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Multi-area economic emission dispatch for large-scale multi-fueled power plants contemplating inter-connected grid tie-lines power flow limitations

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ABSTRACT

The purpose of this research is to investigate the multi-area economic emission dispatch problem (MEEDP) in the presence of renewable energy resources (RES) to improve the energy sustainability and climatic benefits. MEEDP is a multi-objective problem in smart grids, with the purpose of minimizing the operating costs and emissions of thermal units. RES have made a substantial contribution to greenhouse gases emission control and environmental sustainability. The integration of RES into conventional grids, which is becoming increasingly prevalent, spread the research scope of MEEDP and needs to be re-examined. This work considers two renewable sources (wind and solar) along with thermal plants subjected to significant number of previously uncombined system level limitations such as power capacity limit, prohibited zones, transmission network losses, dynamic ramp limits, tie-line limits and multiple fueling options. The operating cost is computed as summation of predictive and stochastic components. The predictive part is calculated by utilization of cumulative distribution function for each wind and solar system. A swarm intelligence-based crow search optimization algorithm (CSOA) is modeled to handle the complex constrained MEEDP with adjusted predictive part of RES. Six benchmark test systems with multi-dimensional constraints have been chosen to validate the adaptability and efficacy of the presented approach. Regardless of the complexity of the problem, the proposed approach provides the best feasible solution with a finer convergence rate. Finally, the simulation results depict that the integration of the corresponding system constraints gives legitimacy to the system and delivers reliable output.

1. Introduction

Economic load dispatch (ELDs) plays a major role in the planning and operation of power system utilities. The ever-growing power demand for industries and domestics purposes has not only increased the operating costs but has also affected the ecological system of our planet habitats. This rapid rise in power demand has led to some additional constraints such as transmission losses and multi-area power sharing making traditional economic environmental load dispatch (EELDs) problem more complex. The classical target of ELDs was to minimize only the fuel cost with generation capacity constraints [1,2] through some analytical techniques such as Newton–Raphson etc. ELDs with dynamic load demand considering VLEs and price variations due to the generating network location are studied in [3,4]. These techniques become ineffective with introduction of some nonlinear constraints namely prohibited operating zones (POZs) and multiple fueling options (MFOs). Sinha et al. [5] proposed evolutionary programming techniques to tackle the nonlinear limitations of ELDs, but the problem complexity increased as environmental concerns attracted researchers' interest. Therefore, the minimization of fuel cost was no more the only concern and the international environmental agencies put-forward emission restrictions to utilities and the dispatch problem become bi-objective.

The authors in [6] presented a squirrel search algorithm to solve single area [7] as well as complex MEEDP. Adeyan et al. [8] proposed centralized, semi-centralized and decentralized meta-heuristic approaches for MEEDP. Zare et al. [9] solved MEEDP by a firework algorithm considering load as hourly variable and proposed a novel

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Acronyms

MEEDP	Multi-area energy emission dispatch problem
CSOA	Crow search optimization algorithm
VLEs	Valve-point loading effects
MFOs	Multiple fueling options
POZs	Prohibited operating zones
ELDs	Economic load dispatch
EELDs	Economic environmental load dispatch
SSA	Salp swarm algorithm
MOSA	Multi-objective simulated annealing
RCGA	Real coded genetic algorithm
EP	Evolutionary programming
ABC	Artificial bee colony
DE	Differential evolution
GSO	Glowworm Swarm Optimization
CQGSO	Continuous quick group search optimizer
KHA	Krill herd algorithm
OKHA	Opposition-based krill herd algorithm
SDE	Stochastic coding differential evolution
EMA	Expectation–maximization algorithm
MILP	Mixed integer linear programming
RES	Renewable energy resources
DA	Dragonfly algorithm
ALO	Ant-lions optimization
ORCCRO	Oppositional Real Coded Chemical Reaction algorithm
BBO	Biogeography-based optimization
PSO	Particle swarm optimization
GA	Genetic algorithm

Nomenclature

ω_r	Rated power of wind unit
Ω	Amount of solar irradiance
Θ	Power temperature coefficient in percentage per centigrade
υ	Current wind speed
c	Scale factor
CU	Total committed units
E_{ct}	Total emission cost
F_{ct}	Total fuel cost
h	Penalty factor
k	Shape factor
N_s	Number of solar panels
N_z	Number of windmills
N_{parl}	Number of cell in parallel
N_{srs}	Number of cell in series
P_{DLA}	Power demand
P_{ij}	Output power
P_{NLA}	Network losses
$R_p(stc)$	Solar power standard test condition
$R_p(t)$	Solar radiation
$R_{rad.stc}$	Solar radiation standard test condition
$S_{p,k}$	Solar power
T_{MA}	Power transfer limits
U_{ambt}	Ambient temperature of cell
$U_{cel.stc}$	Temperature of cell at standard condition
U_{cel}	Temperature of cell
$U_{nrml.temp}$	Normal temperature of cell
Z	Area zones
α_{ij}, β_{ij}, γ_{ij}, η_{ij} and δ_{ij}	Emission coefficients
a_{ij}, b_{ij} and c_{ij}	Input fuel coefficients
f_{ij} and e_{ij}	VLEs coefficients
F_{SC}	Solar generation cost
F_{WC}	Wind generation cost

scheme to design ELDs as a dynamic problem. Hassan et al. in [10], suggested a Manta Ray foraging algorithm to solve the economic emission problem. The main drawback associated with the proposed technique is convergence to local minimum resulting in sub-optimal results.

Zou et al. [11,12] solved emission dispatch problem by incorporating renewable energy sources by means of virus colony optimizer and obtained trade-off curves between fuel and emission costs. The method, although effective, does not consider the probabilistic nature of wind energy and involves high costs with some ecological effects. A fuzzy compromised with home demand allocation emission dispatch problem was solved in [13] by incorporating local energy grid systems. The introduced scheme, however, requires high initial capital investment. Besides, the emission constraints are also compromised in above-mentioned schemes. Clearing algorithms such as MILP and ANNEX generic optimization model for the electrical market are the subject of several studies in academic literature [14,15].

The authors in [16] suggested a memory-based gravitational optimizer for load dispatch but the reported results are shown to be optimal for cost function with soft constraints only. Rawa et al. [17] suggested five different optimizers to solve EELDs with traditional constraints. The presented methodologies are quite inefficient in terms of computational efficiency and involve high computing costs. Stefano et al. [18] proposed the adaptation of efficient materials for storage system of thermal plants but the site occupancy and troubleshooting for such a system requires special skills. A new crisscross optimizer framework is combined with Pareto multi-objective solver in [19] to obtain optimal solution of emission and fuel costs. The proposed scheme is computationally complex and lags in efficient handling of large system constraints . Chen et al. [20] suggested wind turbines integration with traditional thermal units to handle the tie-line and spinning reserves constraints. The integration improved the results by adding a feedback generation to the existing plants, but the stochastic nature of wind energy production remains a concern along with inadequate handling of emission constraints.

Pandit et al. [21] suggested a fuzzy selection based optimizer framework using a differential evolutionary algorithm to solve the economic emission problem. The presented fuzzy-based scheme lags in terms of computational efficacy as more iterations are needed for optimized solution. Xin et al. [22] divided the economic dispatch problem into small micro grids to handle the emissions and promoted the use of renewable energy for low carbon development. The micro-grid energy systems based on renewable energy significantly reduced the carbon emissions but at increased system cost.

The integration of renewable energy sources involve high costs and require the special energy storage to balance the demand load of network with the increase in load. The authors in [23–25] suggested a particle swarm optimizer framework to solve the multi-area dispatch problem by considering real power flow and power transfer limits. The swarm based algorithms pose certain constraints in terms of slow convergence and local minima for high-dimensional search spaces which lead to increased computational costs and performance compromise. In [26], a swarm based optimizer is proposed for voltage stabilization. Lin et al. [27,28] suggested stochastic optimizer for solving the complex objective function of MEEDP with limited constraints. The stochastic algorithms, although feasible, are less accurate as compared to other approaches and have been avoided for critical energy systems with restricted computational capabilities.

Renewable systems do pose certain problems such as the production can never be deterministic as in case of traditional thermal plants raising the risk of handling capacity constraints. The energy production in renewable systems is also dependant on solar or wind profiles of area hence necessitating the region-specific unit designs. Song et al. [29] presented a cooperative distributed optimization to address the economic emission problem that involves the heating and cooling of natural gas model. The main drawbacks of distributed optimization are convergence to local minima and requirement for linearization of non-convex constraints [30]. The authors in [31] presented a secant method to solve the complex objective function of MEEDP. The proposed scheme, however, does not guarantee convergence of all constraints and do not ensure boundedness of fitness function error. Hossein et al. [32] presented a hybrid algorithm to solve combined heat economic dispatch problem. The suggested algorithm has shown to perform better but requires accurate parameter selection and involves higher computational time and iterations for optimal solution.

