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Multi-Objective Squirrel Search Algorithm for Multi-Area Economic Environmental Dispatch With Multiple Fuels and Valve Point Effects

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ABSTRACT The essential goal of multi-area economic environmental dispatch (MAEED) is to determine the optimum power generation schedule of each unit and power transfer between the areas in order to minimize fuel costs and pollutant emissions, when the generation, power balance and tie-line limits are satisfied. This paper focuses on developing multi-objective squirrel search algorithm (MOSSA) to solve the MAEED problem, of which the goal is to simultaneously minimize the total fuel cost and emission considering valve point effects and multi-fuel options. The proposed MOSSA combines squirrel search algorithm along with Pareto-dominance theory to generate non-dominated solutions. It uses an external elitist depository mechanism with crowding distance sorting to preserve the distribution diversity of Pareto-optimal solutions as the evolution continues. In addition, a fuzzy decision maker is used to select the best compromised solution from the obtained Pareto frontiers. Furthermore, the MAEED problem is unraveled by squirrel search algorithm based weighted sum approach with price penalty factors, artificial bee colony and exchange market algorithm. Different case studies are performed on 10-unit with three-area system, 40-unit with four-area system and 140-unit real Korean power system considering valve point effects and multi-fuel options which testify the supremacy of the suggested approach. The comparisons with state-of-the-art approaches suggest that MOSSA can generate more competitive trade-off solutions for solving the MAEED problems.

INDEX TERMS Fuzzy decision maker, multi-area economic and environmental dispatch, multiple fuels, Pareto optimal front, squirrel search algorithm.

I. NOMENCLATURE

ABC	artificial bee colony
BCS	best compromised solution
CD	crowding distance
COA	crisscross optimization algorithm
CQGSO	continuous quick group search optimizer
DA	degree of agreement
DE	differential evolution
DM	diversity metric
ECPI	emission cost performance index
EED	economic and emission dispatch
ELD	economic load dispatch
EMA	exchange market algorithm
EP	evolutionary programming
EPSO	enhanced particle swarm optimization
FCPI	fuel cost performance index
GD	generational distance
HV	hyper-volume
IFA	improved fireworks algorithm
MAED	Multi-area emission dispatch
MAEED	multi-area economic environmental dispatch
MAELD	multi-area economic load dispatch
MFO	multi-fuel options
MODE	multi-objective differential evolution

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MOSSA	multi-objective squirrel search algorithm
NSGA	non-dominated sorting genetic algorithm
OKHA	opposition-based krill herd algorithm
POF	Pareto optimal frontiers
POZ	prohibited operating zone
PSO	particle swarm optimization
RCGA	real-coded genetic algorithm
RNI	ratio to non-dominated index
SDE	shuffled differential evolution
s-metric	spacing metric
SSA	squirrel search algorithm
TLBO	teaching learning-based optimization
VPL	valve point loading
WSA	weighted sum approach
a_{ij}, b_{ij}, c_{ij}	cost coefficients of jth generation unit in ith area
B_{ij}	line loss coefficients
d_g	skimming separation
D	drag power
$\bar{d}$	mean value of ed_i
e_{ij}, f_{ij}	cost coefficients of the VPL effect of generator j in area i
ed_i	Euclidean distance between nondominated solution and the nearest Pareto front solution in objective space
ed_f and ed_l	Euclidean distances between the extreme solutions and the boundary solutions of the obtained non-dominated set
$E_{ij}(P_{ij})$	emission of the generator j in area i
F_{bcs} and E_{bcs}	fuel cost and emission attained by CEED
$F_{\min}$ and $E_{\max}$	fuel cost and emission attained by ELD minimization respectively
$F_{\max}$ and $E_{\min}$	fuel cost and emission attained by EED minimization respectively
$F_{ij}(P_{ij})$	fuel cost of jth generation unit in ith area
G_c	gliding constant
k	number of fuel alternatives
L	lift power
M	number of non-dominated solutions
M_i	number of participated generators in area i
N_p	Population size
ng	total number of generating units
P_{Di}	power demand in area i
P_{dp}	predator presence probability
P_{ij}	real power generation of generator j in area i
$P_{ij,min}$, $P_{ij,max}$	minimum and maximum limits of jth generation unit in ith area
$P_{ij,m}^{L}$, $P_{ij,m}^{U}$	lower and upper power outputs of the m^{th} prohibited zone of the j^{th} generator in area i
P_{Li}	losses in area i
r_1, r_2 and r_3	random numbers in the range of [0, 1]
t	current iteration number
T_{iz}	tie line power stream from area i to area z
X_h	location of squirrel individual that reached the hickory tree
$\bar{X}$	number of non-dominated solutions in population X
α_{ij}, β_{ij}, γ_{ij}	emission coefficients of generator j in area i
η_{ij}, δ_{ij}	emission coefficients of the VPL effect of jth generation unit in ith area
ρ	density of air
β	constant

II. INTRODUCTION

Economic load dispatch (ELD) performs a crucial function in operation planning of modern power systems. The fundamental aim of ELD problem is to minimize the total fuel cost, subject to equality and inequality constraints. With the expanding attention of environmental protection in recent years, economic and emission dispatch (EED) is introduced as a substitute to attain the reduction of fuel cost and emission simultaneously. Heuristic approaches such as bacterial foraging algorithm [1], multi-objective differential evolution (MODE) [2], gravitational search algorithm [3], teaching learning-based optimization (TLBO) [4], artificial bee colony (ABC) [5], backtracking search algorithm [6], opposition-based krill herd algorithm (OKHA) [7], continuous quick group search optimizer (CQGSO) [8] and shuffled differential evolution (SDE) [9] have been proposed to solve the ELD and EED problems.

Classical techniques have been developed for multi-area ELD (MAELD) problems, such as Dantzig-Wolfe decomposition approach [10] and improved Hopfield neural networks [11]. These techniques are likely to be seriously challenged by their high imposition of different constraints, including consistency, convexity and distinguishability of objective functions and high sensitivity towards initial values of the optimized variables involved. In addition, their output is gradually deteriorated by the dimension of the problem.

Many heuristic algorithms such as evolutionary programming (EP) [12], real-coded genetic algorithm (RCGA) [13], particle swarm optimization (PSO) [13], differential evolution (DE) [13], ABC [14], TLBO [15], hybrid cuckoo search algorithm [16] and improved grasshopper optimization algorithm [17] have been developed and applied effectively to solve the MAELD problem due to their ability to find global or near-global solution of a nonconvex optimization problem. In [18] 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 [19].

Multi-area EED (MAEED) issues have not been extensively explored so there is a requirement for additional exploration in this research area. In the recent decade, not many specialists have focused on this area which implies that the information on MAEED has not progressed far.

An enhanced PSO (EPSO) was developed to solve the MAEED problem with reserve constraints [20]. The PSO parameters were adaptively varied to preserve the balance among cognitive and social conduct of the swarm. The EPSO was examined on standard power systems considering the contingency and pooling spinning reserves. Hybrid heuristic algorithm using DE and PSO was developed to solve the reserve constrained MAEED problems with reserve sharing in power system operations [21]. The PSO boundaries were powerfully fluctuated to protect a superior harmony among intellectual and social conduct of the multitude. The EPSO was examined on standard test creating frameworks with turning save necessities by thinking about possibility and pooling turning saves. In [22], chaotic ABC algorithm was proposed to solve the MAEED problem by addressing the VPL, transmission line losses, multi-fuel options (MFO), POZ, tie line capacity and power transfer between different areas of the system. The simulation results showed that the chaotic ABC algorithm was performing better than the other heuristic approaches. Abarghooee *et al.* introduced an improved gradient-based Jaya algorithm for the MAEED problem to determine the power generation of units and the transmission power flow while satisfying system demand and security constraints of each area [23]. In the approach, gradient method, Jaya algorithm, and mutation mechanisms were combined to solve the complex MAEED problem on small and large-scale test systems. Secui applied another cooperative organism search approach to tackle the MAEED issue thinking about various characteristics of the investigated frameworks [24]. The competence of the methodology was examined on five multi-zone power systems with various working attributes and sizes. The different types of complex MAEED problem using crisscross optimization algorithm (COA) were addressed [25]. The COA approach employed horizontal crossover and vertical crossover to enhance the global search ability and to prevent the premature convergence of the algorithm. Li *et al.* presented an improved chemical reaction optimization algorithm for solving the MAEED problems [26].

Narimani *et al.* presented a hybrid technique dependent on the combination of shuffle frog leaping algorithm and PSO to tackle the proposed issue, and confirmed the viability of the proposed hybrid technique on various test systems [27]. Hybrid modified bat algorithm was used to solve a four-area economic environmental dispatch problem [28]. A weighted sum approach (WSA) was used to transfer the multi-objective function into a single objective one, and optimal solutions were selected using cardinal priority ranking. While hybrid approaches deliver the promising results, it is difficult to settle on the correct consolidation between the two heuristic approaches. The underlying multifaceted design of hybrid frameworks also requires an increase in the efforts to modify control parameters accordingly.

Pandit *et al.* proposed MODE based fuzzy determination approach for illuminating the non-convex MAEED problem [29]. Wang and Singh developed an improved PSO for solving the MAEED problem to obtain Pareto-optimal solutions [30]. The local search strategy was employed in the improved PSO to enhance the searching capability. The tie-line limits were considered as a set of constraints to satisfy the power system security. A new encoding mechanism and self-adaptive neighborhood structure selection mechanism were employed to increase the search ability of the algorithm while maintaining population diversity. The non-dominated sorting genetic algorithm II (NSGA II) was suggested to achieve solutions for the MAEED problem [31]. The constraints such as production-demand balance, power production capacity and tie line capacity were considered. These heuristic methods do indeed have some of the following disadvantages: unstable exploring capability, slow convergence, long computation time, reliance on the parameter selection, and poor consistency of Pareto fronts distribution.

In the most of the recently published articles, the WSA is used to transfer the multi-objective functions into a single objective function. This approach can discover the trade-off front by adjusting the weight values in different runs, but the technique does not discover the non-convex Pareto arrangements. Furthermore, this approach does not ensure to prompt the equitably dispersed solutions along the front, and the selection of weight values with different objective functions which prove to be genuinely problematic. Different multi-objective heuristic algorithms such as MODE and NSGA II have been used to address the EED problems. However, these approaches are computational expensive in solving a complex EED problems particularly where multi-area power systems exist.

