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A Modified Crow Search Optimizer for Solving Non-Linear OPF Problem With Emissions

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ABSTRACT This paper proposes a modified crow search optimizer (MCSO) for solving the combined economic emission power flow (EEPF) problem. In the proposed approach, the local search ability is enhanced into the crow search optimizer (CSO) and aggregated with a novel bat algorithm (NBA). Close accord between CSO, NBA, and MCSO is employed for solving the single and multi-objective frameworks. Moreover, the proposed MCSO incorporates external archive and dominance comparison to handle multi-objective frameworks while the best compromise solution is extracted by using a fuzzy based mechanism. The proposed MCSO, CSO, and NBA are developed and tested to on IEEE 30 bus and West Delta power grid (WDPG) systems. Added to the that, the proposed methodology is tested on a large-scale power system, IEEE 118-bus test system, for measure the scalability of the proposed method. Their output results are compared with the reported algorithms in the literature to demonstrate the MCSO outperformance in terms of solution quality and robustness. Significant economical solutions of the EEPF problem are achieved with respecting the environment concerns at acceptable emission levels. Added to that, the multi objective framework is assessed with hypervolume indictor that show the high capability of the proposed MCSO compared with CSO.

INDEX TERMS Crow search optimization, economic emission power flow, fuel costs, novel bat algorithm, valve loading effect.

I. INTRODUCTION

Power systems dispatchers operate the system with multiple economic and environmental dimensions especially with the increased penetration of renewable energy resources and power electronics devices [1]. Thus, the combined EEPF problem is one of the important issues in power system operation which finds out the optimal economic and environmental emissions of power generations for the online units.

Within the recent decades, the combined EEPF problem has been formulated as a very simplified mathematical optimization problem to determine only the power sharing of the generators with two main constraints which are power balance constraint and generator output limits [2] The first one is required that the total generated power has to meet the load and transmission network losses, but Kron's loss formula is usually utilized to model as the network losses [3].

The main defect of this model is the absence of various operational constraints which may be affected by the power sharing of the generators such as the transmission capacity constraint and the limits of the reactive power outputs of the generators. Consequently, the combined EEPF problem could be represented as an optimal power flow (OPF) problem, which is modelled as a high dimensional, nonlinear, multimodal, and multi-objective optimization problem [3]. The OPF problem aims to simultaneously minimizing the fuel cost and the emission level, and searches for the optimal settings of power generation, generator voltages, tap settings of transformers and reactive power sources outputs. The control variables are generated and updated through the optimization process and optimally specified without jeopardizing the operational equality constraints of the power flow balance and the inequality constraints of generator capability, line flow limit, and voltage profile of load buses.

A wide variety of classical optimization techniques have been applied to solve the OPF problem counting a single

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objective function, such as gradient projection method (GPM) [4], Newton-based techniques, second-order cone programming [5], linear, nonlinear, and quadratic programming. But they are very weak in handling multi-objective nonlinear problems as they may also converge to a local optimum.

Through few recent years, modern optimization techniques have been applied to solve the OPF problems such as simulated annealing (SA) [6], hybrid Bernstein global optimization algorithm [7], pathfinder algorithm [8], An improved imperialist competitive algorithm [9], symbiotic organisms search algorithm [10], tabu search (TS) [11], genetic algorithms (GA) [12], enhanced GA [13], [14], adaptive GA with adjusting population size [15], refined GA [16], evolutionary programming (EP) [17], improved EP [18], efficient evolutionary algorithm (EEA) [19], particle swarm optimization (PSO) [20], fuzzy-based hybrid PSO [21], modified DE algorithm (MDEA) [22]–[25], chaotic self-adaptive differential harmony search algorithm (CSDHSA) [26], evolving ant direction DE [27], [28], imperialist competitive algorithm (ICA) [29], [30], gravitational search method (GSM) [31], Black hole-based optimization algorithm (BHBOA) [32], improved moth-flame optimization (IMFO) [33], and improved electromagnetism-like optimization algorithm (IEOA) [34].

The continuous development in the era of optimization methods allow power system planners and operators to seek about the best method that has the capability to achieve the system requirements. CSO and NBA are two recent algorithms designed to find the optimal solution of real-valued optimization problems. They are inspired from the fascinating behavior of two types in the birds' family, crows, and bats, respectively. CSO is a novel population-based meta-heuristic algorithm, firstly proposed by Askarzadeh, which has very simple structure [35]. Bat algorithm is a novel meta-heuristic algorithm which is firstly pro-posed by Yang [36]. It mimics the echolocation process of bats where they fly randomly with automatic variation of their velocities to search for their food. With this fascinating characteristic, they can adapt their flight by adjusting the pulse rates of emission and loudness based on the closeness of their targets. It has been carried out to solve various power system problems. The bat inspired algorithm has been applied to combined economic environmental dispatch (EED) problem without security constraints of the transmission lines [37]. Also, it has been aimed to minimize the fuel costs of generation units as single objective EED problem based on the B-coefficient for losses computation without handling security constraints [38]. Moreover, it has been utilized for finding optimally the power system stabilizer parameters as in Refs [39], [40]. Despite the various applications of the bat algorithm, further improvements have been consolidated to improve its search capability that can avoid trapping into local optima and improve its convergence performance [41], which is addressed NBA. In NBA, the bat's frequency has been modified by an adaptive compensation considering the Doppler Effect in echoes. Added to that, quantum behaviour in updating the bat's velocity has been included where a selection operator has been used to choose between the quantum behaviour and the mechanical behaviour. It has been carried out effectively to solve twenty benchmark and four engineering problems [41].

Various studies have been introduced in solving the OPF topic considered such as efficient fitness-based DE optimizer with a constraint handling technique [42]. In that paper, a population similarity that is dependent on the fitness values was employed to select one of two mutation strategies to create the new mutant individuals. In [43], a memory-based DE optimizer with a dynamical crossover has been carried out. In this work, a repair constraint technique has been utilized for treating the constraints of generation capacity, units' ramp-rate and power balance. In [44], a hybrid multi-objective optimizer between PSO and DE has been presented where PSO were dedicated for exploration features and DE were designed to exploit the sub-space with sparse solutions. In [45], a bare-bones multi-objective PSO (BBPSO) has been applied where the particles' position is randomly picked from the Gaussian distribution with the mean of the personal and global best positions. In [46], BBPSO has been combined with a directionally chaotic search where it was applied as tuning operator for locating optimal solution. Despite the great effectiveness of these studies [42], [43], [44], [45], [46]. Several practical items in power systems were completely ignored such as the constraints of voltage nodes, the reactive power capability through the system, and the power flow through the lines.

In the current paper, a modified crow search optimizer (MCSO) is proposed for solving the combined EEPF problem. It is applied on three test systems with different sizes and objective functions.

The salient features of this paper can be concluded as:

- A parametric analysis of the CSO algorithm is executed for minimizing the fuel generation costs to extract its best values.
- A proposed MCSO incorporates the enchanting feature of the NBA of their local search ability into the CSO.
- A comparative study is executed for handling single and bi-objective functions.
- The proposed MCSO is evolved incorporating external archive and dominance comparison to handle the multi-objective EEPF formulations.
- The hypervolume indicator is added to check the Multiobjective approach capability.
- The proposed optimizer is developed and tested to solve the EEPF problem on the standard IEEE 30 bus and a practical Egyptian West Delta power grid (WDPG).
- The scalability of the proposed method is validated on the IEEE 118-bus test system.
- The simulation results are compared with other previous reported algorithms which demonstrate the outperformance of MCSO in terms of its solution quality and robustness.

II. FORMULATION OF THE COMBINED EEPF PROBLEM

Generally, the combined EEPF problem represents the simultaneous optimization of bi-objective functions related to the fuel generation costs and emissions while maintaining different equality and inequality constraints. Here, the independent/decision variables arethe active power outputs of the generators (Pg_1, Pg_2, ...Pg_{Ng}), generator voltages (Vg_1, Vg_2, ..., Vg_{Ng}), transformer tap settings (Tap_1, Tap_2, ..., Tap_{Nt}), and reactive power injection of switched capacitors and reactors(Qc_1, Qc_2, ..., Qc_{Nq}) where, Ng, Nt, and Nq are the number of generators, the number of on-load tap changing transformers, and the number of the VAR sources, respectively.

On the other side,the dependent variables are generally load bus voltage magnitudes (VL_1, ..., VL_{NPQ}), generator reactive power outputs of the generators (Qg_1, Qg_2, ..., Qg_{Ng}), and transmission line loadings (SF_1, ..., SF_{NF}) where, NPQ, and NF are the number of load buses, and the number of the transmission lines, respectively.

A. PROBLEM MATHEMATICAL REPRESENTATION

The mathematical representation of the combined EEPF problem is detailed as:

$$\text{Min } F = \{J1(x,y), J2(x,y)...., Jm(x,y)\} \tag{1}$$

$$\underline{\text{Subject to :}}$$

$$g(x,y) = 0 \tag{2}$$

$$h(x,y) \leq 0 \tag{3}$$

where, F is the considered vector of m objectives; x is the independent/decision variables; y is the dependent variables.