Concerning the above reported literature, the MEEDP is complex and practical engineering problem which determines the optimal schedule for generators active power and the exchange of active powers among different areas under several operational constraints such as generation–consumption balance, tie-line capacity constraints, generator output constraints, and transmission losses. Furthermore, there has been very fewer work done on MEEDP with RES integration, and the topic has not been thoroughly investigated in the existing literature for large non-convex test systems to the best of our knowledge, by encompassing all of the non-convex constraints. Our aim is to investigate the RES integrated MEEDP with all non-continuous limitations such as MFOs and POZs along with additional constraints of spinning reserves and tie-line constraints. In this paper, crow optimization search algorithm is applied to benchmark real-world thermal plants operating in different zones. The CSOA framework assists the financial institutions, system operators, and policymakers with variety of ways. To begin, by systematically pursuing the optimal generation cost, it assists system operators in providing consumers with affordable, sustainable electricity service. Additionally by incorporating MFOs limitation, the framework allows policymakers and financial actors to use readily available, low-emission fuels such as natural gas, so strengthening the country economy by reducing its dependency on imported fuel and protecting the environment.

The details of computing framework are provided in Section 3. Furthermore, our designed strategy based on bio-inspired framework handles this problem for all possible scenarios. The significant highlights of this investigation are summarized as follows:

- The complex MEEDP objective function is considered with real-world non-convex constraints. All test systems chosen are benchmark test systems and optimal values of emission and cost function are obtained by handling tie-line and spinning reserves limitations as compared to the SSA-MOSA [33], RCGA [34], EP [6], ABC [34], EMA [34], DE [34], GSO [35], CQGSO [35], KHA [36], OKHA [36] and SDE [37].
- The crow search optimization algorithm is employed with relatively straightforward parameter adjustment; knowing probability and flight path awareness. The proposed scheme attains optimum results by handling all limitations in multi-dimensional search space.
- The efficacy and computational performance of presented scheme is showcased along with convergence rate and stability, see e.g. SSA-MOSA [33], RCGA [34], EP [6], ABC [34], EMA [34], DE [34], GSO [35], CQGSO [35], KHA [36], OKHA [36] and SDE [37].
- The obtained optimal statistical results show superior performance under the contiguous hard constraints. The results are compared analytically and graphically with other state-of-art heuristic approaches reported in literature recently, see e.g. SSA-MOSA [33], RCGA [34], EP [6], ABC [34], EMA [34], DE [34], GSO [35], CQGSO [35], KHA [36], OKHA [36] and SDE [37].
- The low emission profiles of proposed scheme also provide a vibrant solution to emission regulatory authorities for developing a robust solution for energy manufacturing industries.
- The integration of renewable systems with conventional thermal plants has significant impact in cost and emission reduction. In this context, a special test system (Test System-IV) is studied. The analysis in the form of mean cost is compared with [38–44].

The rest of the paper is organized in follows: Section 2 compromises problem formulation along with system constraints. Section 3 includes a brief working of optimizer framework. Section 4 contains obtained results and simulations. Finally the conclusions are drawn in Section 5.

2. MEEDP problem formulation

2.1. Convex MEEDP cost function

The objective of MEEDP is to attain optimum generating power output distribution for all predefined operating zones with minimal costs and power shifting among the area zones subject to correlated constraints. The non-convex cost function of committed generating units can be represented as follows [45]:

$$F_{ct} = \sum_{i=1}^{CU} \sum_{j=1}^{Z_i} F_{ij}\left(P_{ij}\right), \tag{1}$$

$$F_{ct} = \sum_{i=1}^{CU} \sum_{j=1}^{Z_i} \left(a_{ij} P_{ij}^2 + b_{ij} P_{ij} + c_{ij}\right), \tag{2}$$

where a_{ij}, b_{ij} and c_{ij} represent the input fuel coefficients of committed units of the jth generator of the Z_j^{th} area zone. P_{ij} is the output power of the jth committed unit in the Z_j^{th} area zone. F_{ct}, CU and Z_i represent the total fuel cost, total committed units and area zone, respectively.

2.2. Non-convex MEEDP cost function

The non-convexity in thermal plants is pop up in fuel cost function due to the valve opening of steam. All thermal plants have special mechanism for valve opening which directs the super heated dry steam to turbine units. When these valves are operated, a slight reduction in power is induced which produces ripples in cost function curve. This effect, known as valve-point loading effect (VLEs), produces increment in fuel cost curve and mathematically can be represented as follows:

$$F_{ct} = \sum_{i=1}^{CU} \sum_{j=1}^{Z_i} \left(a_{ij} P_{ij}^2 + b_{ij} P_{ij} + c_{ij}\right) + \left|e_{ij} \times \sin\{f_{ij} \times (P_{ij(\min)} - P_{ij})\}\right|. \tag{3}$$

The addition of sinusoid function on VLEs produces the power loss and converts the cost function to truly non-convex. Here f_{ij} and e_{ij} are VLEs cost coefficients of the jth committed units in the Z_j^{th} area zone.

2.3. Renewable energy systems modeling

Predicting variables such as airspeed, sun irradiation, and the related demand is crucial to the reliability of a power management system for renewable energy sources, regardless of whether they are connected to conventional power systems or operating independently. Mathematical modeling of RES systems for MEEDP is carried out in this section. The carbon footprint of RES is significantly smaller than that of other energy sources like gas, coal, and other fossil fuels. These key factors have prompted scientists worldwide to connect RES with conventional power systems in order to obtain clean, sustainable and carbon-free energy. The precise characterization of RES uncertainty is essential in stochastic optimizations, and usually the system representation depends on the modeling-method. As a result, the approaches adopted to model uncertainty must be carefully chosen. In our work, we employ beta distribution function and Weibull probability density function to model MEEDP considering RES. The detail of RES modeling is as follow.

Solar modeling. Solar radiation, environmental temperature, and the performance parameters of the photovoltaic module all have a significant impact on the solar electricity generation. Throughout this research, we employ the beta distribution function (BDF) to attain energy output generated, and the mathematical modeling of solar energy using the BDF is as follows [46]:

$$F_{\beta}(\Omega) = \begin{cases} \dfrac{\psi(\varpi + Y)}{\psi(\varpi)\,\psi(Y)} \times \Omega^{\varpi-1}(1-\Omega)^{Y-1} \\ for\ 0 \leqslant \Omega \leqslant 1,\ \varpi \geqslant 0,\ Y \geqslant 0 \\ 0 \qquad \text{Otherwise} \end{cases} \tag{4}$$

where ϖ and Y depict the parameters of F_{β}. Now, it is possible to write the function by utilizing the mean ϕ and the standard deviation Λ. The function can be stated as

$$\varpi = \phi\left(\frac{\phi(\phi+1)}{\Lambda^2} - 1\right), \tag{5}$$

$$Y = (1-\phi)\left(\left(\frac{\phi(\phi+1)}{\Lambda^2} - 1\right)\right). \tag{6}$$

As previously stated, solar radiation and surrounding temperature are significant factors influencing solar generation, and these factors can be modeled as follows.

$$R_p(t) = N_{srs} \times N_{parl}[R_p(stc) \times \frac{R(t)_{rad}}{S_{rad.stc}} \times [1 - \Theta \times (U_{cel} - U_{cel.stc})]], \tag{7}$$

$$U_{cel} = U_{ambt} + \frac{R(t)_{rad}}{R_{rad.stc}} \times (U_{nrml.temp} - 20). \tag{8}$$

Wind modeling. The chaotic nature of wind speed has a significant impact on the production of wind energy and it is necessary to characterize wind speed properties using the Weibull probability density function (WPDF), which can be given as follow [47].

$$WS_{pdf}(\upsilon) = \frac{k}{c}\left(\frac{\upsilon}{c}\right)^{k-1}.\exp\left(-\left(\frac{\upsilon}{c}\right)^{k}\right) \quad (\upsilon > 0). \tag{9}$$

By utilization of speed–power curve the generated power can be given as follows.

$$W(\mathrm{P}) = \begin{cases} 0, & \upsilon < \upsilon_{in} \ \text{ or } \ \upsilon > \upsilon_{out} \\ \dfrac{\omega_r(\upsilon - \upsilon_{in})}{\upsilon_r - \upsilon_{in}} & (\upsilon_{in} \leqslant \upsilon \leqslant \upsilon_r) \\ \omega_r & (\upsilon_r \leqslant \upsilon \leqslant \upsilon_{out}) \end{cases} \tag{10}$$

2.3.1. Solar cost function

The following mathematical model can be used to compute the cost of solar energy generation.

$$F_{SC} = \sum_{k=1}^{N_s} R_{p,k} \times B_i G_k. \tag{11}$$

In this case, the cost of solar generation is denoted by F_{SC}. N_s and $R_{p,k}$ denote the number of solar panels and powers, respectively.