Recently, a new meta-heuristic algorithm, named squirrel search algorithm (SSA) was proposed by Mohit Jain *et al.* [32]. The SSA algorithm models the foraging activities of squirrel individuals. Each squirrel individuals modifies its position using four processes namely,

(1) distributing the population,

(2) dynamic foraging behavior,

(3) seasonal adapting intelligence and

(4) random repositioning of individuals at the end of the winter season.

The SSA algorithm was previously successfully applied for 26 well-known classic benchmark test functions which are described as continuous, discontinuous, linear, non-linear, unimodal, multimodal, convex, non-convex, separable and non-separable forms [32], multi-region combined heat and power economic dispatch [33] and ELD problems [34]. The results of the SSA algorithm show the superiority over some popular heuristic algorithms such as genetic algorithm, PSO, bat algorithm, and firefly algorithm in terms of solving the high-dimensional multimodal problem. Besides, the SSA approach has certain unique features which overcome several demerits of the existing heuristic approaches as follows:

- The gliding constant is used in the location update of squirrels which provides suitable steadiness between exploration and exploitation.
- The predator presence behavior is employed to abruptly change the location of a squirrel which enhances the exploration ability of the algorithm.
- A seasonal monitoring condition is used to prevent the suggested algorithm from being trapped in locally optimal solutions.
- Levy distribution is used to find new solutions far away from the current best solution which improves the global exploration ability of the algorithm.

These features make the SSA algorithm able to overcome the normal drawbacks of other algorithms such as premature convergence, inadequate ability to discover to find nearby extreme points, and absence of efficient constraints handling mechanism. The advantages of the SSA algorithm are less execution time, ability to solve different complex optimization problems, and high capacity in obtaining global optimum solutions.

According to aforementioned papers, this study is the first attempt to propose a multi-objective heuristic algorithm for solving the MAEED problem with MFO and VPL effects. The main motivation of this paper is to propose and develop a new multi-objective squirrel search algorithm (MOSSA) that has its own feasibility and performance capacity to determine the Pareto-optimal solutions of MAEED problems in power systems.

The significant contributions of this article are summarized as follows:

- To the best of our knowledge, this is the first work that extends the SSA to MOSSA to address the multi-objective optimization problems. The suggested MOSSA approach consolidates external depository mechanism, crowding distance and fuzzy clustering mechanism to access the best trade-off solutions.
- The MAEED problem is additionally fathomed by SSA based WSA (SSA-WSA) with penalty price factors, ABC and exchange market algorithm (EMA) strategies.
- The multi-objective performance indicators comprising generational distance (GD), spacing metric (s-metric), ratio to non-dominated index (RNI), hyper volume (HV) and diversity metric (DM) are employed to investigate the Pareto optimal front solutions.
- In order to testify the supremacy of the suggested MOSSA approach, it has been employed on 10-unit with three-area system, 40-unit with four-area system and 140-unit Korean power system considering MFO and VPL effects.
- The findings are compared with SSA-WSA, ABC, EMA and various state-of-the-art heuristic approaches surfaced in the literature.

The rest of this research article is organized as follows: Section II provides the MAEED problem formulation. The review of original SSA, elitist depository mechanism, fuzzy decision maker, MOSSA strategy and the solution procedure of the MAEED are presented in Section III. The case studies are analyzed in Section IV, and the conclusion is given in Section V.

III. PROBLEM FORMULATION OF MAEED

The objective of MAEED problem is to find out the optimal power generation of all units and the power transfer between the area by minimizing the fuel cost and pollutant emissions simultaneously over the whole framework while fulfilling different limitations.

A. MAELD

The goal of MAELD problem is to endeavor the optimal set of generation values in every zone just as shifting power between various zones so as to optimize the fuel cost subject to various imperatives.

The fuel cost function of committed generation units in all zones can be detailed as follows [19]:

$$F_t = \sum_{i=1}^{n_g} \sum_{j=1}^{M_i} F_{ij}\left(P_{ij}\right) \tag{1}$$

$$= \sum_{i=1}^{n_g} \sum_{j=1}^{M_i} \left(a_{ij} + b_{ij}P_{ij} + c_{ij}P_{ij}^2\right) \tag{2}$$

To display the impact of valve-points, a common amended sinusoid commitment is added to the quadratic function which is shown in Fig. 1 as [22]:

$$F_t = \sum_{i=1}^{n_g} \sum_{j=1}^{M_i} a_{ij} + b_{ij}P_{ij} + c_{ij}P_{ij}^2 + \left|e_{ij} \times \sin(f_{ij} \times \left(P_{ij,min} - P_{ij}\right))\right| \tag{3}$$

The aim of the MAELD problem with multiple fuels is to determine the amount of power which can be resourcefully produced in one area and shifted 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 as shown in Fig. 2 [22]. The MAELD problem with VPL and MFO [19] can be modeled by Eq. (4), as shown at the bottom of the next page.

B. MULTI-AREA EMISSION DISPATCH (MAED)

The MAED is to limit the pollutant emissions discharged in the environment subject to equality and inequality imperatives. The sum of emissions discharged in the environment by the generating units from all regions of the system is defined as follows [22]:

$$E_t = \sum_{i=1}^{n_g} \sum_{j=1}^{M_i} E_{ij}\left(P_{ij}\right) \tag{5}$$

$$E_t = \sum_{i=1}^{n_g} \sum_{j=1}^{M_i} \alpha_{ij} + \beta_{ij}P_{ij} + \gamma_{ij}P_{ij}^2 + \eta_{ij}exp(\delta_{ij}P_{ij}) \tag{6}$$

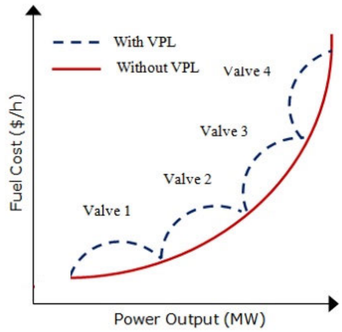

FIGURE 1. Fuel cost curve with VPL impacts.

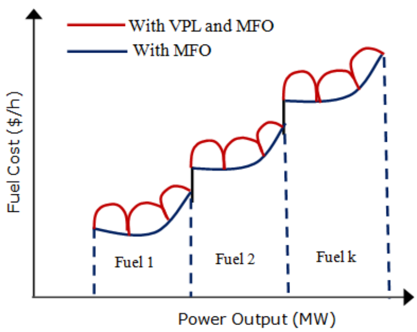

FIGURE 2. Fuel cost curve with VPL and MFO impacts.

The outflow target 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 MFO is introduced in Eq. (7), as shown at the bottom of the page.

C. MAEED BASED ON WSA

The MAEED problem can be formulated as bi-objective function in which fuel cost and emission as rivalling objectives. This bi-objective function can be transferred to a single objective function as follows [6]:

$$(F_t, E_t)=\sum_{i=1}^{n_g}\sum_{j=1}^{M_i} w\times F_{ij}(P_{ij})+h\times(1-w)\times E_{ij}\left(P_{ij}\right) \tag{8}$$

The above equation becomes MAELD objective function when $w = 1$ and becomes MAED objective function when $w = 0$. w is a main function of rand [0,1] which compromises the fuel cost and emission objectives.

D. MAEED BASED ON MULTI-OBJECTIVE APPROACH

In multi-objective heuristic based MAEED, the two competing objective functions such as the economy and emissions are optimized simultaneously. The Pareto-dominance concepts are introduced to find a Pareto optimal set. The multi-objective MAEED problem can be defined as follows [4]:

$$(F_t, E_t) = \sum_{i=1}^{n_g}\sum_{j=1}^{M_i} min\left((F_{ij}(P_{ij}), E_{ij}\left(P_{ij}\right)\right) \tag{9}$$

E. MAEED CONSTRAINTS

The following equality and inequality constraints are addressed for taking care of the MAEED issue.

1) POWER BALANCE CONSTRAINT

The all-out power generated from a set of accessible units must fulfil the all-out load demand and tie line power flow is given by [12],

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

The transmission loss P_{Lj} of region j can be defined by using B-coefficients as follows [12]:

$$P_{Li} = \sum_{l=1}^{M_i}\sum_{j=1}^{M_i} P_{ij}B_{ilj}P_{il} + \sum_{j=1}^{M_i} B_{0ij}P_{ij} + B_{00i} \tag{11}$$

2) GENERATOR CAPACITY LIMITS

The real output power of thermal units ought to be in their range between minimum and maximum limits [12]:

$$P_{ij,min} \leq P_{ij} \leq P_{ij,max} \tag{12}$$

3) TIE-LINE LIMIT

Because of security basis, power shifted between various lines must not surpass their cutoff points. The power transfer

$$\left(P_{ij}\right) = \begin{cases} Fuel\ type\ 1; a_{ij1} + b_{ij1}P_{ij} + c_{ij1}P_{ij}^2 + \left|e_{ij1} \times \sin(f_{ij1} \times \left(P_{ij,min} - P_{ij}\right))\right|; & P_{ij,min} \leq P_{ij} \leq P_{ij1} \\ Fuel\ type\ 2; a_{ij2} + b_{ij2}P_{ij2} + c_{ij2}P_{ij}^2 + \left|e_{ij2} \times \sin(f_{ij2} \times \left(P_{ij,min} - P_{ij}\right))\right|; & P_{ij1} < P_{ij} \leq P_{ij2} \\ \ldots. & \\ Fuel\ type\ k; a_{ijk} + b_{ijk}P_{ij} + c_{ijk}P_{ij}^2 + \left|e_{ijk} \times \sin(f_{ijk} \times \left(P_{ij,min} - P_{ij}\right))\right|; & P_{ij,k-1} < P_{ij} \leq P_{ij,max} \end{cases} \tag{4}$$

$$E_{ij}(P_{ij}) = \begin{cases} Fuel\ type\ 1; \alpha_{ij1} + \beta_{ij1}P_{ij} + \gamma_{ij1}P_{ij}^2; & P_{ij,min} \leq P_{ij} \leq P_{ij1} \\ Fuel\ type\ 2; \alpha_{ij2} + \beta_{ij2}P_{ij} + \gamma_{ij2}P_{ij}^2; & P_{ij1} < P_{ij} \leq P_{ij2} \\ \ldots & \\ Fuel\ type\ k; \alpha_{ijk} + \beta_{ijk}P_{ij} + \gamma_{ijk}P_{ij}^2; & P_{ij,k-1} < P_{ij} \leq P_{ij,max} \end{cases} \tag{7}$$