B. PROBLEM OBJECTIVES

Two types of objective functions are considered. The first objective aims at reducing the fuel costs. The second type is the emission minimization. The mathematical formulation of these two types is represented as:

1) MINIMIZATION OF FUEL GENERATION COSTS

The fuel generation costs can be represented by simple polynomial quadratic cost curve as follows:

$$J1 = \sum_{i=1}^{N_g} a_i Pg_i^2 + b_i Pg_i + c_i \tag{4}$$

where, J1 refers to the fuel generation costs in \$/hr; Pg_i is the MW active power output of each generator i; a_i, b_i, and c_i are the corresponding cost coefficients.

Considering the valve point loading effect that is characterized and accompanied with multiple ripples, as in practical power system, much more complex, nonconvex and nonlinear in the fuel cost of each generating unit is presented. In view of this regard, costs of fuel generation can be modeled as the polynomial quadratic costs in addition to rectified sinusoids and it is expressed as:

$$J2 = \sum_{i=1}^{N_g} a_i Pg_i^2 + b_i Pg_i + c_i + |e_i(\sin f_i(Pg_{i,min}\text{-}Pg_i))| \tag{5}$$

where, J2 refers to the fuel generation costs with valve point loading effect in \$/hr; $Pg_{i,min}$ is the lower limit of the active power output; e_i, and f_i are the valve point loading coefficients.

2) MINIMIZATION OF EMISSIONS OF THE POLLUTANTS

Fossil-fueled generators are the key source of atmospheric contaminants in electrical power systems where sulphur oxides (Sox), second carbon oxide (CO_2) and nitrogen oxides (NOx) are released. The total ton/hr emissions (J3) of these pollutants, in terms of the output power can be modeled as the exponential and quadratic function summation as follows:

$$J3 = \sum_{i=1}^{N_g} (\gamma_i Pg_i^2 + \beta_i Pg_i + \alpha_i)/100 + \zeta_i e^{\lambda_i Pg_i} \tag{6}$$

where γ_i, β_i, α_i, ξ_i, and λ_i are the emission coefficients of the atmospheric pollutants.

C. SYSTEM CONSTRAINTS

The previous objective functions are subjected to two set of constraints: equality and inequality constraints. The equality constraints represent the active and reactive power balance constraints while the inequality constraints represent the operational bending constraints. The formulation of these constraints is expressed as:

1) EQUALITY CONSTRAINTS

The load flow balance equations are usually taken as the equality constraints as follows:

$$Qg_i - QL_i + Qc_i - V_i \sum_{j=1}^{N_b} V_j(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) = 0, \quad i = 1, 2, ...NPQ \tag{7}$$

$$Pg_i - PL_i - V_i \sum_{j=1}^{N_b} V_j(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) = 0, \quad i = 1, ... N_b - \text{slack} \tag{8}$$

where, θ_{ij} is phase angle differences between bus i and j;N_b is the number of buses; PL and QL represent the active and reactive power demand, respectively; G_{ij} and B_{ij} are mutual conductance and susceptance between bus i and j, respectively.

2) INEQUALITY CONSTRAINTS

Moreover, the choice of control variables must respect the following operational constraints as follows:

$$Pg_i^{min} \leq Pg_i \leq Pg_i^{max} \quad, i = 1, 2, ... Ng \tag{9}$$

$$Vg_i^{min} \leq Vg_i \leq Vg_i^{max} \quad, i = 1, 2, \ldots\ldots Ng \tag{10}$$
$$Qg_i^{min} \leq Qg_i \leq Qg_i^{max} \quad, i = 1, 2, \ldots\ldots Ng \tag{11}$$
$$Tap_k^{min} \leq Tap_k \leq Tap_k^{max} \quad, k = 1, 2, \ldots\ldots Nt \tag{12}$$
$$Qc_q^{max} \leq Qc_q \leq Qc_q^{max}, q = 1, 2, \ldots\ldots Nq \tag{13}$$
$$V_{L_i}^{min} \leq V_{L_i} \leq V_{L_i}^{max} \quad, i = 1, 2, \ldots\ldots NPQ \tag{14}$$
$$|S_F| \leq S_F^{max} \quad, L = 1, 2, \ldots\ldots Nf \tag{15}$$

where the "min" and "max" superscripts indicate the minimum and maximum limits, respectively.

III. PROPOSED HYBRID SEARCH OPTIMIZERS

A. CROW SEARCH ALGORITHM

The salient feature of crows lies in their intelligence behavior of storing the excess food in hiding positions and retrieves it when it is needed. Therefore, the crows are searchers for different positions (solutions) in the environment (search space) in order to find the best food source (the optimal solution of optimization problems) [35].

The CSO is initialized step after identifying the population size (flock size) of crows and maximum number of iterations. Their initial positions over the d-dimensional search space are randomly scattered. The memory of each crow is initialized at their initial positions since the crows initially have no experiences where they have hidden their foods. After evaluating the fitness function of each crow, new position ($x^{i,t+1}$) of each crow (i) is generated where it randomly selects another one (j) of the flock crows and follows it to discover the position of the foods hidden by this crow. The new position of crow (i) is updated as follows:-

$$x^{i,t+1} = \begin{cases} x^{i,t} + r_i.fl^{\,i,t}.(m^{i,t}\text{-}x^{i,t}) & \text{if } r_j \geq AP^{j,t} \\ \text{a random position} & \text{otherwise} \end{cases} \tag{16}$$

where r_j and r_i represent random numbers between 0 and 1, t represents the present iteration number, $fl^{i,t}$ represents the flight length, and $AP^{j,t}$ is the awareness probability of crow (j) at iteration (t). It is set to constant value of 0.1 through the iterations. After that, the bounds of the new position of each crow are checked and if there is a violation, the crow moves to a new position randomly within the search space. Then, the new fitness function is computed. The memory ($m^{i,t+1}$) of each crow (i) is updated as follows:

$$m^{i,t+1} = \begin{cases} x^{i,t+1} & \text{if fitness } (x^{i,t+1}) \text{ is better than fitness } (x^{i,t}) \\ m^{i,t} & \text{otherwise} \end{cases} \tag{17}$$

Thus, the crow updates its memory by the new position if its new value of fitness function is better than its concerned value of the memorized position. This process of updating the crows' positions and memories are repeated until the maximum number of iterations is reached.

CSO is easier to implement as it has few parameters to be adjusted which are awareness probability and flight length. They effect on directing and controlling the search space into local search and global search areas during the consecutive iterations. The probability of searching around the neighborhood of the current good solutions increases with higher values of the awareness probability where the probability of searching on a global scale increases by decreasing it. Added to that, the values of flight length control most of the directions and the added increments of the discrimination between the best memorized position and the last position in each generation.

B. CONSTRAINTS HANDLING AND FITNESS FUNCTION EVALUATION

For handling the combined EEPF problem, two types of constraints are generally considered which are the equality constraints and the inequality constraints as explained before. In this study, the load flow balance equations of the electric power system, which represented the equality constraints, are handled inherently by solving the load flow problem using Newton Raphson method since it converges to a solution only if the load flow balance equations are achieved.

The Newton-Raphson (NR) load flow dependent tool is used in this paper to ensure the achievement of the power balance equations (7) and (8). Power flow computing, which defines the steady state of a system, is a main technique for network operators. The load flow is used to determine whether the power network can work adequately for the specified consumption and generation. Also, load flow equations are fulfilled in electrical network planning, control and operation [47].The load flow is the problem of calculating the voltage magnitudes and the angles for all buses of the power system where the power generation and consumption are achieved. Thus, the balance equations of the power generation and consumption for all buses and consequently the whole system is performed. Over the years, different control flow solution methods have been used. The NR method considers 2 distinct mismatch components: power and current balance equations and 3 distinct coordinate forms of complex, polar and cartesian. This results in six separate variations of the NR method. The NR tool is very effective to add to three-phase power flow problems and can be applied in MATPOWER [48].