2.3.2. Wind cost function

The following mathematical model is used for computing the cost of wind power generation.

$$F_{WC} = \sum_{j=1}^{N_z} W_{p,j} \times C_{aj}, \tag{12}$$

In this case, the cost of solar generation is denoted by F_{WC}. N_z and W_p are the number of wind plants and power, respectively.

2.4. Non-convex MEEDP cost function with RES

The following mathematical model is used to represent the non-convex cost function after integration with RES.

$$F_{ct} = \sum_{i=1}^{CU}\sum_{j=1}^{Z_i}\left(a_{ij}P_{ij}^2 + b_{ij}P_{ij} + c_{ij}\right) + \left|e_{ij} \times \sin\{f_{ij} \times (P_{ij(\min)} - P_{ij})\}\right| + \sum_{k=1}^{N_s} S_{p,k} \times B_i G_k + \sum_{j=1}^{N_z} W_{p,j} \times C_{aj}, \tag{13}$$

2.5. Non-convex MEEDP emission cost function

The other objective of MEEDP is to restrict the emission discharge from all committed units by incorporating the equality and inequality limits of generation. The environmental emission of committed units can be represented as emission cost function for all operating regions as

$$E_{ct} = \sum_{i=1}^{CU}\sum_{j=1}^{Z_i} E_{ij}\left(P_{ij}\right), \tag{14}$$

$$E_{ct} = \sum_{i=1}^{CU}\sum_{j=1}^{Z_i}\left(\alpha_{ij}P_{ij}^2 + \beta_{ij}P_{ij} + \gamma_{ij}\right) + \eta_{ij}\exp(\delta_{ij}P_{ij}), \tag{15}$$

where α_{ij}, β_{ij}, γ_{ij}, η_{ij} and δ_{ij} are the emission coefficients of the jth generator of the Z_j^{th} area zone. Here E_{ct}, CU and Z_j represent the total emission cost, total committed units and area zone, respectively.

2.6. Non-convex MEEDP formulation based on CSOA

The MEEDP problem can be formulated as a multi-objective problem that consists of non-convex fuel cost function and emission function as objective goals. The mathematical expression of the combined MEEDP is as follows.

$$K_{ct} = \min(F_{ct}\,,\ E_{ct}). \tag{16}$$

Above MEEDP multi-objective function can be converted into a single optimization function by means of a penalty factor h. Assigning $h = 0$ delivers fuel cost function where $h = \infty$ delivers full emission function. Consequently, the penalty factor component must have a trade-off value. Various methods have been offered [48] for computing the trade-off value for the price penalty factor, one of which is the maximum price penalty factor.

$$\begin{aligned} K_{ct} &= \min(F_{ct}\,,\ E_{ct}) \\ &= \sum_{i=1}^{CU}\sum_{j=1}^{Z_i}[(a_{ij}P_{ij}^2 + b_{ij}P_{ij} + c_{ij}) + \left|e_{ij} \times \sin\{f_{ij} \times (P_{ij(\min)} - P_{ij})\}\right| \\ &+ h_i\left(\alpha_{ij}P_{ij}^2 + \beta_{ij}P_{ij} + \gamma_{ij}\right) + \eta_{ij}\exp(\delta_{ij}P_{ij})] + \sum_{k=1}^{N_s} S_{p,k} \times B_i G_k \\ &+ \sum_{j=1}^{N_z} W_{p,j} \times C_{aj}. \end{aligned} \tag{17}$$

The maximum penalty factor can be computed as follows:

$$h_{i(max)} = \frac{\sum_{i=1}^{CU}\sum_{j=1}^{Z_i}(a_{ij}P_{ij(max)}^2 + b_{ij}P_{ij(max)} + c_{ij})}{\left(\alpha_{ij}P_{ij(max)}^2 + \beta_{ij}P_{ij(max)} + \gamma_{ij}\right) + \eta_{ij}\exp(\delta_{ij}P_{ij(max)})},$$

where $P_{ij(max)}$ is the maximum generation capacity of the ith unit in the jth zone.

2.7. MEEDP constraints

The main goals of MEEDP are the optimal allocation of power transfer in predefined zones and minimization of fuel and emission costs subject to system constraints. These constraints include power balance constraint, power loss constraints, tie-line limitation and other traditional constraints of EELDs such as POZs and MOFs. The mathematical representation of MEEDP associated constraints is developed in subsequent paragraphs.

2.7.1. Prohibited Operating Zones (POZs)

Thermal power plants possess speed governing and control mechanism for the smooth operation of power delivery. As load increases, the mechanical rotation of turbine also increases to produce the required power. However, there are certain system limitations, such as the vibrations on mechanical shaft of turbine due to excessive load, that allow the generation to operate in some limited zones. The mathematical expression for the POZs is given as follows:

$$\begin{aligned} &P_{ij}^{\min} \le P_{ij} \le P_{ij,1}^{L}, \\ &P_{ij,k-1}^{U} \le P_i j \le P_{ij,k}^{L}, \\ &P_{ij,nz}^{U} \le P_i \le P_{ij}^{\max}, \\ &k = 2, \dots \dots nz. \end{aligned} \tag{18}$$

2.7.2. Capacity constraints

All committed units are allowed to operate within the machine power capacities hence the power output is bounded by lower and upper limits. The mathematical expression for MEEDP capacity constraints is given as

$$P_{ij}^{\min} \le P_{ij} \le P_{ij}^{\max}, \tag{19}$$

where $P_{ij}^{\min}$ and $P_{ij}^{\max}$ are the minimum and maximum powers delivered by the jth generator of the Z_j^{th} area zone, respectively.

2.7.3. MFOs constraint

Usually the operation of power plants involves the use of multiple type of fuel according to market prices and specific heat value. The MFOs have a significant impact on fuel cost curves. It can be noted that every fuel type has its own market price and output power. The mathematical expressions for MFOs are provided below.

$$F_{ct} = \begin{cases} \sum_{i=1}^{CU} \sum_{j=1}^{Z_i} F_{ijft1}\left(P_{ij}\right) = \sum_{i=1}^{CU} \sum_{j=1}^{Z_i} \left(a_{ijft1} P_{ij}^2 + b_{ijft1} P_{ij} + c_{ijft1}\right), \\ .. \quad .. \quad .. \quad .. \quad .. \\ .. \quad .. \quad .. \quad .. \quad .. \\ .. \quad .. \quad .. \quad .. \quad .. \\ \sum_{i=1}^{CU} \sum_{j=1}^{Z_i} F_{ijftn}\left(P_{ij}\right) = \sum_{i=1}^{CU} \sum_{j=1}^{Z_i} \left(a_{ijftn} P_{ij}^2 + b_{ijftn} P_{ij} + c_{ijftn}\right), \end{cases} \tag{20}$$

where $ft1$ and ftn denote fuel type one and fuel type n for Z_j^{th} area zone, respectively.

2.7.4. Network generation balance constraints

Total power from committed units must be able to meet the connected load demand, losses and tie-line limits. The expression for balance constraint is as follows:

$$\sum_{j=1}^{MA_i} \left(P_{ij}\right) = P_{DLi} + P_{NLi} + \sum_{MA, MA \neq i} T_{MAi}, \tag{21}$$

where P_{DLi}, P_{NLi} and T_{MAi} are the power demand, associated losses of loads network and active power transfer from zone i to z, respectively.

2.7.5. Tie-line limit constraint

The power transfer from multi-areas is restricted by tie-line limits for security purposes whose violation can result in severe system contingencies. The mathematical models for these limits are given as

$$-T_{MAiz(\min)} \le T_{MAiz} \le T_{MAiz(\max)}. \tag{22}$$

2.8. Ramp rate limitation

These limits assess the rate at which a power plant can change to a different output state of operation depending on machine specification. As a general rule, it is defined as a unit's ability to perform at its lowest and highest levels and expressed in MW/h.

$$-DR_{ij} \le P_{ij,r}(t) - P_{ij,r}(t-\tau) \le UR_{ij}.$$

3. Proposed CSOA framework for MEEDP

The CSOA was first introduced by Askarzadeh et al. [49] to solve complex constrained optimization problems in engineering. Nature has solution for every problem. CSOA is a population based algorithm like other swarm optimization techniques which is inspired from intelligent behavior of crows. Crows are known as highly intelligent living species among birds and they spend their lives in flocks with a social system. For instance, they have large brain as compared to their brain-to body size ratio index. Therefore, crows can easily remember the site locations and also warn other flocks in time of any threat or danger. Moreover, they have capability to store or hide food reserves like other species such as ants, honey bee, etc. They communicate with each other in a very sophisticated way upon retrieval of hidden reserves or under threat [50]. The working of CSOA is based on their social behavior and actions towards the retrieval of food reserves. They take long flights to reach the hideout food places or to steal food from their own species. Besides, they disguise other follower crows as precautionary measures. This novel strategy is the inspiration for CSOA to attain optimal solution in search space containing hard constraints [51].

