel Cost, Emission, and Generation Limits Coefficients [5]

Unit	$P_{Gi}^{\min}$ (MW)	$P_{Gi}^{\max}$ (MW)	a_i (\$/MW^2 h)	b_i (\$/MW h)	c_i (\$/ h)	α_i (ton/MW^2 h)	β_i (ton/MW h)	η_i (ton/h)	ζ_i (ton/h)	λ_i (1/MW)
1	0.05	1.5	10	200	100	4.09E-02	-5.55E-02	6.49E-02	2.00E-04	2.857
2	0.05	1.5	10	150	120	2.54E-02	-6.05E-02	5.64E-02	5.00E-04	3.333
3	0.05	1.5	20	180	40	4.26E-02	-5.09E-02	4.59E-02	1.00E-06	8
4	0.05	1.5	10	100	60	5.33E-02	-3.55E-02	3.38E-02	2.00E-03	2
5	0.05	1.5	20	180	40	4.26E-02	-5.09E-02	4.59E-02	1.00E-06	8
6	0.05	1.5	10	150	100	6.13E-02	-5.56E-02	5.15E-02	1.00E-05	6.667

TABLE II. The B-Loss Matrix Values [5]

B	1.38E-01	-2.99E-02	4.40E-03	-2.20E-03	-1.00E-03	-8.00E-04
	-2.99E-02	4.87E-02	-2.50E-03	4.00E-04	1.60E-03	4.10E-03
	4.40E-03	-2.50E-03	1.82E-02	-7.00E-03	-6.60E-03	-6.60E-03
	-2.20E-03	4.00E-04	-7.00E-03	1.37E-02	5.00E-03	3.30E-03
	-1.00E-03	1.60E-03	-6.60E-03	5.00E-03	1.09E-02	5.00E-04
	-8.00E-04	4.10E-03	-6.60E-03	3.30E-03	5.00E-04	2.44E-02
B0	-1.07E-02	6.00E-03	-1.70E-03	9.00E-04	2.00E-04	3.00E-03
B00	9.86E-04					

TABLE III.
THE OPTIMUM COMPRISES SOLUTION-BASED FUEL AND NO_X EMISSION OBJECTIVES

	w	Generation (MW)						Fuel cost (\$/h)	NO_x emission (ton/h)	Ploss (MW)
		PG1	PG2	PG3	PG4	PG5	PG6			
Case A	1	12.09692	28.6312	58.35573	99.28541	52.39703	35.1899	605.99837	0.21073	2.55619
	0	46.6048	57.59	45.9926	5	87.9023	44.6289	693.50413	0.20661	4.31862
	0.5	13.5214	36.6095	52.9171	82.3318	43.858	57.0731	614.14438	0.20121	2.91082
Case B	1	12.0803	28.7333	58.3171	99.2552	52.3635	35.2091	605.99853	0.22069	-
	0	41.0708	46.3898	54.4184	39.0081	54.4817	51.5636	646.22879	0.19418	-
	0.5	22.6814	35.4529	57.0857	74.4984	54.6753	41.5393	612.29454	0.20253	-

TABLE IV. Case A Optimum Solution

Method	Minimization of fuel cost (w=1)		Minimization of NO_x emission cost (w=0)		Minimization of CEED (w=0.5)	
	Fuel cost (\$/h)	NO_x emission (ton/h)	Fuel cost (\$/h)	NO_x emission (ton/h)	Fuel cost (\$/h)	NO_x emission (ton/h)
MA	605.99837	0.21073	693.50413	0.20661	614.14438	0.20121
JS	606.02704	0.22149	646.17298	0.19418	612.57267	0.20327
DMO	606.18296	0.2223	641.97852	0.1943	611.12151	0.20484
TSA	607.75178	0.22364	646.49853	0.19418	612.23991	0.20358
RDA	605.99946	0.22089	646.17717	0.19418	612.49164	0.20334
TSO	606.55556	0.2221	647.89513	0.19435	613.08269	0.20345
GEO	606.54504	0.21845	645.38505	0.1945	611.6239	0.20494
BES	606.46349	0.22066	648.36264	0.19466	611.96971	0.20475

number for all considered cases.