For the other constraints related to the operational limits in the power system, they can be divided into the constraints of the control and dependent variables. The control variables begin to satisfy their limits but if any of them is outpaced during the iterations, it is regenerated randomly within the acceptable range below. On the other hand, using quadratic penalty terms, the dependent variables constraints in the considered fitness function are augmented. The solution in the next iteration, on this basis, which causes any violation in the constraints of the dependent variables, could not be chosen. Thus, the fitness function (F) is mathematically expressed as follows:

$$F = J + \psi_V \sum_{Nv_V} \Delta V_L^2 + \psi_Q \sum_{Nv_Q} \Delta Qg^2 + \psi_{SF} \sum_{Nv_{SF}} \Delta S_F^2 \tag{18}$$

where, ΔV_L, ΔQg, and ΔS_F are expressed as follows:

$$\Delta V_L = \begin{cases} V_L^{min} - V_L \text{ if } V_L < V_L^{min} \\ V_L^{max} - V_L \text{ if } V_L > V_L^{max} \end{cases} \quad (19)$$

$$\Delta Qg = \begin{cases} Qg^{min} - Qg \text{ if } Qg < Qg^{min} \\ Qg^{max} - Qg \text{ if } Qg > Qg^{max} \end{cases} \quad (20)$$

$$\Delta S_F = S_F^{max} - S_F \text{if } S_F > S_F^{max} \quad (21)$$

C. MODIFIED CROW SEARCH ALGORITHM

By remarking the update process of the CSO in Eq. 16, the new positions of the crows are generated based on the multiplied difference between the memorized position and a selected position of a randomly followed. Although this update process achieves good diversity in the solutions, kindly convergence, and global search ability, it suffers from the lack of local search capability. The CSO incorporates the enchanting NBA's feature of their local search ability [41]. In order to improve the CSO, its update process (Eq. 16) is modified by supporting the local search around the global best position (x^g) and so the new position ($x^{i,t+1}$) of each crow (i) is produced as follows:-

$$x^{i,t+1} = \begin{cases} x^{i,t} + r_j.fl^{\,i,t}.(m^{i,t}\text{-}x^{i,t}) & \text{if } r_j \geq AP^{j,t} \\ x^{g,t} + \dfrac{5 * rand}{1000} * (x^U - x^L) & \text{if } r_j < AP^{j,t} \text{and } rand \geq rand \\ \text{a random position} & \text{otherwise} \end{cases} \quad (22)$$

where x^L and x^U are the lower and upper limit of the crow's position which are specified related to the control variables at iteration (t). Using the proposed MCSO, the local search ability around the global best position (x^g) is incorporated and so the CSO performance is improved.

Fig. 1 demonstrates the major stages of the proposed MCSO for handling the single objective EEPF. From this figure, the MCSO framework can be summarized in the following steps:

Step 1: Specifying the parameters of the optimization method as: N, fl, AP and iter ^{max}.

Step 2: Initializing the crows' positions are randomly scattered over the d-dimensional search space.

Step 3: Checking the boundary limits of the crows' positions.

Step 4: Evaluate each crow fitness function of as Eq. (19).

Step 5: Updating the crows 'memories as Eq. (17).

Step 6: Extraction of the best position.

Step 7: Checking the maximum number of iterations. If it is reached, print the output results. Else, go to the next step.

Step 8: Updating the crows' positions as Eq. (22) and go to the step 3.

D. MULTI-OBJECTIVE MODIFIED CROW SEARCH ALGORITHM

To validate the proposed MCSO in handling the multi-objective combined EEPF Framework, the proposed MCSO

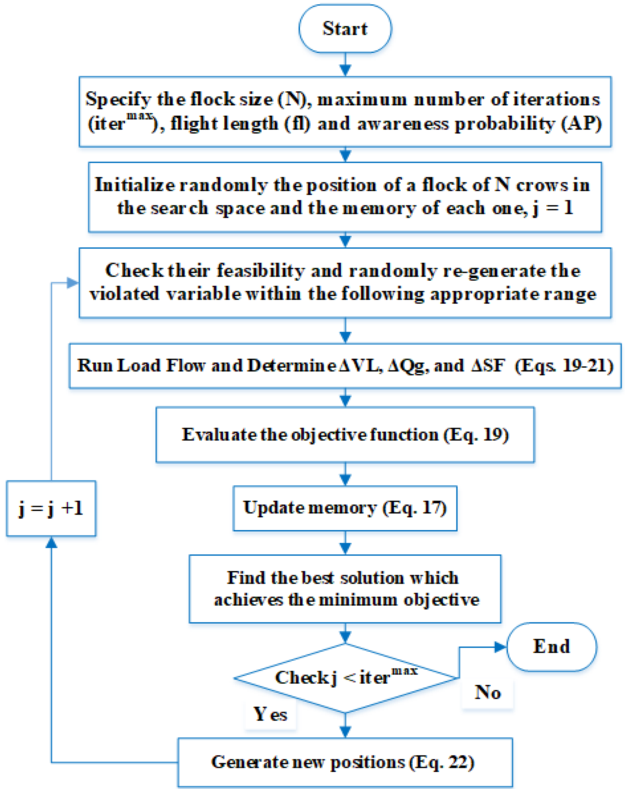

FIGURE 1. Proposed MCSO for handling the single objective EEPF.

is evolved incorporating external archive and dominance comparison. The Pareto dominance is utilized in two phases. The first one is the evolution of crow's memory where each crow compares the new position with its memorized one as follows:

$$m^{i,t+1} = \begin{cases} m^{i,t+1} \text{if } x^{i,t} & \text{dominates } x^{i,t+1} \\ x^{i,t+1} & \text{otherwise} \end{cases} \quad (23)$$

Added to that, an external archive is established to keep the non-dominated solutions. In each iteration, the updated memorized positions are added to the archive and they are compared to remove the dominated solutions. If the archive is oversized, some of them is deleted based on the most crowded portions [49]. Moreover, the update of $X^{g,t}$ in Eq. (22) can be taken from the archive to support the lowest crowded portions.

For the multi-objective combined EEPF problem, two minimization objectives are considered which are the fuel generating costs and environmental emissions. The fuel generating costs is formulated with the simple quadratic model and the sinusoid valve-point loading as expressed in Eqs. (4) and (5), respectively whereas, the environmental emissions are modeled as in Eq. (6). Thus, the proposed MCSO will give a set of pareto optimal solutions. In order to extract the best compromise solution, a membership function (μ_i) can be assigned for each objective function

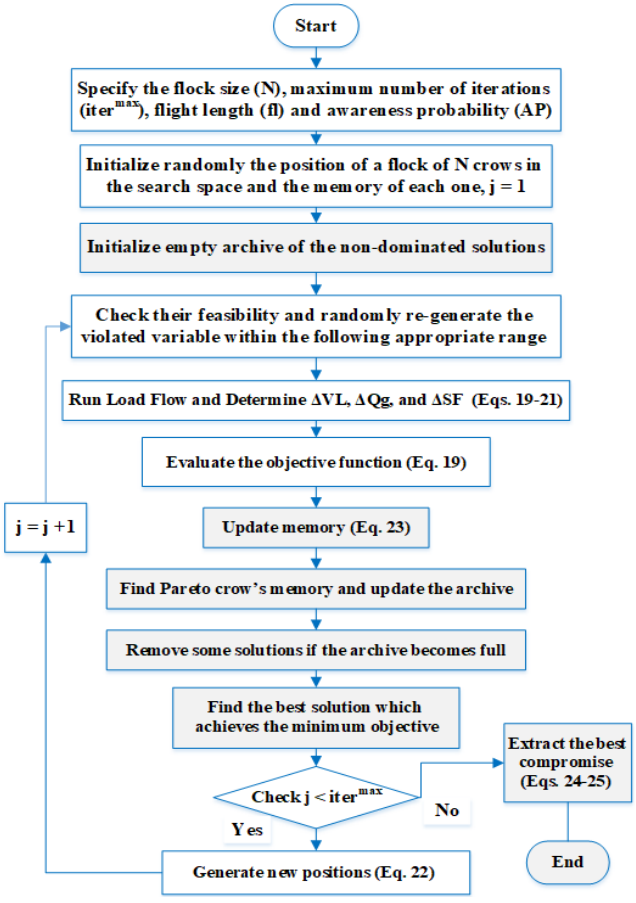

FIGURE 2. MCSO for handling the multi-objective EEPF.

as follows: -

$$\mu_i(J_i) = \begin{cases} 1, & J_i \leq J_i^{min} \\ \dfrac{J_i^{max} - J_i}{J_i^{max} - J_i^{mim}}, & J_i^{min} \leq J_i \leq J_i^{max} \\ 0, & J_i \geq J_i^{max} \end{cases} \tag{24}$$

Then, a distinguished solution is excerpted using a fuzzy based mechanism which acquires the maximum membership (μ^q) as follows: -

$$\mu^q = \frac{\sum_{i=1}^{m} \mu_i(J_i^q)}{\sum_{q=1}^{n} \sum_{i=1}^{m} \mu(J_i^q)} \tag{25}$$

where, q, m, and n refer the output solution related to the non-dominated Pareto set; number of objectives, and number of compromise solutions, respectively. Fig. 2 demonstrates the major stages of the proposed MCSOfor handling the multi-objective EEPF. From this figure, the MCSO framework for handling the multi-objective EEPF can be summarized in the following steps:

Step 1: Specification of N, fl, AP and iter^{max}.

Step 2: Initializing the crows' positions are randomly scattered over the d-dimensional search space.

TABLE 1. Cost coefficients for the IEEE 30-bus test system.