The initializing the CSOA for MEEDP is accomplished by determining the flock (generators size) and iterations size. For the crow position v, the time iteration can be represented by a vector $Y^{v,itr}$ = (v = 1,2, ...N; $iter$ = 1,2, ...$vter_{\max}$) where $vter_{\max}$ is the maximum number of iterations. In a d−dimensional space environment with N groups, their beginning positions are randomly distributed. Suppose we have crows v and w, then two cases arise as follows:

- **Case 1:** Crow w has no information about crow v following him. In this case, the updated position of crow v is given as

$$Y^{v,itr+1} = Y^{v,itr} + R_i \times bl^{v,itr} \times (m^{w,itr} - Y^{v,itr}) \tag{23}$$

where R_i denotes a uniformly distributed random number between 0 to 1 and $bl^{v,itr}$ is the flight path taken by crow v at instant itr. The flight length capability is represented by bl. If the length is long, it depicts the global search where smaller value represents local search.
- **Case 2:** Crow w knows that crow v is behind him then w, select the random position. The combined representation for Case 1 and 2 is formulated as

$$Y^{v,itr+1} = \begin{cases} Y^{v,itr} + R_i \times bl^{v,itr} \times (m^{w,itr} - Y^{v,itr}) & R_i \ge AP^{v,itr}, \\ \text{Random Position} & \text{otherwise} \end{cases} \tag{24}$$

The CSOA keeps a balance of reinforcement and diversification like other heuristic approaches and is controlled by a parameter known as awareness probability (P_A). In CSOA, the parameter P_A is largely responsible for controlling intensification and diversification. By lowering the P_A value, CSOA is more likely to conduct the search in a local search space. Therefore, using low P_A values increases intensity and if the P_A value increases, CSOA tends to explore the search space globally.

Logical steps of CSOA for MEEDP

The implementation of CSOA optimizer framework by extending [49] for MEEDP is described in the form of following logical steps.

Step 1: The first step is known as initialization. The objective function of MEEDP along with constraints and decision variables are defined in this step. CSOA along with its adjustable parameters such as population size, maximum number of iterations, flight length of CSOA framework and P_A are also tuned.

Step 2: This step involves the initialization of a time-varying matrix that deals with the positioning of designated flocks. Here, every single entity in the matrix represents a candidate solution. The initialization procedure assumes that the crows have hidden food reserve site at their initial position.

$$Flock_{Memory} = \begin{bmatrix} m_1^1 & m_2^1 & \cdots & m_d^1 \\ m_1^2 & m_2^2 & \cdots & m_d^2 \\ \vdots & \vdots & \ddots & \vdots \\ m_1^N & m_2^N & \cdots & m_d^N \end{bmatrix}. \tag{25}$$

Step 3: In this step, fitness of MEEDP objective function is computed on the basis of each crow position which is updated by inclusion of a decision variable to MEEDP objective function.

Step 4: In this step, CSOA generates new positions for the crows. As mentioned earlier in search space, the crows update their positions according to Eq. (24). All committed units in MEEDP obtain new positions to attain the objective of MEEDP under associated constraints.

Step 5: The best optimum solution obtained from Step 4 is evaluated for feasibility. If the solution is in a feasible region with all system constraints full-filled, then the crows update the positions.

Step 6: The fitness of MEEDP function for updated position is computed.

Step 7: In this step, birds memory is updated with following mathematical expression. If the new computed fitness value of MEEDP is feasible then its a memorized position and vice-versa otherwise.

$$m^{w,itr+1} = \begin{cases} Y^{v,itr+1} f(Y^{v,itr+1}) \text{ is better then } f(m^{w,itr+1}), \\ m^{w,itr} \text{ otherwise.} \end{cases} \tag{26}$$

Step 8: To validate the termination criteria, Steps 4 and 7 are repeated for maximum defined iterations. The optimum feasible solution for MEEDP objective function, individual generation value, costs of fuel and emission and tie line powers are reported.

Step 9: After attaining optimal generations, the powers are sent to the governing unit to attain the ramp-rate constraint. The instructions for these limitation can be expressed as follow.

$$P_{ij}(t) = \begin{cases} P_{ij}(t) \quad if \quad -DR_{ij} \le P_{ij,r}(t) - P_{ij,r}(t-\tau) \le UR_{ij} \\ UR_{ij} \quad if \quad P_{ij}(t) - P_{ij}(t-\tau) \ge UR_{ij} \\ -DR_{ij} \quad if \quad P_{ij}(t) - P_{ij}(t-\tau) \le -DR_{ij} \end{cases} \tag{27}$$

The proposed MEEDP develops in the same manner as the original, with some alterations. To begin, it adopts a unique mechanism for determining the location of each crow's hiding place. Each crow selects one of the flock's crows as a destination to follow. Additionally, in comparison to the original, parameter selections such as flight length and awareness probability values are updated to produce the most optimal solutions for real-world multi-objective optimization problems subjected to a variety of hard constraints.

Computational framework strategy for MEEDP

The pseudocode of CSOA is provided in Algorithm 1. The MEEDP problem with traditional constraints and tie-line limits is developed and modeled functions are loaded in CSOA environment. The function evaluation is then computed and termination criteria with performance indices are obtained in the form of optimum costs values for emissions and fuel with power transfer and tie-lines limits. The traditional constraints such as POZs and MFOs along with equality and inequality constraints are also satisfied. The flow chart diagram shown in Fig. 1 depicts the overall process of constraint handling along with CSOA parameters. CSOA approach is better than other population-based metaheuristic approaches like GA, PSO and ant colony optimization (ACO) as it uses population in searching the best optimal solution, applies memory concept for searching and does not stuck in local minima due to its adaptation for improvement. CSOA tries to discover optimum solutions of complex constrained optimization problems by simulating the intelligent behavior of crows and it has many advantages as compared to other population-based heuristic techniques such as GA, PSO and brain storm optimization (BSO) with ease of implementation, a small number of parameters and flexibility [52]. Consequently, CSOA is suitable choice for solving complicated hard bounded constrained MEEDP problem with desired accuracy and early convergence, which was lacking in the existing works.

4. Results and simulations

Algorithm 1: CSOA Pseudo Code For MEEDP

Result: Optimum P_{ij} and E_{ij} values.
Input: MEEDP objective function equation (17) with all system constraints from equation (18) to equation (22).
Compute RES generation through equations (4) to (12).
initialization;
Time-varying matrix
Maximum iteration time $iter(max)$
Equation (23) and (24)
Equation (26)
while $itr < iter(max)$ **do**
  for Crow(v) belongs to crows
  do
  Randomly choose a crow.
  Compute P_A
  Update $Y^{v,itr+1}$ using equation (24)
  end for
  Check function feasibility
  Compute fitness of objective function
  Update crow memory by using equation (26)
  Update P_{ij} using (27)
  end while
end

To evaluate the performance of designed CSOA approach, five benchmark test systems are investigated on the multi-area. The considered test systems include ten committed units with three area system, forty committed units with four-area system, a Korean large-scale power system, five units system integrated with wind and solar generation networks and five units system with flexible load demand of 24-hours. The efficacy of the proposed scheme is compared with other novel heuristic approaches recently published in the literature, see e.g. SSA-MOSA [33], RCGA [34], EP [6], ABC [34], EMA [34], DE [34], GSO [35], CQGSO [35], KHA [36], OKHA [36], SDE [37], DA [38], CSA [39], ALO [40], BBO [41], PSO [42] and GA [43]. The CSOA for MEEDP is executed on Intel celeron(R) N2940CPU@1.83 GHz, 4.0 GB of RAM with MATLAB version R2017b. Three case studies are examined for mentioned benchmark test systems including the non-convex associated constraints. The details of case studies for MEEDP are given below.

- The non-convex fuel cost function of multi-area system is considered.
- The non-convex emission cost function (greenhouse gases emission) of multi-area is accounted.