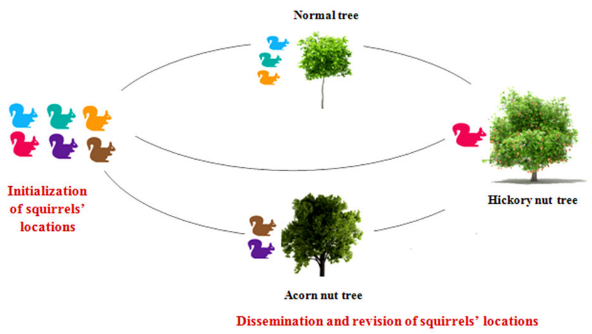

FIGURE 3. Metaphysical paradigm of SSA.

requirement between two unique regions is characterized by [12]

$$-T_{iz,min} \leq T_{iz} \leq T_{iz,max} \tag{13}$$

IV. MULTI-OBJECTIVE SQUIRREL SEARCH ALGORITHM

SSA is the latest emerged swarm intelligence algorithm derived from foraging attitude of squirrels. This concept was first introduced by Jain *et al.* [27]. It is a population-based approach consisting of many squirrels wherein each squirrel is driven in a multi-dimensional search spot in search of food. In this SSA Algorithm, different variables are assigned for different positions of squirrel. The distance of the food from the individual squirrel is related to the fitness value. The metaphysical paradigm of SSA is exhibited in Fig. 3.

In SSA, the individual squirrel modifies its position, thereby shifting them to a better solution. The algorithm starts with n number of squirrels in a deciduous forest and with the assumption as only one squirrel in each tree. It is assumed that the three types of trees, normal, acorn and hickory, are available in the forest. The forest area is supposed to contain N trees in which one is hickory tree, N_a acorn trees, and the remaining are normal trees in which no food is available. The hickory tree is the finest foraging area for the squirrels.

The movement of individuals is persuaded by the following four practices:

- distributing the population,
- dynamic foraging behavior,
- seasonal adapting intelligence, and
- random repositioning at the end of winter season.

A. STANDARD SSA

The positions of N squirrel individuals are randomly generated. Then the population is sorted in ascending order for minimization problem and vice versa. Then the squirrel groups are distributed into three categories: squirrels positioned at hickory trees (F_h), squirrels positioned at acorn trees (F_a) and squirrels positioned at normal trees (F_n). F_h is the squirrel with the minimum fitness value, F_a includes the squirrels that have the fitness rank from 2 to $N_a + 1$ and the remaining squirrels are denoted as F_n.

1) DYNAMIC FORAGING BEHAVIOR

The dynamic conduct in looking for food can be mathematically modelled as follows:

The positions of individuals which are gliding from acorn trees to the hickory tree are updated as follows [27]:

$$X_{ai}^{t+1} = \begin{cases} X_{ai}^t + d_g G_c (X_h^t - X_{ai}^t) & \textit{if } r_1 \geq P_{dp} \\ \textit{Random location} & \textit{otherwise} \end{cases} \tag{14}$$

The positions of remaining individuals which are gliding from normal trees to the acorn and hickory trees are modified by the following equations respectively.

$$X_i^{t+1} = \begin{cases} X_i^t + d_g G_c (X_{ai}^t - X_i^t) & \textit{if } r_2 \geq P_{dp} \\ \textit{Random location} & \textit{otherwise} \end{cases} \tag{15}$$

$$X_i^{t+1} = \begin{cases} x_i^t + d_g G_c \left(X_h^t - X_i^t\right) & \textit{if } r_3 \geq P_{dp} \\ \textit{Random location,} & \textit{otherwise} \end{cases} \tag{16}$$

Gliding constant, G_c is used to stabilize the exploration and exploitation searches in the SSA algorithm. Its value notably influences the performance of proposed algorithm. The gliding distance is expressed as:

$$d_g = \frac{h_g}{tan\,(\varphi)} \tag{17}$$

The gliding angle, tan (ϕ) is defined by

$$tan(\varphi) = \frac{D}{L} \tag{18}$$

The drag and lift forces can be expressed by the following equations respectively:

$$D = \frac{1}{2\rho V^2 S C_D} \tag{19}$$

$$L = \frac{1}{2\rho V^2 S C_L} \tag{20}$$

2) SEASONAL ADAPTING INTELLIGENCE

The foraging behaviors of squirrels are significantly affected by the seasonal fluctuations. The squirrels are more active in autumn as compared to winter. To avert the SSA algorithm from being abused into local optimal solutions, the seasonal adapting intelligence is introduced.

The seasonal constant is given by

$$S_c^t = \sqrt{\sum_{k=1}^{d} (X_{ai,k}^t - X_{h,k}^t)^2} \quad i = 1, 2, .., N_a \tag{21}$$

The minimum seasonal constant is expressed as

$$S_{min} = \frac{10e^{-6}}{365^{t/(t_{max}/2.5)}} \tag{22}$$

The larger S_{min} value facilitates the exploration while smaller one improves the exploitation ability of the algorithm.

3) RANDOM REPOSITIONING AT THE END OF WINTER SPELL

If $S_c^t \leq S_{min}$, winter spell is completed. Then the locations of the flying squirrel individuals are randomly repositioned by the following equation.

$$X_{inew}^{t+1} = X_L + Le'vy(x) \times (X_U - X_L) \tag{23}$$

Levy distribution improves global exploration ability of the algorithm and finds new candidate solutions far away from the current best solution.

The *Le'vy* flight is determined by

$$Le'vy\,(x) = 0.01 \times \frac{\alpha \times r_a}{|r_b|^{\frac{1}{\beta}}} \tag{24}$$

α is expressed as

$$\alpha = \left[\frac{\Gamma\,(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right]^{\frac{1}{\beta}} \tag{25}$$

where, $\Gamma(x) = (x-1)!$ The pseudocode of SSA is shown in Algorithm 1.

Algorithm 1 SSA

Begin
Read input parameters of SSA
Generate random positions for n number of squirrels
Evaluate fitness of each squirrel's position
Arrange the positions of squirrel individuals in ascending manner based ontheir cost function value
Distribute the squirrel individuals on hickory nut tree, acorn nuts trees and normal trees
Arbitrarily choose a number of squirrel individuals from normal trees to shift towards hickory nut tree and to transfer the residual squirrels to acorn nuts trees
while *(Termination criterion is false)*
  For $t = 1$ *to* n_1 *(*n_1 *= Number of squirrel individuals which are gliding from acorn trees to hickory nut tree)*
    if $r_1 \geq P_{dp}$
      Update the position of squirrel individual using Eq. (14)
    else
      Randomly generate the position of squirrel individual within the search domain.
    end
  end
  For $t = 1$ *to* n_2 *(*n_2 *= Number of squirrel individuals which are gliding from normal trees to acorn trees)*
    if $r_2 \geq P_{dp}$
      Update the position of squirrel individual using Eq. (15)
    else
      Randomly generate the position of squirrel individual within the search domain.
    end
  end
  For $t = 1$ *to* n_3 *(*n_3 *= Number of squirrel individuals which are gliding from normal trees to hickory tree)*
    if $r_3 \geq P_{dp}$
      Update the position of squirrel individual using Eq. (16)
    else
      Randomly generate the position of squirrel individual within the search domain.
    end
  end
  Evaluate seasonal constant (*Sc*) by Eq. (21)
  if $\mathrm{S_c} < \mathrm{S_{min}}$
Randomly reposition the squirrel individuals using Eq. (23)
  end
Adjust $\mathrm{S_{min}}$ by Eq. (22)
end
Output the optimal solution as the squirrel's position on hickory nut tree
End

B. EXTERNAL ELITIST DEPOSITORY MECHANISM

In this paper, an external elitist depository mechanism is implemented. An external depository is used to store non-dominated solutions found so far in the evolution process. The depository is initially empty. The non-dominated squirrel individuals found in iterations are added to the depository using the following mechanism:

- If the new squirrel individual (X_i) dominates some of the depository members (X_{ext}), the dominated members are removed from the depository and the new squirrel individual is added to the depository.
- If the new squirrel individual is dominated by a depository member, the new squirrel individual is rejected.
- If the new squirrel individual does not dominate any depository members and vice versa, which entails that the new squirrel individual owned to the depository and it is added to the depository.
- If the number of non-dominated squirrel individuals exceeds the size of depository, a measure known as crowding distance (CD) is determined for all individuals in the depository. Then, all the solutions are arranged in descendant order based on their CD values. Then the extra squirrel individuals are eliminated to obtain the required depository's size. The process of exterior elitist vault system is explained in Algorithm 2.

C. CROWDING DISTANCE MEASURE

The *CD* measure of a non-dominated solution offers an estimate of the density of solutions enveloping that solution. *CD* measure of an individual solution is the average distance of its two neighboring solutions, which is defined by the following equation:

$$CD_i = \sum\nolimits_{j=1}^{m} \frac{F_j\,(i+1) - F_j\,(i-1)}{F_j^{max} - F_j^{min}} \tag{26}$$

Algorithm 2 Process of Exterior Elitist Vault System

1: **if** $X_i \prec$ a group of individuals in X_{ext}, then
2: Erase these individuals from X_{ext}
3: Include X_i into X_{ext}
4: **else**
5: **if** Any squirrel individual in $X_{ext} \prec X_i$, then
6: Dismiss X_i
7: **else**
8: Include X_i into X_{ext}
9: **end if**
10: **end if**

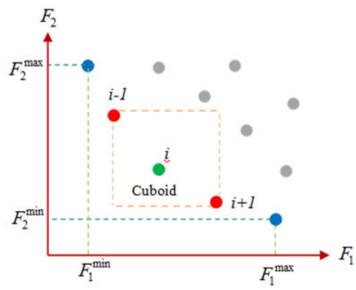

FIGURE 4. The crowding distance calculation.