Bus	a	b	c	e	f
1	0	2	0.00375	18	0.037
2	0	1.75	0.0175	16	0.038
5	0	1	0.0625	14	0.04
8	0	3.25	0.00834	12	0.045
11	0	3	0.025	13	0.042
13	0	3	0.025	13.5	0.041

TABLE 2. Emission coefficients for the IEEE 30-bus test system.

Bus	Γ	β	α	ξ	λ
1	4.091	-5.554	6.49	0.0002	2.857
2	2.543	-6.047	5.638	0.0005	3.333
5	4.258	-5.094	4.586	0.000001	8
8	5.326	-3.55	3.38	0.002	2
11	4.258	-5.094	4.586	0.000001	8
13	6.131	-5.555	5.151	0.00001	6.667

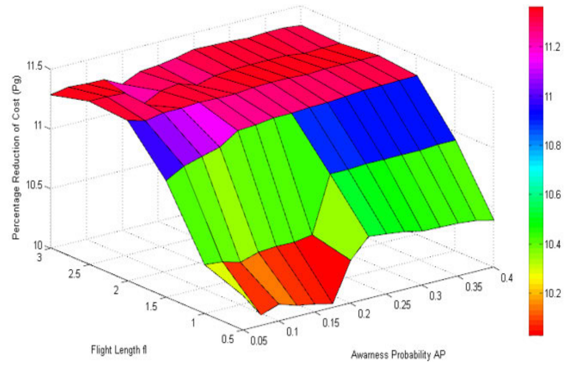

FIGURE 3. Effect of varying CSO parameters for minimizing the fuel generation costs.

Step 3: Initializing an empty archive to store the non-dominated solutions.

Step 4: Checking the boundary limits of the crows' positions.

Step 5: Evaluating each crow fitness function of as Eq. (19).

Step 6: Updating the crows 'memories via Eq. (23).

Step 7: Updating the archive to store the non-dominated solutions.

Step 8: Remove some solutions from the archive if it becomes full.

Step 9: Extraction of the best compromise position.

Step 10: Checking the maximum number of iterations. If it is reached, go to step 12. Else, go to the next step.

Step 11: Updating the crows' positions as Eq. (22) and go to the step 4.

Step 12: Apply Eqs. (24-25) to extract the best solution and print the output results

E. PARAMETRIC ANALYSIS OF CSO

For CSO algorithm, two parameters are necessary to be adjusted which are the awareness probability and flight length. In this section, a parametric analysis of varying them is studied for minimizing the fuel generation costs and thus the optimal tuning of the awareness probability (AP) and the

TABLE 3. Optimal results of CSO, NBA, and MCSO for Cases 1-3.

Variables	Initial	Case 1			Case 2			Case 3		
		CSO	NBA	MCSO	CSO	NBA	MCSO	CSO	NBA	MCSO
Pg_1	99.24	177.9469	178.2412	177.3806	193.401	193.06024	194.3064	63.45604	62.550345	63.797771
Pg_2	80	47.96531	48.49051	48.37716	46.83737	44.379653	47.0069	69.03579	69.875461	68.023902
Pg_5	50	20.96091	22.06557	21.06754	19.11272	18.343681	19.99696	49.97946	49.732885	49.982801
Pg_8	20	20.17398	18.00288	21.34746	10.45844	15.402699	10.10781	34.88771	35	34.974457
Pg_{11}	20	12.47427	13.43181	11.86799	11.6778	10.1836	10.13166	29.97441	29.999897	29.983921
Pg_{13}	20	12.74453	12.00308	12.07041	12.15345	12.075431	12.06438	39.9395	39.59735	39.996208
Vg_1	1.05	1.099625	1.099991	1.099947	1.096869	1.0996183	1.099741	1.07693	1.0779587	1.079127
Vg_2	1.04	1.085509	1.089153	1.085965	1.075388	1.0776362	1.078755	1.067067	1.0763583	1.0793066
Vg_5	1.01	1.05455	1.067514	1.056108	1.057434	1.0375211	1.048548	1.03831	1.0665001	1.0537384
Vg_8	1.01	1.061552	1.067956	1.067651	1.054002	1.0450355	1.059669	1.021921	1.06594	1.061507
Vg_{11}	1.05	1.068338	1.09887	1.099433	1.095232	1.0986521	1.031474	1.054431	1.0743655	1.0591337
Vg_{13}	1.05	1.067791	1.089725	1.098362	1.044548	1.097693	1.098908	1.017924	1.0489585	1.0312712
Tap_{6-9}	1.078	0.971298	1.049783	0.9935341	0.969594	1.0640091	1.00256	1.078954	0.9494958	1.0813739
Tap_{6-10}	1.069	1.044253	1.066483	0.9627101	1.039099	0.9133678	0.938854	0.967206	1.0772022	0.9546124
Tap_{4-12}	1.032	1.041707	1.071882	0.9753389	0.975999	0.9781457	1.036122	1.041287	1.0424701	1.0465819
Tap_{28-27}	1.068	0.976595	0.9953713	0.9672678	0.981737	0.9833765	1.031202	0.924277	1.0379917	1.0180144
Qc_{10}	0	3.357921	2.474448	4.231311	3.464998	2.1315304	2.440953	1.793663	4.0261839	1.9395212
Qc_{12}	0	4.575399	1.869648	1.698412	3.350395	3.2021289	0.654319	2.026773	4.4230503	1.6217145
Qc_{15}	0	2.064652	1.414391	2.935065	4.390435	1.2646539	3.621192	3.400612	1.0618252	3.4331457
Qc_{17}	0	2.86074	3.932666	3.687713	0.894978	0.5512738	1.130666	3.191422	0.5625221	0.9288512
Qc_{20}	0	1.985778	3.201136	4.063746	2.861983	2.3719301	3.173386	3.83256	4.9389171	2.6894673
Qc_{21}	0	2.085459	4.894799	3.050749	0.674316	0.4646686	2.999132	4.387908	2.9981094	0.7516873
Qc_{23}	0	3.142051	1.974769	2.246753	1.138963	3.3717978	4.026354	4.200116	2.1212593	0.8856497
Qc_{24}	0	3.553219	3.845593	3.685882	4.493178	3.7903701	2.53109	2.047322	3.7574729	2.2084581
Qc_{29}	0	0.951617	2.98529	3.986623	3.792734	4.2568298	3.604695	1.73174	1.4291255	1.7932539
Time (Sec)/iteration		0.279325	0.284566	0.27176	0.271485	0.2858	0.2717	0.270679	0.286955	0.269853
J1 ($/hr)	901.96	799.8266	799.7516	**799.3332**						
J2 ($/hr)	960.22				834.9663	835.19554	**833.8211**			
J3 (ton/hr)	0.23909633	**Note: Bold value shows best values**						0.2051355	0.2052063	**0.2048911**

flight length (fl) is extracted. Various combinations of AP and fl with different values is utilized and the CSO program is run for each combination to minimize the quadratic model of the fuel generation costs (Eq. 4) and the related percentage reduction is evaluated as follows:-

Percentage reduction of fuel costs

$$= \frac{F^{\text{initial}} - F^{\text{optimal}}}{F^{\text{initial}}} \times 100\ \% \qquad (26)$$

where, F^{optimal} denotes the optimal value of the fuel costs that acquired using CSO and F^{initial} is the fuel costs respect to the initial condition.

IV. SIMULATION RESULTS

A. TEST SYSTEMS

In this section, three test systems are considered to check the capability of the proposed optimizers. These systems are: the standard IEEE 30 bus, the West Delta power grid (WDPG) as a portion of the Egyptian system and the large scale IEEE 118-bus test system. The IEEE 118-bus is considered to prove the scalability of the proposed solution methodology.

The first system is the IEEE 30 bus which consists of 30 buses, 41 lines, 6 generators, 4 on-load tap changing transformers and 9 capacitive sources. The data for buses, transmission lines, and the minimum and maximum limits of reactive power generations are taken from [48]. The maximum and minimum values for the generator voltage are 1.1 and 0.95 p.u., respectively. The maximum and minimum voltages for the load buses and tap changing transformer are considered to be 1.05 and 0.95 p.u., respectively. Cost coefficients, emission coefficients are given in Tables 1 and 2. The VAR injections of the capacitive sources are limited by 5 MVA. The 2nd system is the practical WDPG which consists of 52 buses, 108 lines and 8 generators [50], [51]. The upper and lower voltages equal 1.06 and 0.94 p.u., respectively. The lower and upper boundaries for all generators are 10 MW and 250 MW. The upper limit of Generator at bus 5 equals 375 MW.

The third test system is the large-scale power network includes 54 generators, 118 buses, 14 Var compensators, 186 branches, and 9 transformers tap which means 130 control variables. This system is tested to show the scalability degree of the proposed approach.

The simulation runs were performed for CSO, NBA, and MCSO with NP = 50, and maximum of 300 iterations. The archive size equals 100 nondominated solution. The proposed MCSO, CSO, and NBA are developed MATLAB environment. Appendix A reports the parameters of various tested methods.