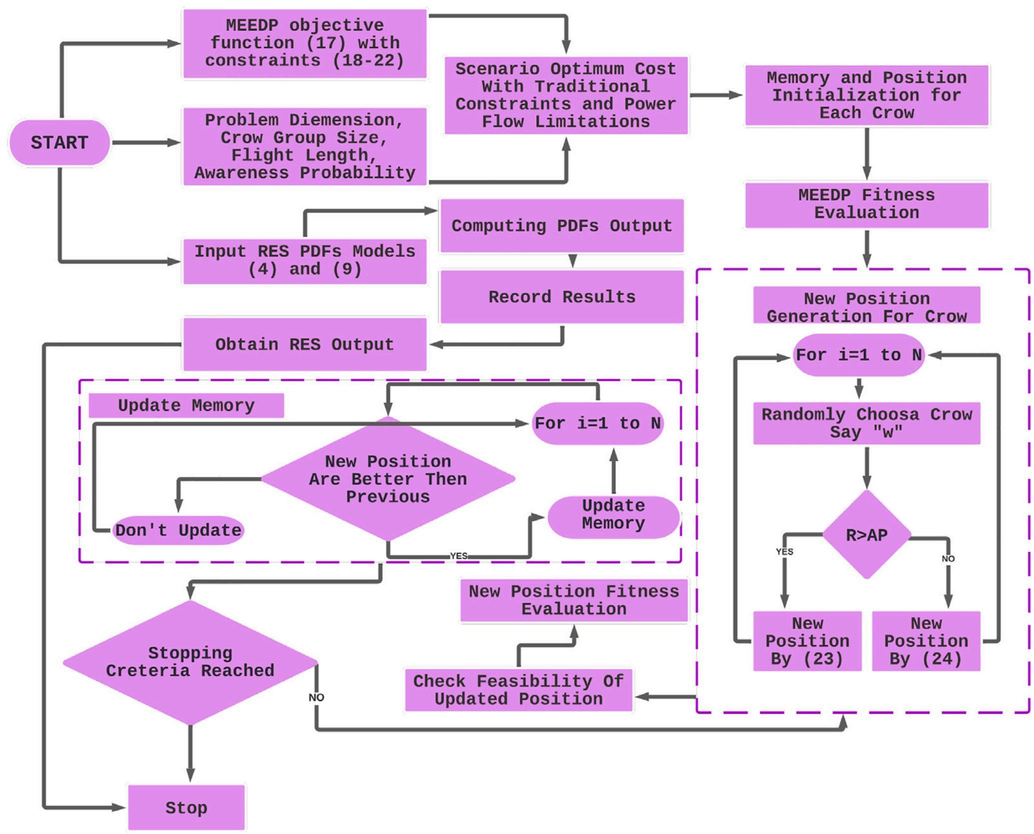

Fig. 1. MEEDP computational framework flowchart.

Table 1
CSOA parameter setting.

Parameters	Test System-I	Test System-II	Test System-III	Test System-IV	Test System-V
Dimensions	10	40	140	5	5
Flock size	10	40	140	5	5
Awareness probability	0.00001	0.00001	0.00001	0.00001	0.00001
Number of iterations	200	200	300	200	200
Flight length	2	2	2	2.5	2.5

- Both non-convex and competitive bi-objective functions are transformed into a single objective function by introducing penalty factor as mentioned in Eq. (17) and optimized simultaneously.
- The non-convex fuel cost function (3), along with system constraints in Eqs. (18) to (21) is considered.
- A special test system with RES integration in traditional non-convex cost function.

To achieve the best optimal solution for MEEDP under all constraints, the parameter selection is provided in Table 1. These parameters include flight length, number of iterations, flock size and awareness probability. It is worth noticing that a singularity optimal parameter setting is chosen for all benchmark test systems.

4.1. Test System-I

This benchmark test system has ten committed units with three area power system subject to nonlinear contiguous system constraints such as VLEs, MFOs and system network losses. Input cost coefficient data with multiple fuel types and VLEs are provided in [34]. The total load demand and tie-line power flow limitation are 2700 MW and 120 MW, respectively. The Area-1 shares load demand of 50% with four committed units (1 to 4), Area-2 shares load demand of 25% with three committed units (5 to 7) and Area-3 shares load demand of 25% with three committed units (8 to 10) as depicted in Fig. 2.

4.1.1. Case Study-I

In this case study, we achieved an optimal solution of non-convex fuel cost of MEEDP Test System-I by incorporating MFOs along with other system constraints as presented in Table 2. The optimal cost acquired by CSOA approach is 644.2474 $/h. A total of 200 independent iterations were performed, and COSA attained quality convergence. The obtained fuel cost by CSOA scheme is compared with other meta-heuristic techniques SSA [33] 654.6061 $/h, RCGA [34] 657.3078 $/h, EP [6] 655.2031 $/h, ABC [34] 654.9888 $/h and EMA [34] 654.7809 $/h. It is evident, from Table 3, that CSOA approach finds best optimum solution as compared to other advance approaches. Furthermore, the convergence for MEEDP cost function via CSOA is more stable and faster convergence.

4.1.2. Case Study-II

In this case study, we achieved the finest emission rate for Test System-I as shown in Table 4 along with optimum powers, tie-line and losses. Its worth highlighting that CSOA finds finest feasible solution 6314.13 kg/h for emissions as compared to SSA [6], ABC [34] and EMA approaches. The 200 iterations have been performed and CSOA has again shown stable convergence. Also the comparison of CSOA for emission with respect to other state of the art heuristic techniques is provided in Table 5.

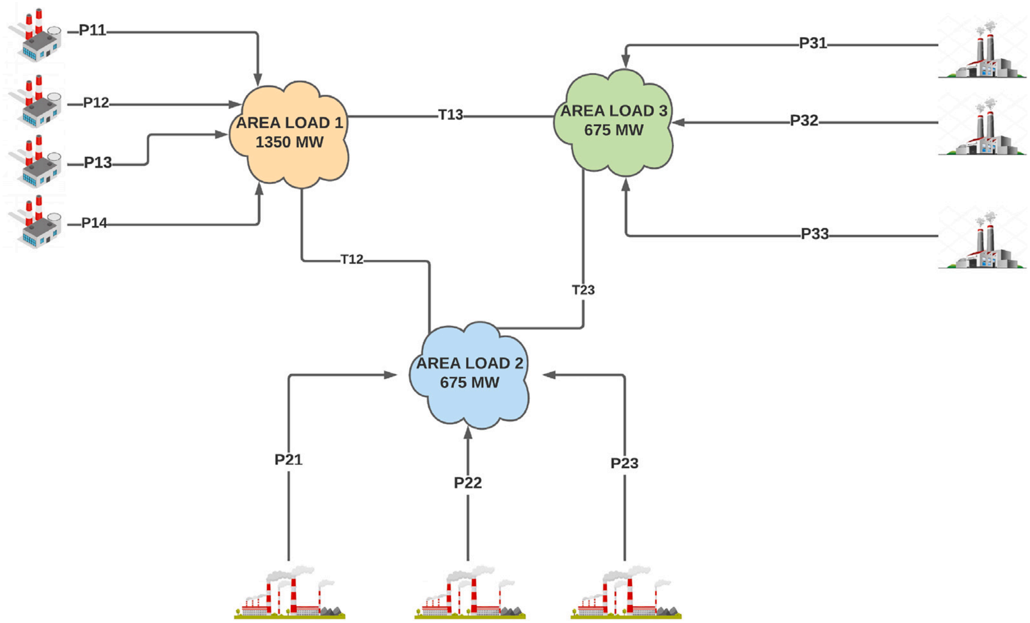

Fig. 2. Schematic diagram of Test System-I.

Table 2
Optimal dispatch results obtained by CSOA of Test System-I for Case Study-I.

Area	Units	Fuel type	Power generation
1	1	2	224.354
	2	1	199.902
	3	2	459.852
	4	3	236.734
2	5	1	266.217
	6	3	230.833
	7	1	260.670
3	8	3	248.291
	9	1	316.878
	10	1	256.265
Tie-line powers	T21		106.231
	T31		108.251
	T32		7.172
Losses	Area Load-1		9.21
	Area Load-2		6.732
	Area Load-3		6.538
Generation cost ($/h)			644.2474
Emission (KG/h)			6447.03

Table 3
CSOA cost comparison with other heuristic approaches, Test System-I for Case Study-I.