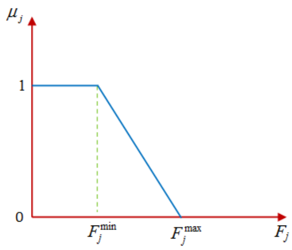

FIGURE 5. The membership function.

For each objective function, the frontier solutions (solutions with smallest and largest objective values) are designated an infinite to ensure that these solutions are always chosen. The solution with the greater *CD* value is retained in the depository. The *CD* estimation is illustrated in Fig. 4.

D. MEASURE FUZZY DECISION MAKER

In multi-objective optimization problem, it is difficult to find the best solution from many non-dominated solutions. In order to compare these outcomes and get the best compromised solution, a certain mechanism is essential to combine both the objectives in conformity with the decision maker's preference. Fuzzy set theory is repeatedly used by researchers to get the best compromised solution (BCS) from many uncontrolled solutions. Degree of agreement (DA) to each objective is assigned by fuzzy membership functions, where DA reflects the merit of their objective in a linear scale of 0 – 1(worst to best). If F_j is a solution in the Pareto-optimal set in the *j*th objective function and is represented by a membership function, which is shown in Fig. 5 as [1]:

$$\mu(F_j) = \begin{cases} 1 & if\ F_j \leq F_j^{min} \\ \dfrac{F_j^{max} - F_j}{F_j^{max} - F_j^{min}} & if\ F_j^{min} \leq F_j \leq F_j^{max} \\ 0 & if\ F_j \geq F_j^{max} \end{cases} \tag{27}$$

For each non-dominated solution, the normalized membership function μ_D^k can be calculated as [1]:

$$\mu_D^k = \frac{\sum_{i=1}^{2} \mu\left(F_i^k\right)}{\sum_{k=1}^{M} \sum_{i=1}^{2} \mu\left(F_i^k\right)} \tag{28}$$

The solution that contains the maximum of μ_D^k based on cardinal priority ranking is the BCS.

$$Max\left\{\mu_D^k : k = 1, 2, .., M\right\} \tag{29}$$

E. MULTI-OBJECTIVE SSA (MOSSA)

SSA deals with the population of squirrels, $P^t = \left[X_1^t, X_2^t, ..X_{Np}^t\right]$ with $X_i^t = \left[x_{i1}^t, x_{i2}^t, .x_{iNa}^t\right]$ in every iteration of the evolution process. The dynamic foraging behavior, seasonal adapting intelligence and random repositioning processes are applied to produce new population of squirrels, x_{new}^t. To extend the SSA approach to multi-objective optimization problems, Pareto-dominance based selection mechanism and *CD* measure are to be adopted. For a multi-objective optimization problem, any two solutions x^t and x_{new}^t can have one of the following three promises:

- x^t dominates x_{new}^t $\left(x^t \prec x_{new}^t\right)$,
- x_{new}^t dominatesx^t $\left(x_{new}^t \prec x^t\right)$,
- x^t and x_{new}^t are not dominated each other.

Thus, the Pareto-dominance selection strategy is modeled as follows:

$$x^{t+1} = \begin{cases} x^t & if\ x^t \prec x_{new}^t \\ x_{new}^t & if\ x_{new}^t \prec x^t \\ LC(x^t, x_{new}^t) & otherwise \end{cases} \tag{30}$$

where $LC(x^t, x_{new}^t)$ indicates the less crowded solution between x^t and x_{new}^t.

The implementation of MOSSA for MAEED optimization is described as follows:

Step 1. Generate initial population of squirrels with size randomly distributed across the domain of the problem.
Step 2. Evaluate the multi-objective values of each squirrel individual using Eq. (9).
Step 3. Sort the squirrels' population based on non-domination. Each squirrel is ranked according to their dominance level as front 1, front 2 and so on using Eq. (30) and store them in the depository.
Step 4. Declare the flying squirrel with front 1 solution as it is on the hickory nut tree (optimal food source),

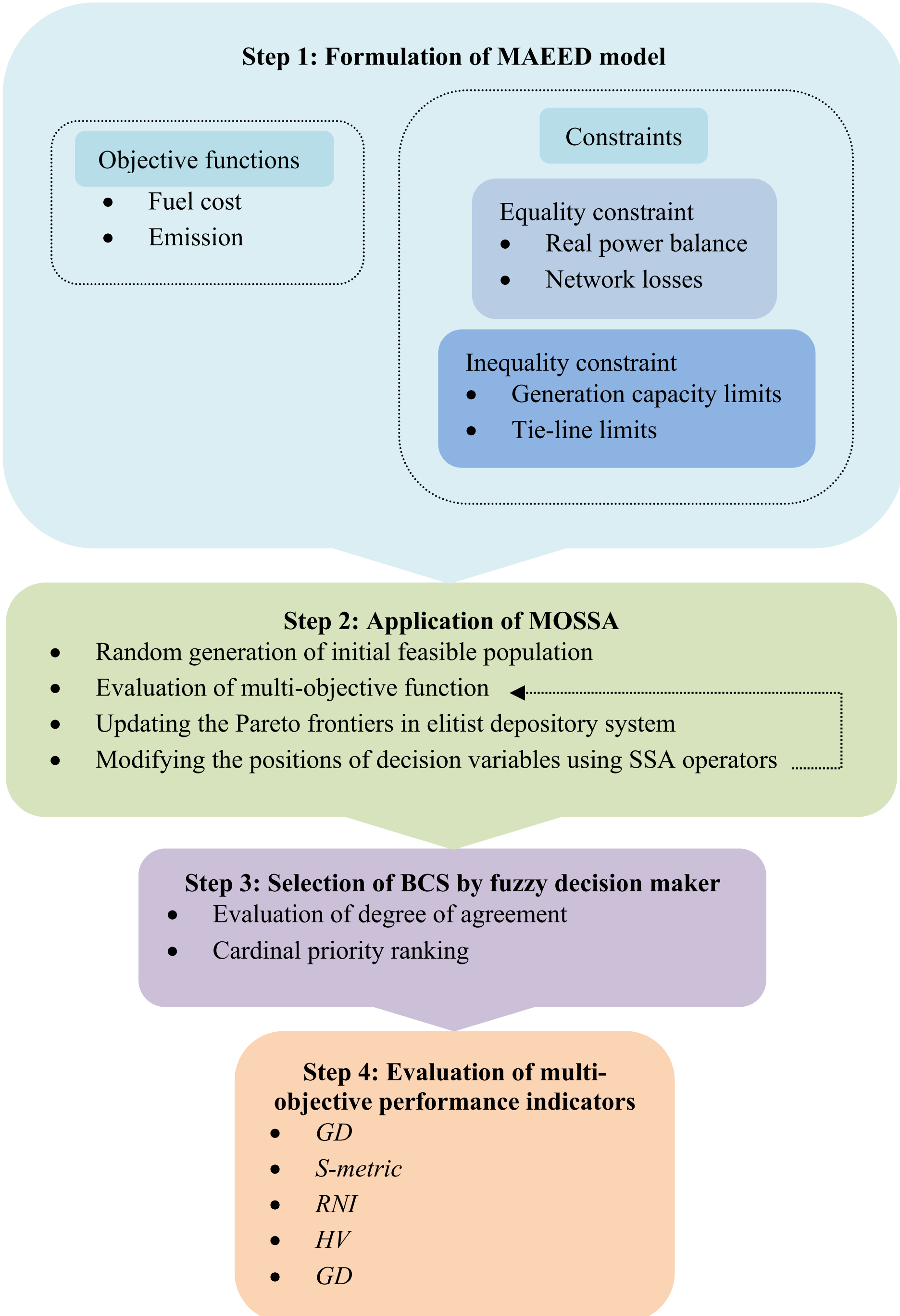

FIGURE 6. Computational framework of the proposed methodology.

the next three best flying squirrels are on the acorn tree (normal food source), and the rest of the squirrels are on the normal trees (no food source).

Step 5. Update the new position of squirrels, located on the acorn and normal trees using Eqs. (14), (15) and (16).

Step 6. Randomly relocate the positions of some squirrels, when seasonal monitoring condition is satisfied.

Step 7. Update the depository by comparing the new squirrel individuals with the members of depository based on Pareto-dominance strategy using Eq. (30).

Step 8. If the depository exceeds the maximum size, delete the less crowded solutions based on the *CD* measure to maintain constant depository size.

Step 9. If the maximum number of iterations is reached, then go to next step. Or else go to Step 2.