B. CASES STUDIED

Single and Multiobjective cases are considered as:

Case 1: aims at minimizing the quadratic fuel costs,

Case 2: aims at minimizing the non-smooth sinusoidal fuel costs. The effect of the valve point loadings of thermal generators is considered as Eq. 5.

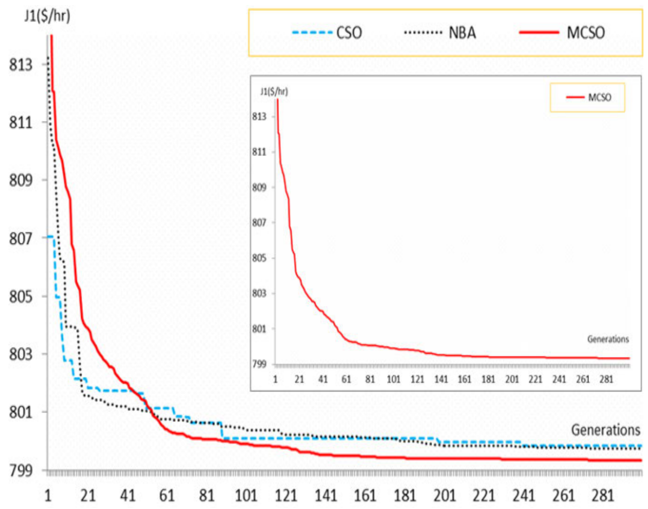

FIGURE 4. Convergence characteristics of CSO, NBA and MCSO for Case 1.

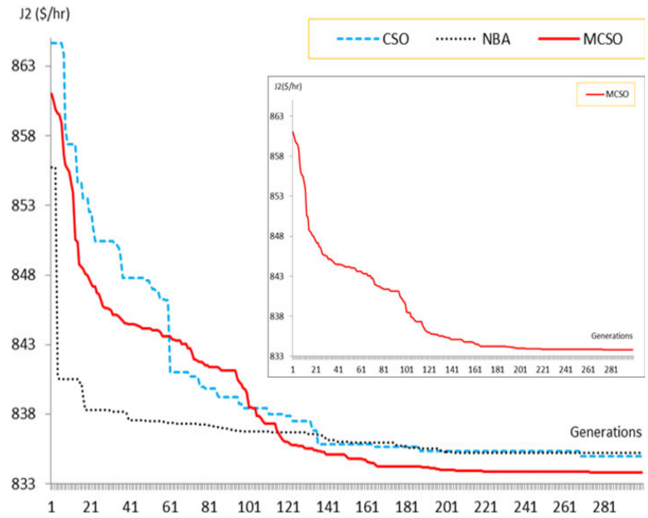

FIGURE 5. Convergence characteristics of CSO, NBA and MCSO for Case 2.

TABLE 4. Comparison results for minimizing the fuel costs (Case 1).

Method	J1 ($/HR)	METHOD	J1 ($/HR)
Proposed MCSO	**799.3332**	FEA [19]	800.0831
SA [6]	799.45	CSDHSA [26]	801.5888
Enhanced GA [13]	799.56	ICA [29]	801.843
NBA	799.7516	DHSA [26]	802.2966
CSO	799.8266	MDEA [25]	802.376
AGAPOP [15]	799.8441	EP [17]	802.62
BHBOA [32]	799.9217	GPM [4]	804.853
IGA [52]	800.805	EADHDE [27]	800.1579
IEOA [34]	799.688	Enhanced GA [14]	802.06
EADDEA [28]	800.2041	TS [11]	802.2900
PSO [20]	800.41	Improved EP [18]	802.465
IMFO [33]	800.3848	Refined GA [16]	804.02

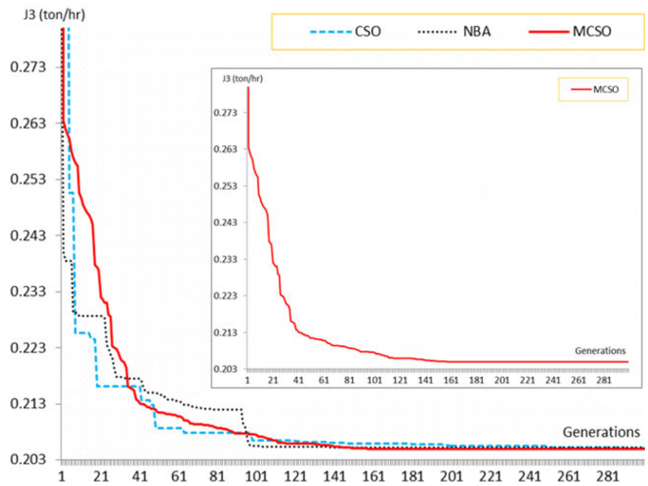

FIGURE 6. Convergence characteristics of CSO, NBA and MCSO for Case 3.

Case 3: aims at minimizing the pollutant emissions, the summation of quadratic and exponential function in terms of the output power (Eq. 6) is considered which represents the total ton/hr emissions of these environment pollutants.

Case 4: Bi-objective minimization of quadratic fuel costs (J1) and environmental emissions (J3) are simultaneously optimized together.

Case 5: Bi-objective minimization of fuel costs with sinusoids (J2) and environmental emissions (J3) are simultaneously optimized.

C. PARAMETRIC ANALYSIS OF CSO

Fig. 3 displays the effect of utilizing different values of AP and fl for minimizing the fuel costs where AP is varied from 0 to 0.4 with step 0.05, and simultaneously fl is varied from 0 to 3 with step 0.5. As shown, the optimal tuning of both AP and fl to be within the ranges [0.2-0.4] and [1.5-3], respectively in solving the EEPF problem. From this conclusion, the control parameters for CSO can be taken simply with AP = 0.3 and fl = 2.

D. SIMULATION RESULTS FOR IEEE 30 BUS SYSTEM

1) RESULTS OF SINGLE OBJECTIVE CASES

In the first case, the minimization of the quadratic model of the fuel generation costs (Eq. 4) is considered. The proposed MCSO, CSO and NBA have been run for Case 1 and the optimal results are tabulated in Table 3. In addition, the convergence characteristics related to them for this objective over iterations is shown in Fig. 4. Table 3 and Fig. 4 evince that the minimum fuel cost is obtained using the proposed MCSO that the fuel costs of generation units is reduced from 901.96 $/hr to 799.3332 $/hr compared with the initial case. On the other side, the fuel costs of generation units using CSO and NBA is minimized to 799.8266 $/hr, and 799.7516 $/hr compared with the initial case. Also, the outperformance of the proposed MCSO over various reported techniques for minimizing the quadratic model of the fuel generation costs is demonstrated in Table 4 since the obtained value using the proposed MCSO (799.3332 $/hr) is quite competitive and better than most of reported techniques that are previously cited.

In the second case, the non-smooth cost curve of the fuel generation costs is considered which introduces more nonlinearity in the fitness function. The effect of the valve

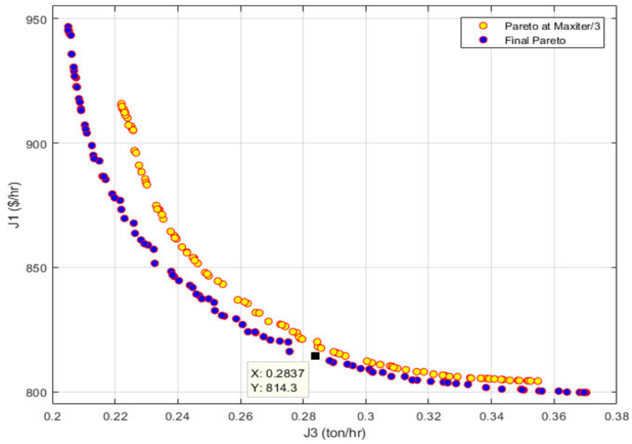

FIGURE 7. Pareto solutions attained by the proposed MCSO for Case 4.

TABLE 5. Extracting the best compromise solution based on fuzzy based mechanism (Case4).

Solution No. (q)	J1 ($/hr)	J3 (ton/hr)	μ(J1)	μ(J3)	μ^q
1	799.7369	0.37024	1	0	0.011764
2	799.79233	0.36929856	0.99963	0.0000599	0.01176
..					
..					
17	804.16313	0.320676192	0.969931	0.300042	0.014949
..	..	..	..	..	..
28	814.3	0.2837	0.90094	0.523945	0.016763
..	..	..	..	..	..
70	873.28744	0.2220005	0.4996	0.89842	0.01644
..	..	..	..	..	..
100	946.7386	0.20507	0	1	0.011764

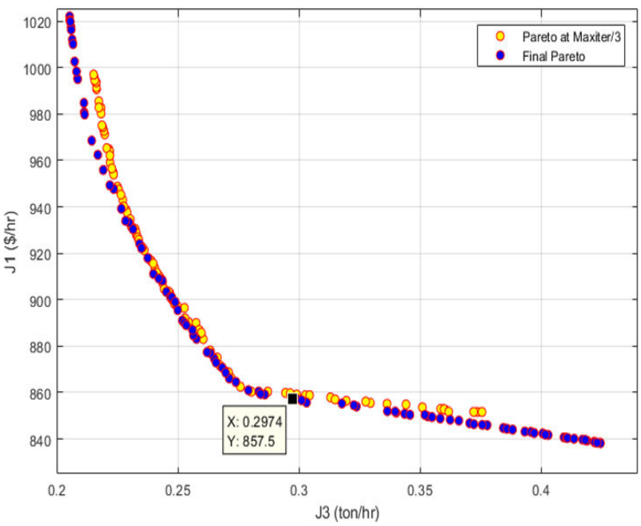

FIGURE 8. Pareto solutions attained by the proposed MCSO for Case 5.