Approach	Fuel cost ($/h)	Approach	Fuel cost ($/h)
ABC	654.9888	RCGA	657.3078
EMA	654.7809	SSA	654.6061
EP	655.203	CSOA	**644.2474**

4.1.3. *Case Study-III*

In this case study, we converted MEEDP into a single objective function according to Eq. (17). The weighting factors are selected according to the maximum penalty factor. The results show that CSOA attains feasible solution as compared to other heuristic approaches shown in Table 6. The obtained non-convex fuel cost and emission for combined function are 636.4110$/h and 6420.6 kG/h, respectively. Tables 5 7, shows the power distribution of all committed units along with tie-line power transfers by incorporating all associated constraints for both non-convex functions.

Table 4
Optimal dispatch results obtained by CSOA of Test System-I for Case Study-II.

Area	Units	Fuel type	Power generation
1	1	2	218.240
	2	1	194.672
	3	2	452.345
	4	3	248.579
2	5	1	269.580
	6	3	225.660
	7	1	250.894
3	8	3	242.926
	9	1	332.146
	10	1	264.952
Tie-line powers	T21		116.597
	T31		119.564
	T32		45.463
Losses	Area-1		0.00
	Area-2		0.00
	Area-3		0.00
Generation cost ($/h)			644.2474
Emission (KG/h)			6314.10

Table 5
CSOA cost comparison with other heuristic approaches, Test System-I for Case Study-II.

Approach	Emission cost (KG/h)	Approach	Fuel cost (KG/h)
ABC	6380	SSA	6370
EMA	6370.82	CSOA	**6314**

Table 6
Comparison of CSOA combined cost and emission results with others heuristic approaches, Test System-I for Case Study-III.

Approach	Fuel cost ($/h)	Emissions (KG/h)
ABC [34]	660.4672	6443.2378
EMA [34]	661.0337	6445.5173
SSA-WSA [6]	658.9930	6459.1875
MOSSA [6]	660.2238	6441.1696
CSOA	636.4110	6420.50

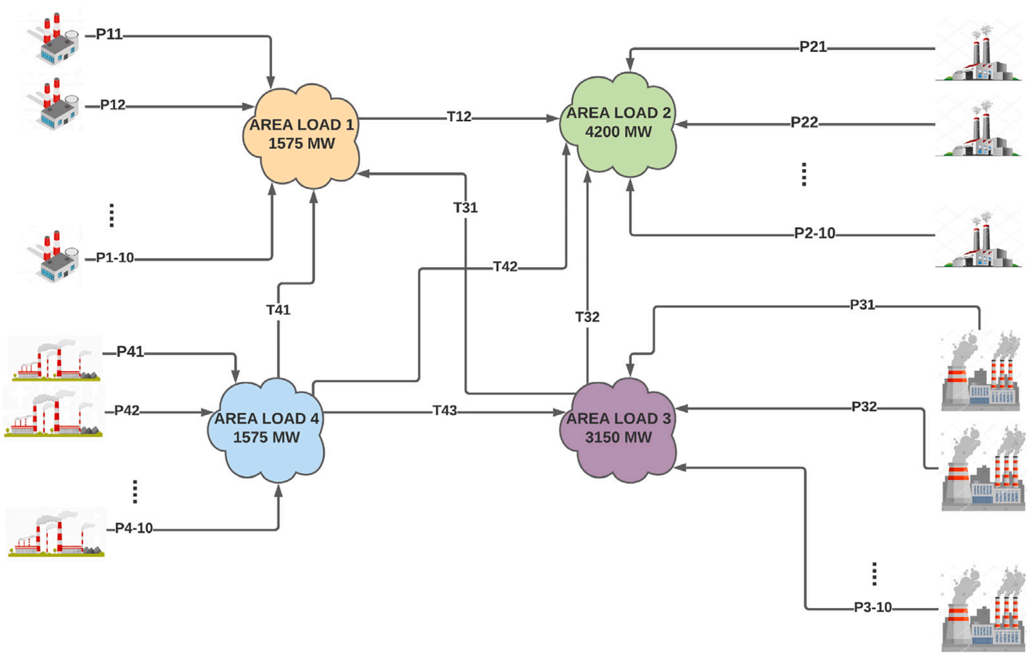

Fig. 3. Schematic diagram of Test System-II.

Table 7
Optimal dispatch results obtained by CSOA of Test System-I for Case Study-III.

Area	Units	Fuel type	Power generation
1	1	2	228.216
	2	1	208.352
	3	2	433.028
	4	3	228.157
2	5	1	232.012
	6	3	244.274
	7	1	289.512
3	8	3	248.848
	9	1	323.424
	10	1	264.172
Tie-line powers	T21		107.536
	T31		109.237
	T32		15.585
Losses	Area-1		0.00
	Area-2		0.00
	Area-3		0.00
Generation cost ($/h)			636.4110
Emission (KG/h)			6420.5

4.2. Test System-II

This standard test system consists of forty committed units connected to a four-area power system via tie-lines. We consider various nonlinear contiguous system constraints such as VLEs and system network losses for the system under investigation. A data set containing input cost coefficient information as well as other constraints is provided in [53]. The total load demand for the entire area is assumed to be $10,500$ MW, with a power transfer limitation of 100 MW on each of the six tie-lines. Based on the distribution of load demand shown in Fig. 3, Area-1 shares load demand of 15% with ten committed units (1 to 10), Area-2 shares load demand of 40% with ten committed units (11 to 20), Area-3 shares load demand of 30% with ten committed units (21 to 30), and Area-4 shares load demand of 15% with ten committed units (31 to 40).

4.2.1. Case Study-I

In this case study, we achieved finest optimal solution of non-convex fuel cost of MEEDP for Test System-II by incorporating system constraints, and results are presented in Table 8. The finest optimal cost obtained by CSOA approach is $113\,660.59$\$/h. The 200 independent iterations were performed to examine the quality of CSOA convergence. The obtained fuel cost by CSOA scheme is compared with other meta-heuristic techniques SSA [33], RCGA [34], EP [6], ABC [34], EMA [34] and DE [34]. It is evident from comparison that CSOA approach finds the best optimum solution for MEEDP with finer convergence rate.

4.2.2. Case Study-II

The best emission rate for Test System-II was achieved in this case study, as shown in Table 8, along with the best powers combination, tie-line powers, and system loss values for the test system. Again, it is worth noting that CSOA attains the best possible solution ($113\,940$ tons/h) for emissions as compared to SSA [6], ABC [34] and EMA [34] approaches. The convergence profile of emission for 200 iterations reveals that CSOA converged towards optimum solution with finer rate as compared to existing heuristic techniques presented in [6].

4.2.3. Case Study-III

As part of this case study, we converted MEEDP into a single objective function based on Eq. (17). The weighting factors are selected according to maximum penalty mechanism, and the feasible solutions obtained are compared with those obtained by existing heuristic approaches, as illustrated in Table 9. While, Table 8, shows the optimum distribution of powers for committed load. The non-convex fuel cost and emissions for the combined function were determined to be $124\,330.50$\$/h and $116\,560.5$ tons/h, respectively. The achieved results for system-II are compared with ABC, EMA, NSGA-II [54], MODE [54], SSA-WSA [6] and MOSSA [6]. CSOA attains feasible solution with finer time convergence as compared to other heuristic techniques. Its evident that CSOA performed well while dealing combined cost and emission as compared to other heuristic techniques ABC, EMA, NSGA-II [54], MODE [54], SSA-WSA [6] and MOSSA [6].

4.3. Test System-III

To demonstrate the applicability and efficacy of CSOA towards practical implementation, a real world large scale Korean power plants Test System with nonlinear cost function is considered as shown in

Table 8
Optimal dispatch results obtained by CSOA for Case Studies I, II & III for Test System-II.