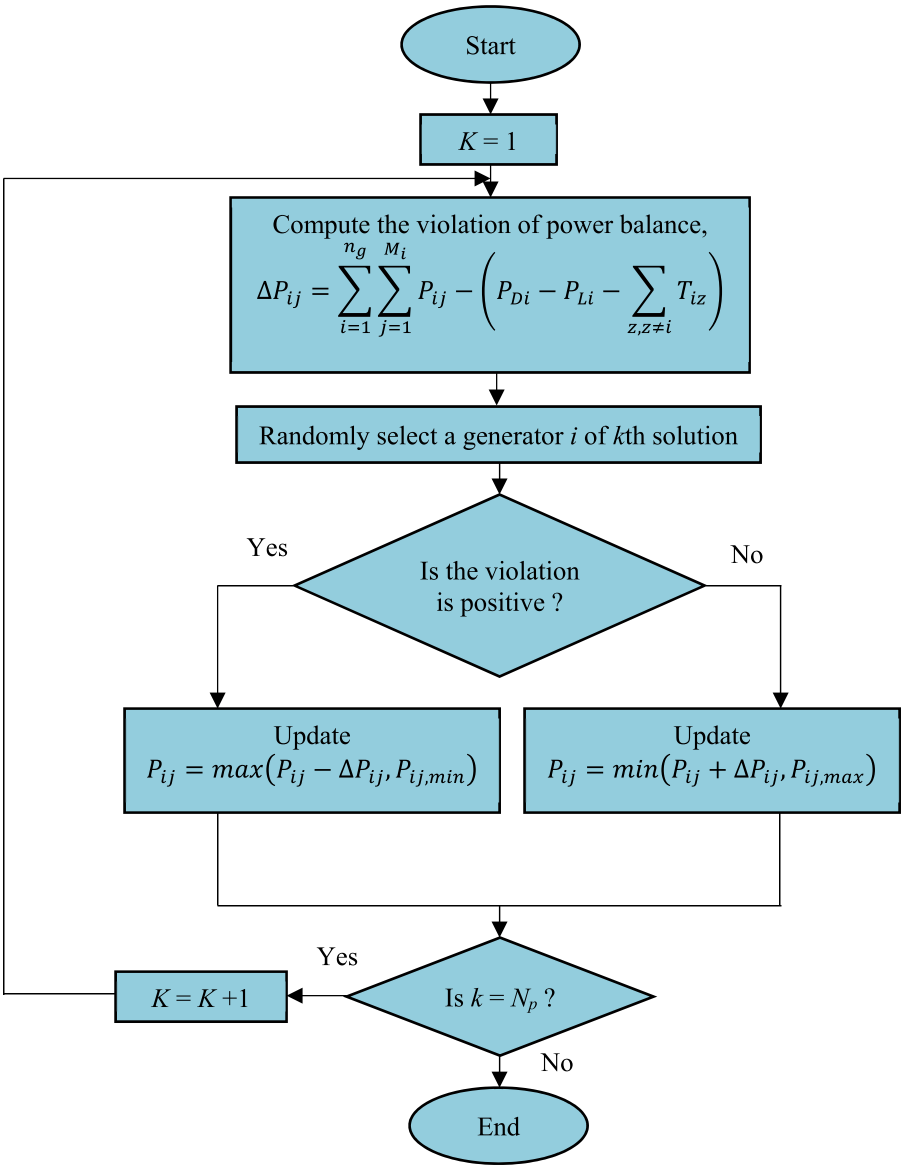

FIGURE 7. Constraint handling mechanism.

Step 10. Determine the best concessive solution from the Pareto-optimal set solutions stored in the depository using fuzzy-based approach as described in the previous section.

The computational framework of the proposed methodology and the constraint handling mechanism are depicted in Figs. 6 and 7 respectively.

V. CASE STUDIES

To testify the preeminence of the suggested MOSSA, four case studies are analyzed on two multi-area power systems including a three-area system with ten generating units, a four-area system with forty generating units and a practical large-scale system. The original SSA, ABC, EMA and other state-of-the-art heuristic approaches are used to compare with the suggested MOSSA. The MOSSA is executed 100 runs independently and the multi-objective performance indicators including the RNI, GD, s-metric, HV and DM are recorded in box-plots. The exterior vault size is chosen as 50. The MOSSA, SSA, ABC and EMA strategies are executed using MATLAB 7.1 on an Intel core i3 processor with 4 GB RAM.

The case studies which are accompanied with both the multi-area power systems are detailed below.

Case 1: Fuel cost function of the multi-area power system is minimized.

Case 2: Pollutant emission function of the multi-area power system is minimized.

Case 3: The two competitive objectives such as fuel cost and emission are transferred into a single objective function using WSA and price penalty factors, and then solved by the SSA approach.

TABLE 1. Calibration of MOSSA.

Parameters	Level 1	Level 2	Level 3
a: Number of iterations	100	200	500
b: Population size	10	20	40
c: P_{dp}	0.05	0.1	0.15
d: G_c	1.8	1.9	2

TABLE 2. Tuned parameters of MOSSA.

Parameters	Test system 1	Test system 2	Test system 3
Number of iterations	200	200	500
Population size	10	20	40
P_{dp}	0.1	0.15	0.1
G_c	2	1.8	1.8

Case 4: The fuel cost and emission functions are simultaneously minimized by the MOSSA approach.

A. PARAMETER TUNING

Taguchi method is used to tune the parameters of the suggested MOSSA. The parameters such as number of iterations, population size, P_{dp} and G_c are chosen as independent design variables. Each variable has three set values (level values) as given in Table 1. Then, L_9 orthogonal array is used to determine the optimal MOSSA parameters. Table 2 presents the tuned MOSSA parameters. The parameters are tuned at Run # 4 (a, b, c, d: 2, 1, 2, 3) for test system 1, Run # 5 (a, b, c, d: 2, 2, 3, 1) for test system 2, and Run # 9 (a, b, c, d: 3, 3, 2, 1) for test systems 3 and 4 in the Taguchi array.

B. TEST SYSTEM 1: THREE- AREA WITH TEN UNITS

This test system is a 10-unit three areas power system considering transmission losses, MFO and VPL effects. The input data of cost coefficients and multi-fuel type definitions are given in Ref. [12]. The tie-line power flow and the total power demand are chosen as 100 MW and 2700 MW respectively. The power demand in area 1 (1, 2, 3 and 4 units), area 2 (5, 6 and 7 units), and area 3 (8, 9 and 10 units) are 50%, 25%, and 25% of total power demand respectively as displayed in Fig. 8.

1) CASE 1

The optimal economic dispatch obtained by SSA is presented in Table 3. The optimal fuel cost obtained by SSA is 654.6016$/h. The fuel cost obtained from SSA is compared with RCGA [11], EP [11], ABC [11] and EMA in Fig. 9. When Fig. 9 is analyzed; it is evident that the SSA approach offers the lowest fuel cost among the compared approaches, proving the best solution quality of SSA approach.

2) CASE 2

Table 4 bestows the optimum emission dispatch obtained by the SSA approach and compared with those obtained by the ABC and EMA approaches in Fig. 10. It is observed from the Fig. 10 that, although feasible solutions can be obtained by ABC and EMA approaches, SSA discovers the lowest emission of 6374.7471kg/h.

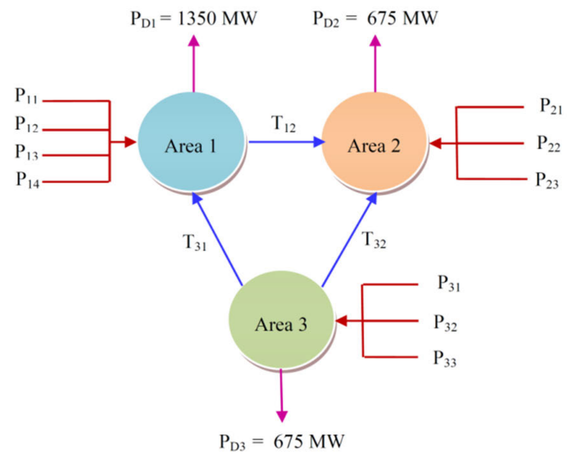

FIGURE 8. Schematic diagram of three-area with ten units' system.

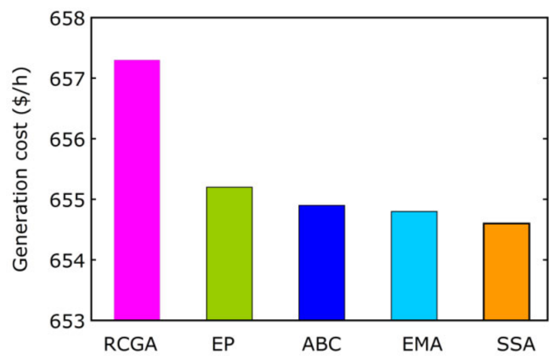

FIGURE 9. Comparison of fuel costs obtained by various heuristic approaches for case 1 of test system 1.

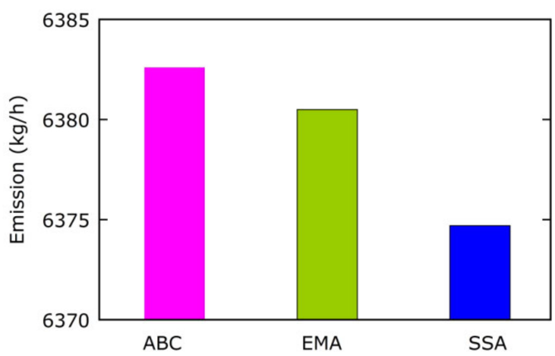

FIGURE 10. Comparison of emissions obtained by various heuristic approaches for case 1 of test system 1.

3) CASE 3

The MAEED problem is deciphered by transferring the bi-objective functions into a single objective function using Eq. 8. The weighting factor is varied between 0 and 1, and the non-dominated solution set is acquired by SSA-WSM approach.

TABLE 3. Optimal dispatch results obtained by SSA for case 1 of test system 1.

Area	Unit	Fuel types	Power generation (MW)
1	1	2	225.7694
	2	1	211.5842
	3	2	491.3265
	4	3	238.5371
2	5	1	252.6869
	6	3	235.7538
	7	1	264.7952
3	8	3	236.4286
	9	1	330.8961
	10	1	247.9518
Tie-line power	2-1		99.9792
	3-1		100.0848
	3-2		31.5594
Losses	Area1		17.2813
	Area2		9.8161
	Area 3		8.6328
Generation cost ($/h)			654.4665
Emission (kg/h)			6486.0937

TABLE 4. Optimal dispatch results obtained by SSA for case 2 of test system 1.

Area	Unit	Fuel types	Power generation (MW)
1	1	2	240.6146
	2	1	229.0357
	3	1	330.8491
	4	3	264.6587
2	5	1	240.7631
	6	1	170.3922
	7	2	374.1752
3	8	3	230.2365
	9	3	438.3571
	10	1	217.2769
Tie-line power	2-1		100
	3-1		100
	3-2		99.8644
Losses	Area1		12.0226
	Area2		13.0924
	Area 3		11.2486
Generation cost ($/h)			654.4665
Emission (kg/h)			6486.0937

The MAEED problem is deciphered by transferring the bi-objective functions into a single objective function using Eq. 8. The weighting factor is varied between 0 and 1, and the non-dominated solution set is acquired by SSA-WSM approach. The Pareto optimal frontiers (POF) acquired by the suggested approach for various weight values are presented in Table 5. The solution with the highest membership value is selected as the BCS of the MAEED problem. From Table 5, it is to be noted that the BCS is obtained when w = 0.7.

4) CASE 4

The MAEED problem is solved by MOSSA approach. An elitist external depository mechanism is used to store 20 non-dominated solutions. Then, the fuzzy decision maker is employed to decide the BCS for MAEED problem. The performance indices of MAEED problem such as fuel cost performance index (FCPI) and emission cost performance index (ECPI) are determined as follows [6]:

$$FCPI = \frac{F_{bcs} - F_{min}}{F_{max} - F_{min}} \times 100 \tag{31}$$

$$ECPI = \frac{E_{bcs} - E_{min}}{E_{max} - E_{min}} \times 100 \tag{32}$$

$$\boldsymbol{Divergence} = |\boldsymbol{FCPI} - \boldsymbol{ECPI}| \tag{33}$$

TABLE 5. Non-dominated solutions of different weighting values obtained by SSA-WSA for case 3 of test system 1.