VI. CONCLUSION

This article proposes a modern metaheuristic optimization algorithm named Mayfly algorithm (MA) for solving complex

TABLE V. Case B Optimum Solution

Method	Minimization of fuel cost (w=1)		Minimization of NO_x emission cost (w=0)		Minimization of CEED (w=0.5)	
	Fuel cost ($/h)	NO_x emission (ton/h)	Fuel cost ($/h)	NO_x emission (ton/h)	Fuel cost ($/h)	NO_x emission (ton/h)
MA	605.99853	0.22069	646.22879	0.19418	612.29454	0.20253
JS	605.99895	0.22079	646.21306	0.19418	612.25702	0.20357
DMO	607.00276	0.22533	663.08038	0.19674	612.25427	0.20357
TSA	606.00844	0.22079	646.41592	0.19418	612.30821	0.20352
RDA	606.0746	0.2223	648.6505	0.19428	612.89744	0.20331
TSO	605.99855	0.2207	645.0639	0.19419	613.23698	0.20268
GEO	606.00341	0.22089	646.19853	0.19418	612.30972	0.20351
BES	606.91365	0.22756	646.32606	0.19418	617.73048	0.207

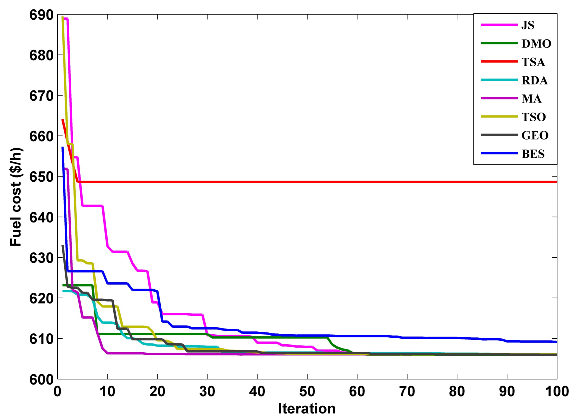

Fig. 3. Convergence Curve for Case A, w=1.

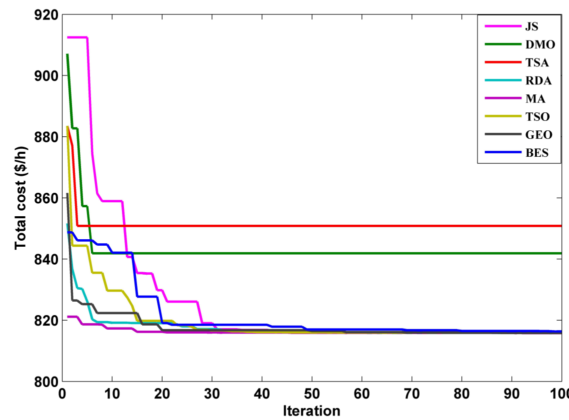

Fig. 5. Convergence Curve for Case A, w=0.5.

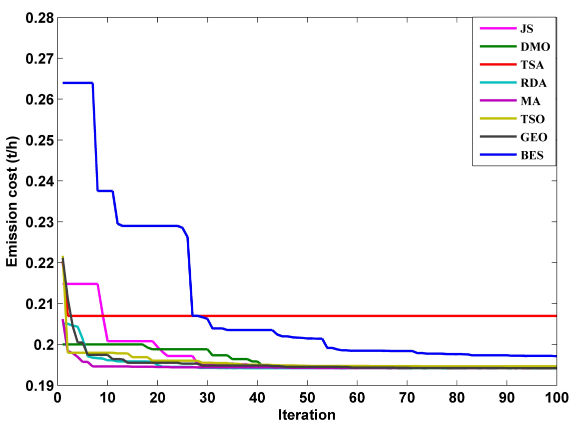

Fig. 4. Convergence Curve for Case A, w=0.