TABLE 6. Statistical results for Cases 1-3.

	Initial	Average	STD	STE
Case 1	MCSO	**799.614**	0.153765	0.028074
	CSO	800.281	0.378754	0.069151
	NBA	800.4961	0.523783	0.095629
Case 2	MCSO	**835.102**	0.834367	0.152334
	CSO	837.185	1.356164	0.2476
	NBA	838.119	2.350478	0.429137
Case 3	MCSO	**0.20518219**	1.18E-04	2.16E-05
	CSO	0.20578510	5.73E-04	1.05E-04
	NBA	0.2083627	3.45E-03	6.30E-04

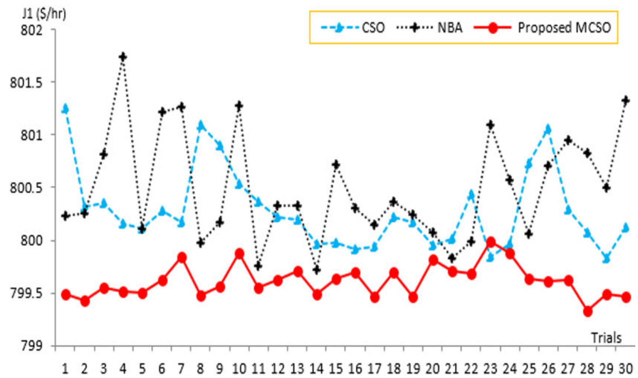

FIGURE 9. Optimal J1 attained by the compared optimizers for Case 1.

TABLE 7. Hypervolume indicators of CSO and MCSO for Cases 4 and 5.

	CSO	Proposed MCSO
Case 4	0.194	0.1956
Case 5	0.1477	0.1619

point loadings of thermal generators is considered as Eq. 5. Table 3 shows the optimal control variables of the proposed CSO, NBA, and MCSO for Case 2, and Fig. 5 plots the regarding convergence characteristics for minimizing the sinusoidal fuel costs over iterations. It can be noticed from Table 3 and Fig. 5 that the best fuel costs are obtained using the proposed MCSO that the fuel costs of generation units is reduced from 960.22.96 $/hr to 833.8211$/hr compared with the initial case. On the other side, the fuel costs of generation units using CSO and NBA is minimized to 834.9663 $/hr, and 835.19554 $/hr compared with the initial case.

In the third case, the summation of quadratic and exponential function in terms of the output power (Eq. 6) is considered which represents the total ton/hr emissions of these pollutants in the environment. Table 3 shows the related results of the proposed CSO, NBA, and MCSO for Case 3 and the convergence of this objective is depicted in Fig. 6. As shown, the acquired results using the proposed MCSO algorithm outperforms the above CSO and NBA. This confirms the effectiveness and potential of the proposed MCSO in solving the EEPF problem.

The computational burdens of CSO, NBA, proposed MCSO for Cases 1, 2 and 3 are measured in Table 3. They are estimated via the taken seconds per each iteration along with the NR load flow tool. It indicates that the operating times for the applied algorithm is not considerably different whereas the developed MCSO provides the least time by 0.27176, 0.2717 and 0.2698 seconds for the three cases respectively. This is key to the opportunity to target the quest for the right candidate in the previous iteration.

TABLE 8. Optimal results of CSO, NBA, and MCSO for minimizing the fuel costs (Case 1).

	Min	Max	Initial	SSA	NBA	CSO	ISHO	GWO	MCSO
Pg_1	10	250	85.69	199.957	189.6562	188.6092	190.457	188.8009	188.6438
Pg_2	10	250	157.4	10.99513	10.0011	10.0769	12.55756	10.10499	10.0027
Pg_3	10	250	139.31	208.9112	217.6427	212.4916	213.0466	211.9435	214.2164
Pg_4	10	250	113.69	171.4405	175.6998	185.001	178.6136	185.0775	182.4447
Pg_5	10	375	166.48	10.80346	10.4021	10.0163	10.22916	10.18727	10.0295
Pg_6	10	250	31.71	245.1195	224.2499	236.1791	232.5844	241.5001	233.9896
Pg_7	10	250	92	58.68968	59.5161	53.3116	55.84246	54.93508	51.3972
Pg_8	10	250	122.49	20.78929	39.3715	32.2604	33.80792	25.32619	36.7826
Vg_1	0.94	1.06	1	1.06	1.06	1.0587	1.06	1.059923	1.06
Vg_2	0.94	1.06	1	1.06	1.06	1.0595	1.06	1.059333	1.0592
Vg_3	0.94	1.06	1	1.059953	1.0562	1.0596	1.06	1.058511	1.0599
Vg_4	0.94	1.06	1	1.059016	1.0556	1.055	1.06	1.058678	1.0576
Vg_5	0.94	1.06	1	1.058172	1.054	1.0505	1.06	1.057554	1.0598
Vg_6	0.94	1.06	1	1.055967	1.0476	1.0561	1.06	1.05531	1.0571
Vg_7	0.94	1.06	1	1.041037	1.0311	1.0436	1.04593	1.04314	1.0409
Vg_8	0.94	1.06	1	1.048812	1.0455	1.0484	1.050413	1.047502	1.0497
J1 ($/hr)	-	-	25098.7	22965.59	22960.81	22959.36	22958.78	22957.72	**22955.55**
Loss (MW)	-	-	19.015	36.95583	36.7895	38.1969	37.38872	38.12547	37.75

2) RESULTS OF BI-OBJECTIVE COMBINED EEPF OPTIMIZATION

Bi-objective combined EEPF optimization problem is handled considering simultaneously two objectives. The proposed MCSO (Fig. 2) are applied where the archive size is fixed at 100 nondominated solutions. In Case 4, the proposed MCSO are carried out for minimizing the quadratic model of the fuel generation costs (J1) and the environmental emissions (J3). Therefore, Pareto solutions are attained by running the proposed MCSO as depicted in Fig. 7. As shown, the contour of the improvements in the Pareto solutions are declared from one-third to full maximum iterations. It can be noticed that the obtained solutions have good diversity which demonstrate wide possible operating points to the power system operator.

The best compromise is extracted by fuzzy based mechanism with fuel cost and environmental emissions of 814.3 $/hr and 0.2837 ton/hr, respectively. For this case, Table 5 shows the methodology of extracting the best compromise solution based on fuzzy based mechanism. As shown, the maximum values of the fuel costs and the emissions are 946.7386 $/hr and 0.37024 ton/hr, respectively. Based on these values, the evaluation of the membership values for each objective and each solution is carried out. Then, the best compromise solution is extracted that has the maximum membership (μq) of 0.016763.

In Case 5, the fuel costs considering the valve point loadings (J2) and the environmental emissions (J3) are simultaneously considered as bi-objective functions. The procured Pareto set for this case is illustrated in Fig. 8. As shown, the improvements in the Pareto solutions are guaranteed with good diversity to validate wide possible operating points to the power system operator. The best compromise can be extracted by fuzzy based mechanism with fuel cost and environmental emissions of 857.5 $/hr and 0.2974 ton/hr, respectively.

3) STATISTICAL COMPARISON

To analyze the robustness performance of the proposed MCSO, CSO and NBA. They have been run for Cases 1, 2 and 3 for 30 times and an assessment via the acquired average value, the standard deviation (STD) and the standard error (STE) are calculated in Table 6. The acquired average of the proposed MCSO is always the minimum where it has the lowest STD and STE. Additionally, Fig. 9 displays the obtained optimal objectives for Case 1. As shown, the proposed MCSO has greater stability and outperformance over CSO and NBA as it is always capable to find the minimum value.

Hypervolume is one of the most popular indicators in evaluating the comprehensive performance of MCSO for Cases 4 and 5. Table 7 illustrates this indicator to investigate the quality of the Pareto-optimal solutions obtained by CSO and MCSO for Cases 4 and 5 considering a reference point of 1000 $/hr and 100 ton/hr. As shown, the proposed MCSO declares better performance than CSO for both cases. The proposed MCSO has the highest value of hyber volume indicators of 0.1956 and 0.1619 whereas the CSO obtains hyber volume indicators of 0.194 and 0.1477 for Cases 4 and 5, respectively.