Area	Units	Power generation Case Study-I	Power generation Case Study-II	Power generation Case Study-III
1	1	134.614	103.442	80.959
	2	136.773	103.6893	91.624
	3	74.551	119.8821	110.122
	4	141.279	200.0059	132.589
	5	98.747	53.7337	100.002
	6	130.003	145.5000	132.304
	7	253.308	280.2219	201.965
	8	222.419	279.4900	288.007
	9	249.342	299.9996	254.479
	10	299.997	221.0448	196.762
2	11	286.356	366.2801	335.598
	12	295.089	365.7256	301.705
	13	492.540	499.9811	499.388
	14	170.088	366.1751	344.973
	15	465.869	466.3891	432.046
	16	432.285	340.4538	472.276
	17	440.369	495.9665	306.127
	18	447.840	407.7216	385.293
	19	463.860	538.6979	479.057
	20	515.443	326.4059	531.647
3	21	450.883	473.4471	518.149
	22	498.749	526.6789	436.660
	23	486.129	458.0370	549.998
	24	493.773	404.4211	458.476
	25	532.550	416.0825	365.743
	26	460.095	464.0562	545.569
	27	10.010	33.5355	69.413
	28	43.477	52.5359	96.777
	29	108.066	83.7142	75.383
	30	88.633	69.0575	74.226
4	31	164.124	145.8391	189.999
	32	185.186	96.8602	156.275
	33	199.122	126.2700	94.961
	34	189.982	144.6138	102.346
	35	200.000	198.3812	199.999
	36	181.00	152.9257	136.941
	37	71.859	81.5942	125.222
	38	54.870	79.1052	37.977
	39	102.959	69.6676	64.954
	40	450.663	543.4941	552.009
Tie-line power	T12	99.583	51.203	0
	T13	54.444	99.573	−13.947
	T32	90.433	0	26.367
	T41	19.742	−55.083	0
	T42	99.745	0	85.675
	T43	74.124	93.861	0
Generation cost ($/h)		113 660.5	123 390.5	124 330.50
Emissions (tons/h)		124 050.5	113 940	116 560.5

Table 9
Comparison of CSOA with other heuristic techniques of Test System-II for Case Study-III.

Computational approach	Fuel cost $/h	Emission tons/h
ABC	126 480.56	209 285.74
EMA	125 910.69	210 238.19
NSGA-II [54]	125 830	210 950
MODE [54]	125 792	211 190
SSA-WSA [6]	125 760.05	206 705.97
MOSSA [6]	125 591.29	205 965.40
CSOA	124 330.5	116 560.5

Fig. 4. The system consists of total 140 committed units across the country where 1–40 units are thermal (mostly coal powered), 41–91 are gas powered plants, 92–111 are nuclear powered plants and 112–140 are oil powered plants. The VLEs and POZs constraints are considered for selective 12 and 4 committed units, respectively. The input cost coefficients data along with non-convex constraints is provided in [36] with load demand of 49,342 MW. The optimum power generated from all committed units along with non-convex cost solution is provided in Table 10. The obtained non-convex cost solution which is 1 550 606.6$/h by CSOA optimizer is compared with existing meta-heuristic techniques SSA [6], GSO [35], CQGSO [35], KHA [36], OKHA [36] and SDE [37] and tabulated in Table 11. Its worth highlighting that the fuel cost attained by CSOA is lowest among other reported approaches which shows the superior performance of the algorithm for large scale systems.

4.4. Test System-IV

Five thermal power generating plants are integrated with two wind turbines and two solar PV systems in this test system. To demonstrate the CSOA adaptability and efficacy, all non-convex system limitations such as VLEs, MFOs and capacity constraints are included. The maximum installed capacity for solar PV system is 10$/MW with bid rate 2.854 MWh, where the total load demand of network is 730 MW. The traditional thermal power plants can create electricity regardless of the weather, but RES rely on the climatic strength to generate power, making it imperative to have an accurate and reliable model for dealing with the unpredictability of climate circumstances. In this study, we have used the beta distribution function (4) and Weibull probability

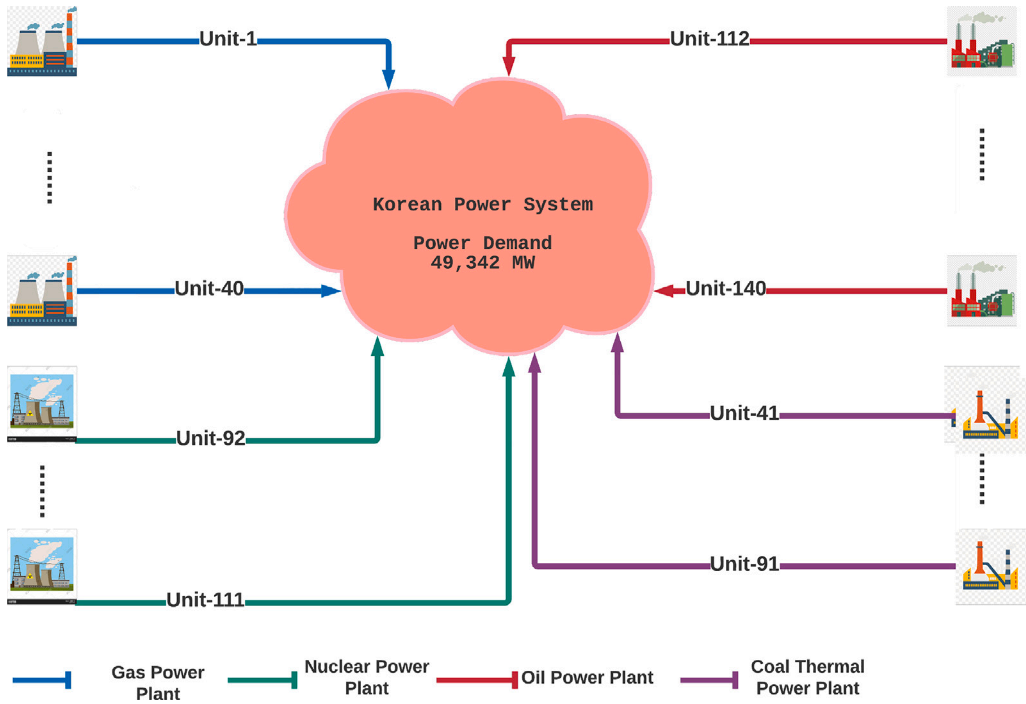

Fig. 4. Korean power system schematic diagram for Test System-III.

Table 10
Optimum Non-convex cost of Test System-III.

Units	Optimum power (MW)	Units	Optimum power (MW)	Units	Optimum power (MW)	Units	Optimum power (MW)
1	118.912	36	438.982	71	307.944	106	884.301
2	178.477	37	150.770	72	423.648	107	918.521
3	169.237	38	137.196	73	384.051	108	893.513
4	182.449	39	573.431	74	438.229	109	972.798
5	137.255	40	649.657	75	441.792	110	910.317
6	144.353	41	7.7938	76	401.104	111	887.118
7	372.561	42	14.025	77	439.328	112	166.979
8	339.095	43	206.103	78	399.944	113	175.328
9	335.731	44	218.238	79	386.897	114	142.862
10	391.234	45	212.744	80	349.261	115	309.485
11	378.554	46	223.171	81	442.603	116	331.658
12	370.543	47	224.3734	82	85.0779	117	310.758
13	504.565	48	223.776	83	228.322	118	124.182
14	508.999	49	237.759	84	196.063	119	144.682
15	333.841	50	189.961	85	138.250	120	168.580
16	477.860	51	356.014	86	260.255	121	248.416
17	449.328	52	221.819	87	274.834	122	10.965
18	389.466	53	400.101	88	266.987	123	42.5056
19	341.923	54	361.016	89	234.003	124	46.667
20	429.543	55	333.069	90	283.220	125	35.774
21	439.042	56	502.699	91	298.048	126	22.256
22	404.543	57	281.586	92	440.113	127	25.5170
23	401.298	58	354.839	93	492.213	128	192.95
24	383.722	59	161.603	94	936.529	129	10.607
25	440.455	60	313.467	95	915.441	130	16.253
26	502.778	61	499.869	96	663.841	131	9.465
27	413.550	62	101.791	97	615.385	132	72.377
28	410.692	63	367.828	98	654.375	133	8.410
29	484.813	64	272.442	99	683.536	134	71.15
30	487.046	65	377.503	100	841.585	135	56.190
31	408.495	66	430.333	101	790.577	136	80.145
32	466.757	67	343.178	102	913.962	137	23.754
33	425.614	68	409.800	103	978.010	138	12.548
34	373.784	69	249.510	104	903.141	139	8.238
35	419.043	70	384.893	105	1015.40	140	35.834
COST ($/h)	**1 550 606.65**						

density function (9) to model the uncertainty of RES. The wind PDF is computed using (9) under scaling factor c and wind turbine blade profile shape factor K. The values of c and υ for the Kings park site are 3.23 and 5.8 meters per second, respectively. Once the unpredictability of the wind has been classified as a stochastic process, the output power of the wind generator can be measured as a random variable by

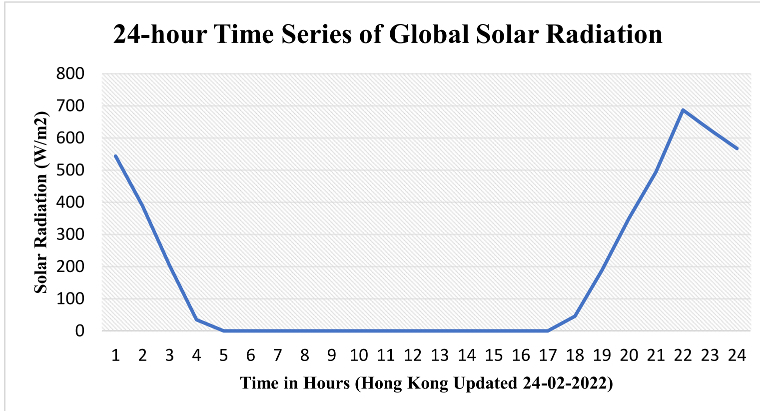

Fig. 5. Solar radiation in Kings Park (Hong Kong).