W_1	W_2	Fuel cost ($/h)	Emission (Kg/h)	Membership value (μ_D)
1	0	654.6	6486.1	0.088973
0.9	0.1	656.0	6478.1	0.089649
0.8	0.2	657.4	6468.3	0.091762
0.7	**0.3**	**658.9**	**6459.2**	**0.092908**
0.6	0.4	659.9	6454.6	0.092500
0.5	0.5	661.4	6447.3	0.092209
0.4	0.6	664.1	6433.4	0.092291
0.3	0.7	666.7	6421.6	0.091104
0.2	0.8	669.6	6407.9	0.090210
0.1	0.9	672.2	6395.6	0.089422
0	1	676.4	6374.7	0.088973

TABLE 6. Optimal MAEED results obtained by SSA-WSA and MOSSA strategies for test system 1.

Area	Unit	Fuel types	Power generation (MW) SSA-WSA	Power generation (MW) MOSSA
1	1	2	225.7694	210.1975
	2	1	211.5842	211.6324
	3	2	491.3265	495.9134
	4	3	238.5371	230.7270
2	5	1	252.6869	245.4854
	6	3	235.7538	240.8023
	7	1	264.7952	280.9157
3	8	3	236.4286	261.7922
	9	1	330.8961	330.6595
	10	1	247.9518	227.4576
Tie-line power	2-1		99.9792	100
	3-1		100.0848	95.0785
	3-2		31.5594	41.7618
Losses	Area1		17.2813	17.5488
	Area2		9.8161	9.9651
	Area 3		8.6328	8.0690
Generation cost ($/h)			654.4665	660.2238
Emission (kg/h)			6486.0937	6441.1696

TABLE 7. Comparison of BCS obtained by various heuristic approaches for test system 1.

Approach	Fuel cost ($/h)	Emission (kg/h)
ABC	660.4672	6443.2378
EMA	661.0337	6445.5173
SSA-WSA	658.9930	6459.1875
MOSSA	660.2238	6441.1696

The BCS obtained by the suggested MOSSA approach are compared with SSA-WSA, ABC and EMA approaches in Tables 6 and 7. It is worth noting that the MOSSA provides a better POF solution as compared with the other approaches. Fig. 11 shows the MAEED performance indices of various heuristic approaches and demonstrates that the divergence between the FCPI and ECPI acquired by the MOSSA is lesser

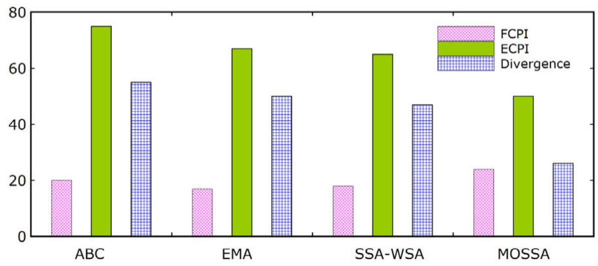

FIGURE 11. Comparison of performance indices obtained by various heuristic approaches for test system 1.

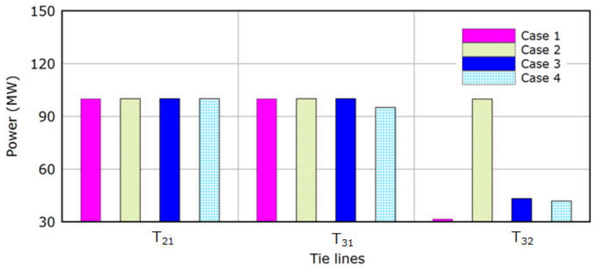

FIGURE 12. Tie-line power flows obtained by the suggested approaches for test system 1.

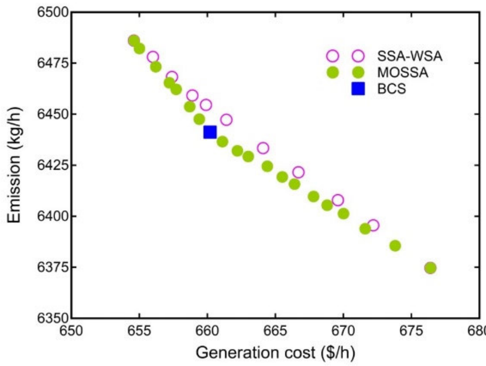

FIGURE 13. POF curves obtained by the suggested approaches for test system 1.

than the SSA-WSA, ABC and EMA approaches which prove the reliability of the proposed approach in offering the BCS. The tie-line power flows for the four different case studies are displayed in Fig. 12. It is observed from Fig. 12 that the tie-line power flows are not same for various case studies because of the different characteristics of objective functions. The POF obtained by SSA-WSA and MOSSA approaches are compared in Fig. 13. It is evident that the MOSSA procures lesser fuel costs and emissions as compared to the SSA-WSA approach.

C. TEST SYSTEM 2: FOUR- AREA WITH FORTY UNITS

The fuel and emission coefficients, power generation limits and tie-line limits of the four-area with forty generating units can be found in Ref. [12]. The total power demand is chosen as 10500 MW. The power demand in area 1 (1 - 10 units), area 2 (11- 20 units), area 3 (21 -30 units) and area 4 (31 - 40 units) are 15%, 40%, 30% and 15% of total power demand respectively as displayed in Fig. 14. The tie-line power flow limit between areas 1 and 4, areas 2 and 4, and areas 3 and 4 are 100 MW. For areas 1 to 3, 2 to 3 and 2 to 4, the power flow is limited to 200 MW.

TABLE 8. Optimal dispatch results obtained by SSA for cases 1 and 2 of test system 2.

Area	Unit	Power generation (MW)	
		Case 1	Case 2
1	1	110.8909	114
	2	110.5472	114
	3	97.9593	120
	4	178.5386	168.4705
	5	88.2575	96.9505
	6	140	125.6313
	7	258.8407	298.3848
	8	284.2543	298.7097
	9	284.5497	298.8816
	10	130	130
2	11	164.7045	297.6975
	12	168.9706	297.7663
	13	141.9572	432.8276
	14	393.5854	420.9538
	15	393.8418	420.8454
	16	470.9157	421.6216
	17	489.7922	439.3368
	18	489.9491	439.8560
	19	510.9340	438.7179
	20	510.7577	438.7825
3	21	523.8627	439.8781
	22	523.558	439.6768
	23	523.7572	439.9973
	24	523.7537	439.3547
	25	523.3404	440.6091
	26	523.5308	440.9733
	27	10	29.4819
	28	10	29.5798
	29	10	29.3591
	30	86.4694	97
4	31	190	172.6020
	32	153.5285	172.9375
	33	189.7943	172.4273
	34	164.1622	200
	35	164.6892	200
	36	164.3112	200
	37	87.6541	100.7058
	38	87.2630	100.6849
	39	108.1656	100.4015
	40	512.9133	440.8971
Tie-line power	1-2	195.1514	195.9614
	3-1	35.7749	-92.6034
	3-2	178.4934	-136.1517
	4-1	60.5383	98.5364
	4-2	90.9470	91.7849
	4-3	95.9961	95.3348
Cost ($/h)		122268.8214	130025.9210
Emission (ton/h)		362571.3553	176713.4121

1) CASE 1

Table 8 summarizes the results for solving the fuel cost minimization by the suggested SSA. The comparison of fuel

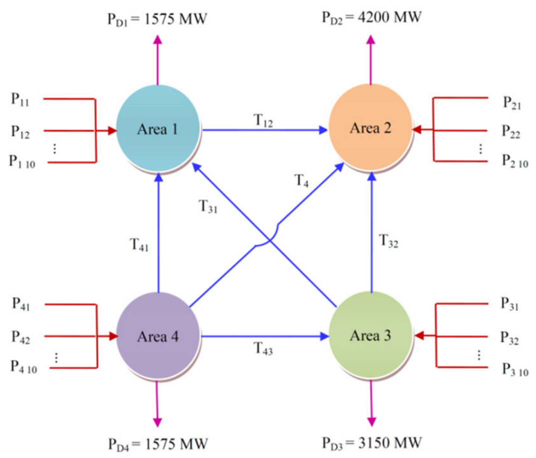

FIGURE 14. Schematic diagram of four-area with forty units system.

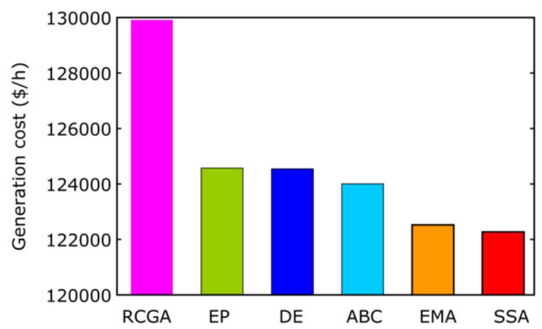

FIGURE 15. Comparison of fuel costs obtained by various heuristic approaches for case 1 of test system 2.

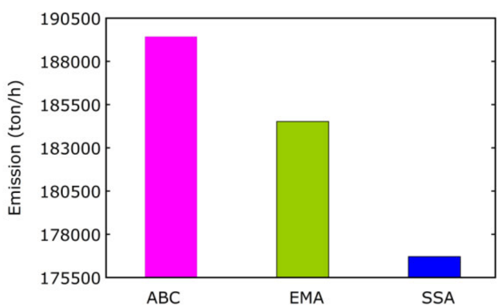

FIGURE 16. Comparison of emissions obtained by various heuristic approaches for case 2 of test system 2.

costs obtained by the SSA, RCGA [11], EP [11], DE [11], ABC [11] and EMA approaches is displayed in Fig. 15. The SSA approach reduces the cost by 7642.98 $/h, 2305.68 $/h, 2275.18 $/h, 1740.58 $/h and 256.53 $/h. This demonstrates the effectiveness of SSA approach in terms of solution quality for large scale MAEED problems.