E. SIMULATION RESULTS OF WDPG

1) COMPARATIVE RESULTS

The second system is the practical WDPG which consists of 52 buses, 108 lines and 8 generators [50], [51]. The maximum and minimum values for the generator voltage are 1.06 and 0.94 p.u., respectively. For this system, the minimization of the quadratic model of the fuel generation costs (Eq. 4) is considered. The proposed MCSO, salp swarm algorithm (SSA) [49], NBA, CSO, GWO [53], and improved spotted hyena optimizer (ISHO) [54] have been run and the optimal results are tabulated in Table 8. In addition, the convergence characteristics related to them is shown in Fig. 10.

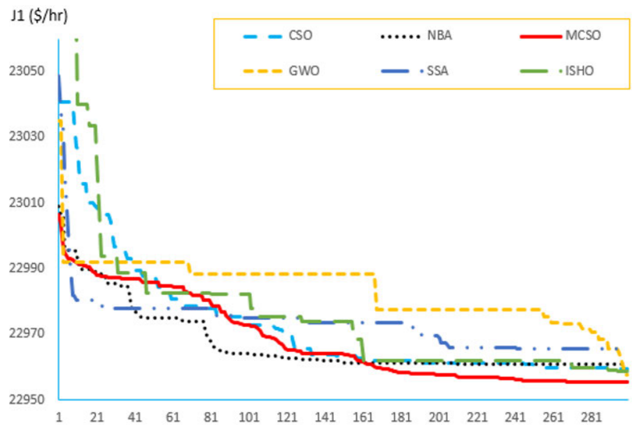

FIGURE 10. Convergence characteristics for minimizing the quadratic fuel costs.

TABLE 9. Statistical results for minimizing the fuel costs (Case 1).

	Min	Mean	Max	Std
MCSO	22955.55	22961.88	22969.013	3.6574
CSO	22959.37	22964.5633	22972.5594	3.5200
NBA	22960.81	22969	22983.4436	5.5289
SSA	22965.59	22981.13	23003.56	10.59803
GWO	22957.72	22961.77	22966.76	2.233786
ISHO	22958.78	22961.49	22963.71	1.321819

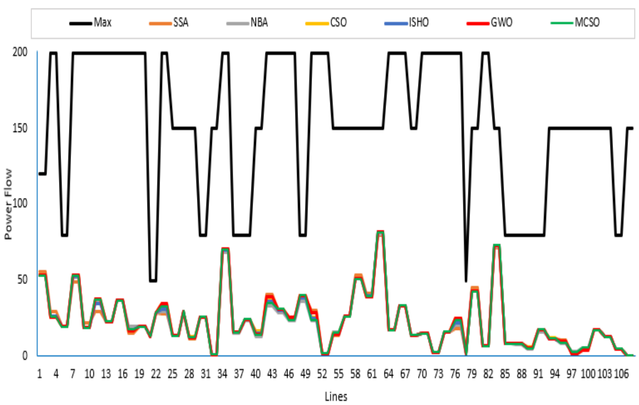

FIGURE 11. Power flow through the lines versus the maximum limits.

Table 8 and Fig. 10 evince that the minimum fuel cost is obtained using the proposed MCSO that the fuel costs of generation units is reduced from 25098.7 \$/hr to 22955.55 \$/hr compared with the initial case. In addition, the assessment of their statistical comparison in Table 9 shows that the capability of the proposed MCSO in finding the minimum compared to the others with a small STD value.

2) DISCUSSION ON THE VIOLATION OF THE CONSTRAINTS

For all applied algorithms, the power flow through the lines versus the maximum limits are displayed in Fig. 11. Added to that, Fig. 12 depicts the per unit voltages of the buses versus the considered limits. Also, Fig. 13 shows the generated reactive power outputs versus the considered limits.

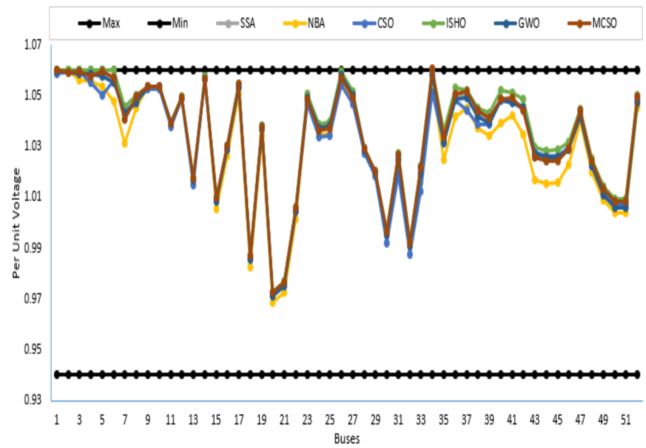

FIGURE 12. Per unit voltages of the buses versus the considered limits.

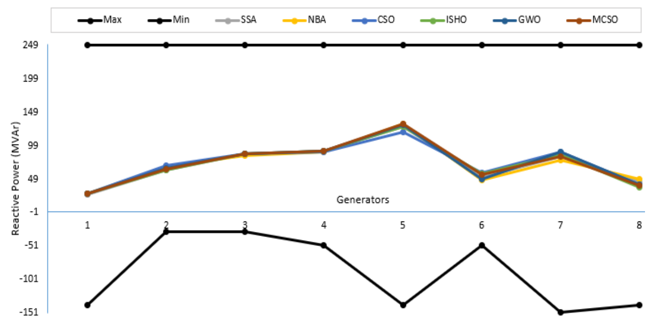

FIGURE 13. Generated reactive power outputs versus the considered limits.

From these figures, it is clear that there is no violation in the constraints for all applied algorithms. This elucidates the high effectiveness in obtaining high quality solutions.

F. SIMULATION RESULTS OF IEEE 118 BUS SYSTEM

In this section, the third system called IEEE 118-bus test system is used to prove the scalability of the proposed method. The CSO, NBA and the proposed MCSO are applied to minimize the fuel costs and the regarding outputs are tabulated in Table 10. Also, their convergence characteristics are displayed in Fig. 14. From Table 10 and Fig. 14, the minimum fuel cost is obtained using the proposed MCSO that the fuel costs of generation units are minimized to 129873.6 \$/hr compared to 130175.7 \$/hr by the CSO, and 130328\$/hr by the NBA. Table 11 illustrates a comparison between the obtained costs based on the proposed MCSO and other reported results. As shown, great effectiveness of the proposed MCSO in finding the least costs.

Finally, the improvement of the CSO can be highlighted as:

- For single objective EEPF, its update process is supported via the local search ability around the global best position. While for multi-objective EEPF, the update process is supported via dominance preference in the evolution of crow's memory.

TABLE 10. Output results for minimizing the fuel costs for IEEE 118 bus network.