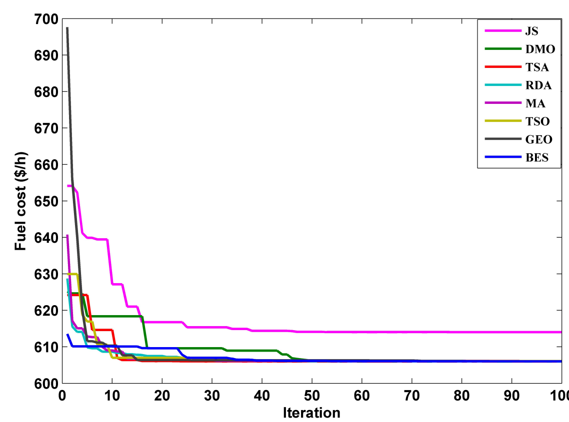

Fig. 6. Convergence Curve for Case B, w=1.

multi-objective CEED problems. The proposed technique is confirmed on IEEE 30-bus test system. To verify the proposed approach, the results are compared with correspondents' results obtained from several modern approaches such as Jellyfish Search (JS) optimizer, Dwarf Mongoose Optimization (DMO), Tunicate Swarm Algorithm (TSA), Red Deer Algo-

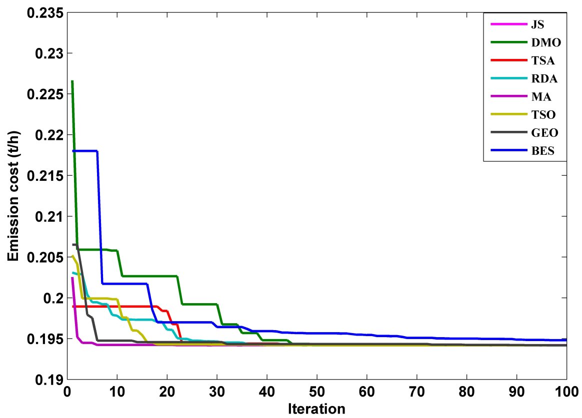

Fig. 7. Convergence Curve for Case B, w=0.

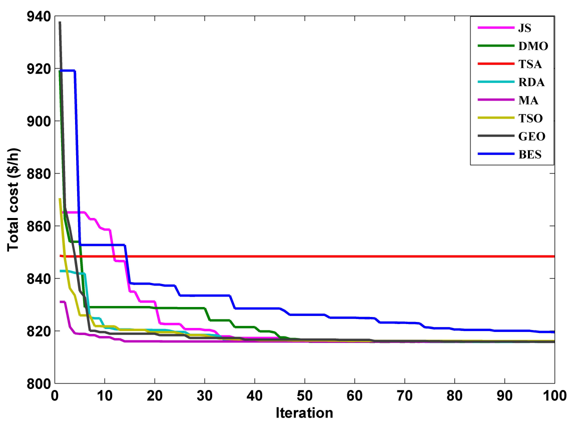

Fig. 8. Convergence Curve for Case B, w=0.5.

rithm (RDA), Tuna Swarm Optimization (TSO), Golden Eagle Optimizer (GEO), Bald Eagle Search Optimization Algorithm (BES). Simulation results show that all proposed algorithms optimize the CEED problem effectively for all considered cases and approaches while maintaining all system constraints. Some proposed algorithms offer comparable features. The MA algorithm gives a robust, effective, high-quality solution with the fastest convergence rate and lower iteration number, considering reducing the fuel cost ($/h) and NO_x emission cost (ton/h) individually and collectively while maintaining all system constraints. MA shows advanced features in optimizing CCED for all considered cases as illustrated in table (IV) and table (V). All proposed algorithms are proper for solving a complex problem such as CEED. Still, the best technique is MA due to its advantages of having the right exploration and exploitation balance.

Conflict of Interest

No conflict of interest in this work.

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