2) CASE 2

The optimal results obtained by the suggested SSA approach for solving the emission minimization are tabulated in Table 8. Fig. 16 shows the emissions obtained by SSA, ABC and EMA strategies. As shown in Fig. 16, the emission

TABLE 9. Non-dominated solutions of different weighting values obtained by SSA-WSA for case 3 of test system 2.

W_1	W_2	Fuel cost ($/h)	Emission (Kg/h)	Membership value (μ_D)
1	0	122268.8	362571.3	0.076797
0.9	0.1	123056.3	327269.4	0.083587
0.8	0.2	124025.9	283931.2	0.091895
0.7	0.3	125013.2	238543.2	0.100875
0.6	**0.4**	**125760.0**	**206705.9**	**0.106637**
0.5	0.5	126388.3	202232.8	0.102265
0.4	0.6	127093.5	197547.6	0.097219
0.3	0.7	127657.7	193448.0	0.093327
0.2	0.8	128404.0	188177.2	0.088117
0.1	0.9	129156.2	183784.8	0.082485
0	1	130025.9	176713.4	0.076797

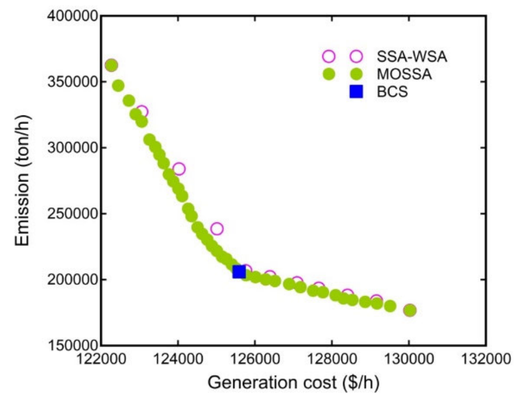

FIGURE 17. POF curves obtained by the suggested approaches for test system 2.

obtained by the suggested SSA approach is better than other compared approaches.

3) CASE 3

The bi-objective function is minimized and non-dominated solutions are acquired by executing the SSA-WSA approach with different weighting values. The POFs obtained by SSA-WSA approach are bestowed in Table 9. The table shows that the best concessive solution obtained by the suggested approach is 125760.0 $/h and 206705.9 ton/h when w = 0.6.

4) CASE 4

The optimal dispatch results acquired by SSA-WSA and MOSSA are tabulated in Table 10. Table 11 presents the BCS obtained by ABC, EMA, SSA-WSA, NSGA II [2], MODE [2] and MOSSA approaches. The BCS acquired by SSA-WSA and MOSSA are depicted in Fig 17.

It can again be dissected that the suggested MOSSA approach is proficient of finding the best compromise non-dominated solutions by successfully solving the MAEED problem.

Furthermore, the performance indices of MAEED procured by SSA-WSA, MOSSA and other heuristic approaches are displayed in Fig. 18. The divergence between the performances indices for this test system ensures ascendancy of

TABLE 10. Optimal MAEED results obtained by SSA-WSA and MOSSA strategies for test system 2.

Area	Unit	Power generation (MW)	
		SSA-WSA	MOSSA
1	1	111.8462	110.9538
	2	111.5728	110.8816
	3	120	120
	4	179.4692	179.7097
	5	96.5825	89.4135
	6	139.9594	139.9382
	7	298.9183	299.9273
	8	285.3418	284.6758
	9	285.5432	284.6154
	10	130	130
2	11	317.6829	318.3747
	12	317.5074	318.5792
	13	394.8213	394.4819
	14	394.4323	394.4273
	15	394.7807	394.4847
	16	394.4285	394.4019
	17	487.5579	488.9985
	18	487.7379	488.9246
	19	420.8462	420.9319
	20	510.3568	512
3	21	432.7510	434.5725
	22	432.8681	434.4692
	23	467.9573	450.5827
	24	432.9132	434.5625
	25	432.6851	434.3924
	26	432.7357	434.3848
	27	10	10
	28	10	10
	29	10	10
	30	89.5109	97
4	31	150.4178	150.6829
	32	190	189.8213
	33	190	189.9506
	34	193.3462	198.9723
	35	200	200
	36	200	200
	37	110	108.6298
	38	110	108.9851
	39	110	108.4175
	40	415.4294	418.8564
Tie-line power	1-2	158.3422	145.5769
	3-1	-125.8912	-129.5384
	3-2	-172.6875	-170.5059
	4-1	100	100
	4-2	94.1934	99.3243
	4-3	100	99.9916
Cost ($/h)		125760.0557	125591.3223
Emission (ton/h)		206705.9772	205965.4061

MOSSA in comparison to the SSA-WSA and other aforementioned approaches in rendering the BCS. Fig. 19 shows the tie-line power flows obtained by MOSSA for all the case studies. When Fig. 19 is examined, it is seen that the tie-line power flows are varied with objective functions and altered them in reliance on a considered objective function.

TABLE 11. Comparison of BCS obtained by various heuristic approaches for test system 2.

Approach	Fuel cost ($/h)	Emission (ton/h)
ABC	126480.56	209285.74
EMA	125910.69	210238.19
NSGA-II [2]	125830	210950
MODE [2]	125792	211190
SSA-WSA	125760.0557	206705.9772
MOSSA	125591.3223	205965.4061

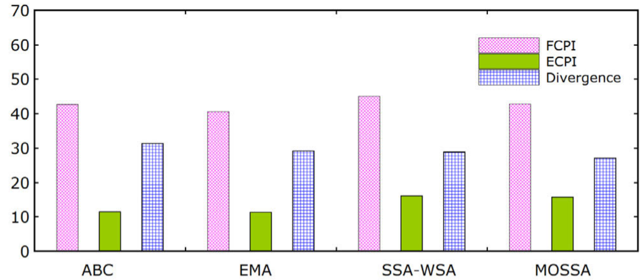

FIGURE 18. Comparison of performance indices obtained by various heuristic approaches for test system 2.

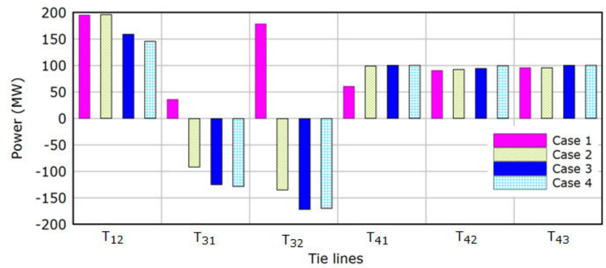

FIGURE 19. Tie-line power flows obtained by the suggested approaches for test system 2.

D. TEST SYSTEM 3: 140-UNIT KOREAN POWER SYSTEM

To examine the feasibility of the proposed SSA in solving real large-scale power system, the Korean power system with non-convex fuel cost is solved. The Korean system consists of 140 generating units, where units 1 to 40 are thermal power plants, units 41 to 91 are gas power plants, units 92 to 111 are nuclear power plants, and units 112 to 140 are oil power plants. The VPL effects are considered in 6 thermal, 4 gas and 2 oil power plants. The POZs are deliberated in 4 generating units. The system data are specified in Ref. [7]. The total demand is 49,342 MW. The optimal dispatch solution with proposed SSA approach is conferred in Table 12. The minimum, mean and maximum fuel costs among 100 runs of solutions obtained from proposed SSA, GSO [8], CQGSO [8], KHA [7], OKHA [7] and SDE [9] are compared in Table 13. It is noticeable from Table 12 that the fuel cost acquired through SSA for Korean non-convex system is 1559818.7289 $/h which is the lowest among the state-of-the-art algorithms. Furthermore, As can be seen from Table 13, the SSA is converged to an approximately similar solution in 100 independent runs, which demonstrates the robustness of the suggested SSA in solving the Korean non-convex system.

TABLE 12. Optimal generations schedule of SSA technique for test system 3.

Unit	Output power (MW)	Unit	Output power (MW)	Unit	Output power (MW)	Unit	Output power (MW)
1	116.5799	36	500	71	137	106	954
2	189	37	241	72	326.0975	107	952
3	190	38	241	73	195	108	1006
4	190	39	774	74	175	109	1013
5	168.6899	40	769	75	175	110	1021
6	190	41	3	76	175	111	1015
7	490	42	3	77	175	112	94
8	490	43	248.8932	78	330	113	94
9	496	44	247.3674	79	531	114	94
10	496	45	250	80	531	115	244
11	496	46	250	81	395.7215	116	244
12	496	47	240.6137	82	56.9652	117	244
13	506	48	250	83	115.3572	118	95
14	509	49	250	84	115	119	95
15	506	50	250	85	115	120	116
16	505	51	165	86	207	121	175
17	506	52	165	87	207	122	2
18	506	53	165	88	175	123	4
19	505	54	165	89	175	124	15
20	505	55	180	90	175	125	9
21	505	56	180	91	175	126	12
22	505	57	103	92	580	127	10
23	505	58	198	93	645	128	112
24	505	59	312	94	984	129	4
25	537	60	281.1698	95	978	130	5
26	537	61	163	96	682	131	5
27	549	62	95	97	720	132	50
28	549	63	160	98	718	133	5
29	501	64	160	99	720	134	42
30	501	65	490	100	964	135	42
31	506	66	196	101	958	136	41
32	506	67	490	102	1007	137	17
33	506	68	488.6475	103	1006	138	7
34	506	69	130	104	1013	139	7
35	500	70	233.8972	105	1020	140	27
Minimum cost ($/h)	1559818.7289						

TABLE 13. Comparison and statistical analysis of various algorithms for test system 3.

Approach	Min. cost ($/h)	Mean cost ($/h)	Max. cost ($/h)
GSO [8]	1728151.1680	1745514.9975	1753229.5636
CQGSO [8]	1657962.727	1657962.741	1657962.776
KHA [7]	1560173.88	1560176.7448	1560177.8061
OKHA [7]	1560146.95	1560148.9264	1560149.9764
SDE [9]	1560236.85	-	-
SSA	1559818.7289	1559839.5832	1559875.3959

E. ANALYSIS OF PARETO OPTIMAL FRONTIERS

To testify the effectiveness of the suggested MOSSA approach, the three distinctive multi-objective performance indicators, the RNI, GD, s-metric, HV and DM are assessed.