	CSO	NBA	MCSO		CSO	NBA	MCSO		CSO	NBA	MCSO
Vg_{1}	0.98214	0.984316	0.987777	Vg_{80}	1.018337	1.018447	1.031935	Pg_{31}	9.10121	10.45845	7.142893
Vg_{4}	1.007729	1.004224	1.017287	Vg_{85}	0.981609	0.986966	1.017302	Pg_{32}	18.62236	15.14445	17.6243
Vg_{6}	0.995501	0.992887	1.008043	Vg_{87}	1.011508	0.99116	1.017006	Pg_{34}	6.427886	4.872608	7.972355
Vg_{8}	0.994536	1.018251	1.028962	Vg_{89}	0.991598	1.000016	1.038692	Pg_{36}	9.830257	11.08163	12.17604
Vg_{10}	0.985124	0.987963	1.057147	Vg_{90}	0.988434	0.996476	1.004291	Pg_{40}	47.71871	48.52704	50.85145
Vg_{12}	1.001336	1.004853	1.004994	Vg_{91}	0.980902	1.003911	1.007502	Pg_{42}	42.8984	38.02109	39.43219
Vg_{15}	0.986684	0.994935	1.002363	Vg_{92}	0.984036	0.992545	1.020191	Pg_{46}	16.9351	13.55459	18.68081
Vg_{18}	0.985982	1.000388	1.002433	Vg_{99}	1.014529	1.006701	1.01794	Pg_{49}	191.3283	193.5522	191.9474
Vg_{19}	0.981764	0.992125	0.999241	Vg_{100}	1.004213	1.004768	1.020643	Pg_{54}	46.49148	52.82352	49.26603
Vg_{24}	1.010933	0.995563	1.022409	Vg_{103}	1.002034	1.005052	1.01273	Pg_{55}	33.01362	31.24771	33.50091
Vg_{25}	1.006522	1.002289	1.051994	Vg_{104}	0.988868	0.988318	1.000059	Pg_{56}	32.79813	32.20836	28.68977
Vg_{26}	0.984578	0.995776	1.043426	Vg_{105}	0.985706	0.986969	0.996676	Pg_{59}	150.236	144.2465	148.4185
Vg_{27}	1.00736	0.998077	1.012358	Vg_{107}	0.977007	1.007398	0.991734	Pg_{61}	146.7947	146.4662	145.5609
Vg_{31}	0.985702	1.000705	1.004703	Vg_{110}	0.994691	0.995143	0.997463	Pg_{62}	3.075373	5.409727	0.919869
Vg_{32}	1.001315	0.994796	1.009654	Vg_{111}	1.000761	0.996128	1.008984	Pg_{65}	340.24	343.1779	347.14
Vg_{34}	0.998826	1.001995	1.01423	Vg_{112}	0.995104	0.998419	0.989119	Pg_{66}	338.8979	333.383	345.5017
Vg_{36}	0.996872	1.000512	1.011564	Vg_{113}	1.003272	0.999511	1.014351	Pg_{69}	435.1995	420.0408	447.172
Vg_{40}	0.995017	1.007938	0.995252	Vg_{116}	0.99221	0.989888	1.028376	Pg_{70}	3.3153	4.952	3.554469
Vg_{42}	0.998501	0.992327	0.999179	Qc_{110}	3.433403	2.747985	1.921634	Pg_{72}	4.10617	5.957473	6.958749
Vg_{46}	0.98471	0.993103	1.009174	T_{8-5}	0.980853	0.990739	0.982669	Pg_{73}	5.173819	5.367425	3.620331
Vg_{49}	1.013694	0.996964	1.025023	T_{26-25}	1.040272	0.990994	1.030434	Pg_{74}	17.76658	18.54868	18.57015
Vg_{54}	1.001168	0.999054	1.000393	T_{30-17}	1.007093	0.993033	1.000503	Pg_{76}	23.83948	22.78672	23.27477
Vg_{55}	0.997003	0.988823	1.000056	T_{38-37}	0.989779	0.985453	0.978436	Pg_{77}	5.30136	4.990874	5.01496
Vg_{56}	0.99727	0.991884	0.999946	T_{63-59}	0.97811	0.98031	0.9865	Pg_{80}	413.6035	431.1988	424.8214
Vg_{59}	0.999804	0.984918	1.019087	T_{64-61}	1.022857	0.986531	1.005752	Pg_{85}	3.428681	3.511341	1.501542
Vg_{61}	1.003803	1.003375	1.023109	T_{65-66}	1.018381	0.978714	0.991853	Pg_{87}	4.640827	8.704353	3.696617
Vg_{62}	1.002465	1.001473	1.020533	T_{68-69}	0.990064	1.030147	0.968144	Pg_{89}	498.6183	508.0404	489.0252
Vg_{65}	1.019278	1.000651	1.034182	T_{81-80}	1.017001	0.991456	0.994161	Pg_{90}	4.750069	6.756458	4.586402
Vg_{66}	1.013705	1.012503	1.037543	Qc_{34}	3.160126	3.087901	1.150959	Pg_{91}	4.177038	5.32284	2.555376
Vg_{69}	1.052881	1.020604	1.041747	Qc_{44}	1.444551	3.346518	2.091185	Pg_{92}	3.003547	5.081245	3.93183
Vg_{70}	1.012551	1.001192	1.011341	Qc_{45}	1.18188	3.473862	1.785974	Pg_{99}	4.32297	6.103572	6.03406
Vg_{72}	1.005235	0.999073	1.015182	Pg_{1}	26.28358	25.42102	26.54415	Pg_{100}	235.0426	222.1833	226.96
Qc_{46}	1.861114	2.023086	2.686768	Pg_{4}	4.294837	4.012869	3.693149	Pg_{103}	40.59621	37.07055	36.7585
Qc_{48}	2.597947	2.1977	1.720663	Pg_{6}	4.236527	6.190472	4.905669	Pg_{104}	4.382992	2.123044	0.312447
Qc_{74}	2.820211	1.861555	2.682434	Pg_{8}	4.327845	5.457846	6.222592	Pg_{105}	6.223345	5.144801	7.232248
Qc_{79}	2.673192	2.399119	2.612964	Pg_{10}	398.5607	403.9986	392.6066	Pg_{107}	25.55481	29.36573	30.00723
Qc_{82}	3.05824	2.464496	3.193171	Pg_{12}	80.27043	81.63004	85.65711	Pg_{110}	7.003971	11.74894	6.275507
Qc_{83}	2.6372	2.95837	2.960937	Pg_{15}	22.89133	21.74721	21.38944	Pg_{111}	34.5408	36.70812	36.73564
Qc_{105}	2.950314	3.411313	3.38705	Pg_{18}	11.9989	11.80954	10.61896	Pg_{112}	35.57717	37.03873	34.00411
Qc_{107}	3.582273	2.888965	1.267831	Pg_{19}	21.64319	16.89857	20.33499	Pg_{113}	3.537151	4.995061	5.048399
Vg_{73}	1.002366	1.004955	1.009536	Pg_{24}	5.025808	5.705384	4.815462	Pg_{116}	5.87423	6.328332	4.445068
Vg_{74}	0.990387	0.983319	0.989306	Pg_{25}	192.0747	194.2544	188.9902	J1	130175.7	130328	**129873.6**
Vg_{76}	0.977369	1.002086	0.980728	Pg_{26}	284.734	265.1669	273.4047	Ploss	86.03009	86.63589	78.66545
Vg_{77}	1.00638	1.003881	1.015787	Pg_{27}	7.698354	12.09849	4.560537				

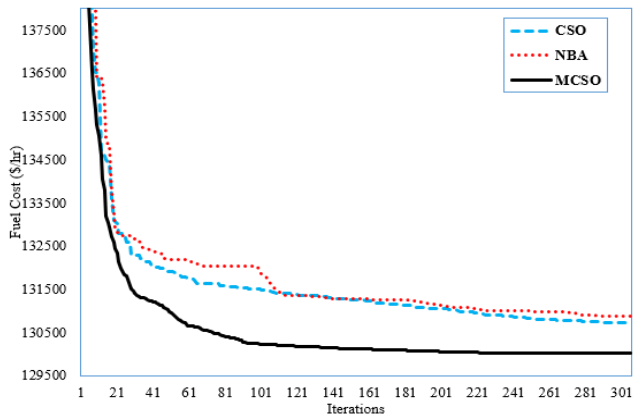

FIGURE 14. Convergence characteristics for IEEE 118 bus system.

- The proposed MCSO is evolved incorporating external archive to store and upgrade the non-dominated solutions for handling the multi-objective EEPF.

TABLE 11. Comparative results of IEEE 118 bus system for fuel cost minimization.

Algorithm	**J1 ($/hr)**
CSO	**130175.7**
NBA	130328
MCSO	129873.6
Colliding Bodies Optimization (CBO)[55]	135072.999
Artificial Bee colony (ABC) [55]	135145.1889
DE [23]	130518.5
Enhanced CBO [55]	135172.266
Backtracking search algorithm (BSA)[56]	135333.5
Differential Evaluation (DE) [55]	142751.1178
PSO [20]	130288.210
Biogeography Based Optimization(BBO) [55]	135272.1959

V. CONCLUSION

In this paper, a modified approach of crow search optimizer (MCSO) is developed for solving the combined EEPF problem. The combined EEPF problem is handled considering the quadratic polynomial fuel generation costs, the valve point loading effect, and emissions. For this target, the proposed MCSO incorporates the enchanting NBA's feature of their local search ability into the CSO. Not only that but the proposed MCSO is also involved with an external archive and dominance comparison. Also, a parametric analysis of the CSO algorithm is executed for minimizing the fuel generation costs to extract its best values. Moreover, a comparative study of CSO, NBA, and MCSO in solving the EEPF problem with different objective functions, and they are tested to solve the EEPF problem on the standard IEEE 30 bus and a practical West Delta power grid. The scalability of the proposed method has been approved on the IEEE 118-bus test system as a large-scale power system. The simulation results of the proposed MCSO for minimizing the quadratic model of the fuel generation costs are compared with the other heuristic methods that were informed in the literature and demonstrated its effectiveness and superiority. The statistical comparative study between CSO, NBA and MCSO for solving various EEPF optimization problems establishes the MCSO's high degree of robustness in all the studied cases in terms of its acquired objectives are much trustable than CSO and NBA. The hypervolume indicator proves the high capability of the proposed MCSO compared with the CSO method for multiobjective cases. The future works of this study can be extended to involve the influence of various types of reactive power resources based flexible AC transmission systems. Applications of optimal power flow problem in virtual power plants. Also, dealing with emergency events and assure the capability of the power generation settings after the occurrence of emergency events. Also, applications of new optimization methods can be considered as extension in the viewpoint of solution methodology.

APPENDIX A

Table 12 shows the control parameters of the developed optimization algorithms NBA, CSO, and MCSO.

TABLE 12. Control parameters of NBA and MCSO.

Parameter	NBA	CSO	MCSO
pop size (NP)	50	50	50
Maximum iteration ($Iter^{max}$)	300	300	300
Archive size of non-dominated solution	100	100	100
Awareness probability (AP)		0.3	
Flight length (fl)		2	

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