1) RNI

RNI is defined as the proportion of number of non-dominated solutions for the populace size. It can be expressed as:

$$RNI = \frac{|\hat{x}|}{n} \tag{34}$$

The higher the RNI measure, better the solution quality. The RNI obtained by the SSA-WSA and MOSSA are compared in Fig. 20. It can be seen from Fig. 20 that the suggested MOSSA acquires higher RNI values than the SSA-WSA,

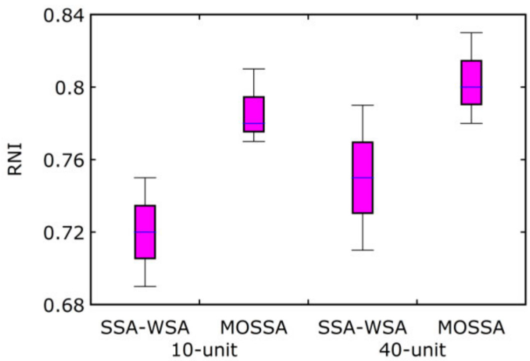

FIGURE 20. Comparison of RNI obtained by the suggested approaches.

which indicates that MOSSA has transmuted better populace.

2) GD

GD estimates the entirety of contiguous separations of solution sets. A smaller value of GD measure indicates the better convergence of solutions. The mathematical formulation for GD is as follows [27]:

$$GD = \frac{\sqrt{\sum_{i=1}^{n} ed_i^2}}{n} \tag{35}$$

3) s-METRIC

The s-metric estimates the distance between the variance of neighboring points in the POF curve. The lower the spread value, the better the dissemination of solutions. It can be defined as follows [27]:

$$S - metric = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left(ed_i - \bar{d}\right)^2} \tag{36}$$

Figs. 21 and 22 parade the GD and s-metric of the suggested approaches. It can be noticed that the MOSSA approach establishes better convergence, diversity and well distributed POF solutions.

4) HV

This indicator determines the volume (in the objective space) covered by solutions of a POF set for multi-objective problems where all objectives are to be minimized. A higher HV value is desirable for optimization algorithms. The normalized HV measure for the POF obtained for each algorithm is depicted in Fig. 23. It is evident that a higher HV is obtained by the MOSSA approach, which demonstrates the POF generated by the suggested approach is better than the SSA-WSA.

5) DM

The Euclidean distance between consecutive solutions in the POF and the mean of these distances are calculated. Then,

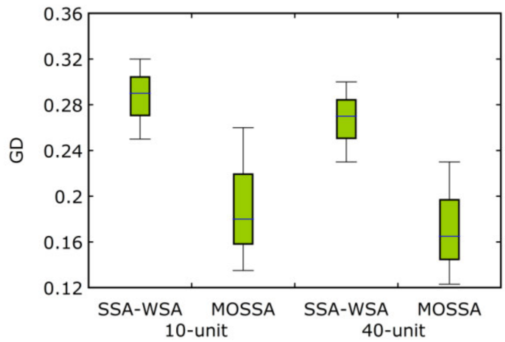

FIGURE 21. Comparison of GD measures obtained by the suggested approaches.

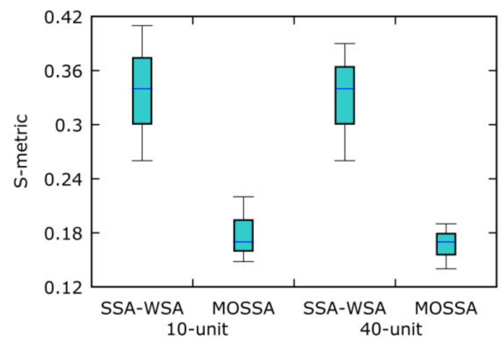

FIGURE 22. Comparison of s-metric obtained by the suggested approaches.

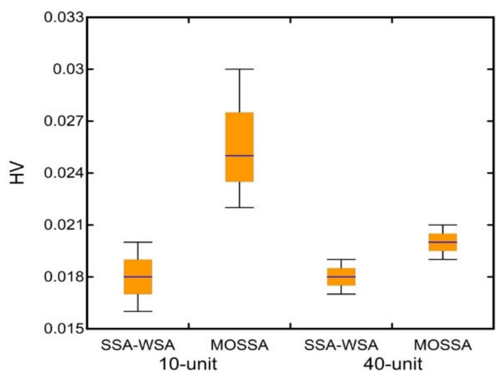

FIGURE 23. Comparison of HV measure obtained by the suggested approaches.

the DM is defined as [27]:

$$DM = \frac{ed_f + ed_l + \sum_{i=1}^{n-1} \left|ed_i - \bar{d}\right|}{ed_f + ed_l + (n-1)\bar{d}} \tag{37}$$

If the *DM* is zero, then all the solutions of the POF are equidistantly spaced. A smaller value of *DM* indicates a better distribution and diversity of the non-dominated solutions. The comparison of *DM* obtained from SSA-WSA and MOSSA for the test systems is displayed in Fig. 24. It is obvious from the figure that the MOSSA is better than SSA-WSA in preserving the diversity.

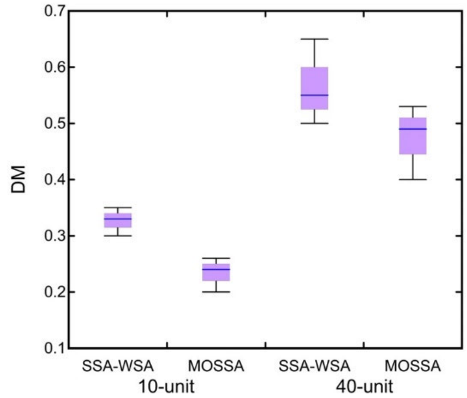

FIGURE 24. Comparison of DM measure obtained by the suggested approaches.

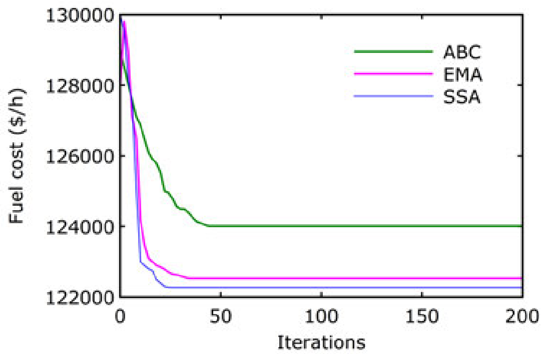

FIGURE 25. Convergence behaviors of various approaches for Case 1 of test system 2.

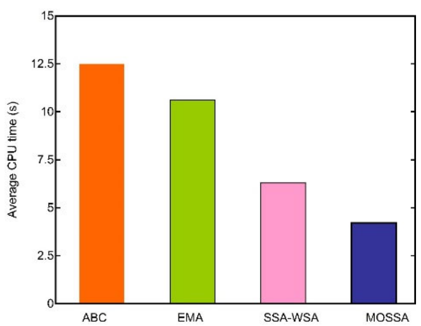

FIGURE 26. Comparison of average CPU time adopted by various heuristic approaches for test system 1.

F. CONVERGENCE BEHAVIOR AND COMPUTATIONAL EFFICIENCY

The convergence behaviors of ABC, EMA and SSA for test system 2 are depicted in Fig. 25. It is worth noting that the SSA strategy is the quickest in uniting to its final solution and furthermore offers the least fuel cost for the MAELD problem. Consequently, the results demonstrate the quicker intermingling behavior of the suggested SSA approach. The average CPU time adopted by different heuristic strategies for all the test systems are displayed in Figs. 26, 27 and 28. It may be noted that the MOSSA approach takes the least execution time with quicker union and better solution quality.

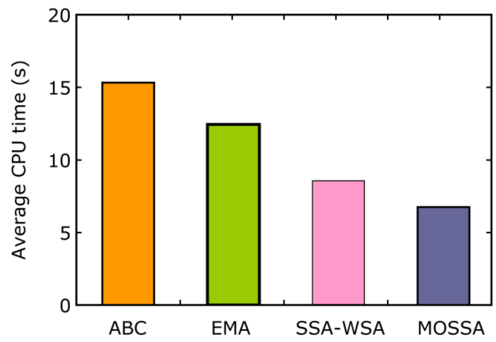

FIGURE 27. Comparison of average CPU time adopted by various heuristic approaches for test system 2.

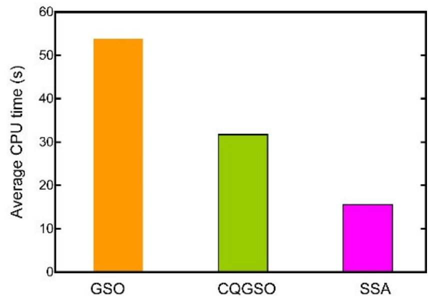

FIGURE 28. Comparison of average CPU time adopted by various heuristic approaches for test system 3.

G. DISCUSSIONS

In this research article, the merits are summarized hereunder.

- To the best of authors' knowledge, this research article is the first research work of extending SSA approach for solving multi-objective power system optimization problems.
- The MOSSA demonstrates the superior performance to discover the best POF for MAEED problems with MFO and VPL effects. The BCS procured by the MOSSA for the test system 1 is 660.2238 \$/h and 6441.1696 kg/h. In the test system 2, the BCS obtained from the suggested approach is 125591.3223 \$/h and 205965.4061 ton/h.
- The difference between FCPI and ECPI obtained from MOSSA is lesser than those obtained from the other compared approaches, indicating the superiority of MOSSA in obtaining the BCSs.
- The MOSSA provides better POF solution compared with SSA-WSA, ABC, EMA and other state-of-the-art meta-heuristic approaches surfaced in the literature.
- The suggested approach has very fast convergence speed when compared with ABC and EMA approaches. Consequently, the suggested MOSSA is an efficient meta-heuristic approach for solving the MAEED problems.

VI. CONCLUSION

This paper proposes a new swarm optimization approach, MOSSA for solving the MAEED problem with MFO and VPL effects. Three power systems were tested to solve interconnected (multi-area) EED problems by the efficacy of the proposed MOSSA. MOSSA findings are contrasted with SSA-WSA, ABC, EMA and other recent heuristic approaches in the literature. The non-dominated POF solutions are widely disseminated and have the fastest convergence behavior with less computational effort. The proposed MOSSA is therefore a promising method for optimizing economic dispatch problems in large and small systems. It will be very fascinating to study the MAEED of hybrid renewable thermal power system in the further research.

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