Table 11
CSOA cost comparison of Test System-III with other heuristic approaches.

Approach	Cost ($/h)	Approach	Cost ($/h)
GSO [35]	1 728 151.16	OKHA [36]	1 560 146.95
CQGSO [35]	1 657 962.72	SDE [37]	1 560 236.85
KHA [36]	1 560 173.88	**CSOA**	**1 550 606.65**
SSA [6]	1 559 818.72	–	–

Table 12
Performance analysis of CSOA comparing other approaches Test system-VI.

Methods	Generation cost ($/h) mean cost	Computational time (s)
CSOA	**1937.232**	**11.62**
DA [38]	2018.0762	12
CSA [39]	2021.5229	12.6
ALO [40]	2025.8236	14.5
ORCCRO [40]	2046.6344	17.2
BBO [41]	2058.5299	21
PSO [42]	2060.80	25
GA [43]	2073.8957	28

transforming the wind speed into output power. Eq. (10) can be applied to determine the output power of the wind based on the wind velocity W_P, and it can be used in wind cost function Eq. (12) to compute the cost. To account for the uncertainty in the solar cost function, the solar irradiance is classified as a random variable by using the beta distribution. Here $F_\beta(\Omega)$ is characterized as a random variable of solar irradiance (kW/m^2). To acquire the power from solar panels, we can apply $R_{P,k} = R_{P0} \times F_\beta(\Omega)$, which can be applied in the solar cost function (11) to compute the overall cost. Tables 13 and 14 contain the RES input data taken from Kings Park Meteorological Station (Hong Kong Observatory) as shown in Fig. 5, whereas Table 15 contains fuel coefficient data of thermal units. The integration of RES plays a vital role in optimizing the overall fuel cost upto 1937.2$/h. The total production of powers from thermal unit is 726.0649 MW, whereas wind turbine produced 0.2 MW and solar production is 4.4 MW. The wind generated electricity is less as it depends upon the speed of wind which is less than limitation presented in Eq. (22). The comparison of CSOA performance with other state of the art heuristic approaches is shown in Table 12. Fig. 6 shows the CSOA convergence of cost for RES integrated Test System-IV and it can be seen that CSOA attains optimal cost with finer convergence rate.

4.5. Test System-V

This test system considers a flexible load demand of 24 h while considering non-convex cost function. All system limitations such as MFOs, generation capacity and VLEs are also incorporated to verify

Table 13
Wind power units input data.

Units	v_{in}	v_{out}	v_r	k	c	w_r	C_a
1	5	45	15	1.5	15	10	1.25
2	5	45	15	1.5	15	10	1

Table 14
Solar power input data.

Unit	ϖ	Υ	Θ	N_{srs}	N_{Parl}
1	6.30	3.43	0.043	20	20
2	5.38	5.43	0.043	20	20
Unit	$U_{nrml.temp}$	U_{ambt}	$U_{cell.stc}$	$R_{rad.stc}$	$R_{p(stc)}$
1	45.5	20	25	1000	10
2	45.5	20	25	1000	10

Table 15
Thermal units cost input data for Test System-IV.

Unit	a_i	b_i	c_i	e_i	f_i	p_i^{min}	p_i^{max}
1	0.0015	1.8	40	200	0.035	50	300
2	0.0030	1.8	60	140	0.040	20	125
3	0.0012	2.1	100	160	0.038	30	175
4	0.0080	2	25	100	0.042	10	75
5	0.0010	2	120	180	0.037	40	250

the robustness against time-based demands. Input cost coefficients data of test system are provided in Table 15, while the comparison of cost with other advance approaches is tabulated in Table 16. The dynamic load demand curve is shown in Fig. 8, while the cost curve response convergence is depicted in Fig. 9. A dynamic load is variable with time due to fluctuations in the demand, which can cause the frequency-related effects on a power system. These types of loads exert forces on a structure or a machine that are often much greater than their static equivalents. Dynamic loads produce stress on the generation machines, leading to a more complicated dynamic dispatch problem. Its evident from Fig. 9, that CSOA again performs efficiently to attain best optimal cost as compared to other advanced meta-heuristic approaches. The Fig. 7 shows the optimal allocation of output powers for the flexible load demand varying from 400 MW to 750 MW. Moreover, it can be seen from Fig. 9 that CSOA attains convergence with finer time interval.

Additionally, RES penetration in traditional power systems plays a crucial role, not only in terms of cost savings, but also in terms of ensuring the quality of energy supply and RES industrial development, which further creates jobs. The effect is readily apparent at 12 o'clock, when the load demands of both test systems (IV and V) are about equal, as illustrated in Fig. 9. Furthermore, as illustrated in the Tables 12 and 16, a significant variation in both costs can be observed. RES integration also contributes to the development of sustainable energy hubs,

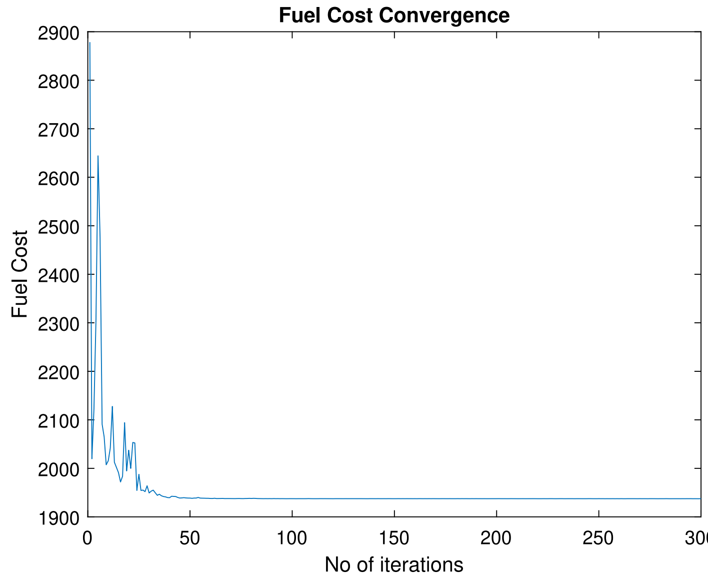

Fig. 6. CSOA convergence for cost of Test System-IV.

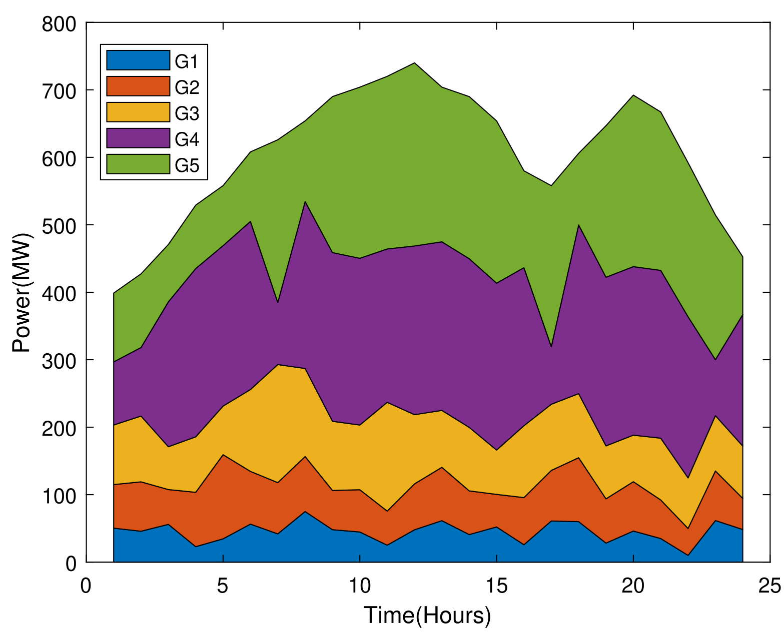

Fig. 7. Optimal power allocation for Test System-V.

emission reduction, and the transition to carbon-free energy. However, RES also have certain disadvantages. For example, the technology is still in its infancy, and the current prices of equipment (batteries, solar cells, and wind turbines) are still prohibitively costly.

5. Conclusions

In this paper, CSOA optimizer framework is proposed for large scale MEEDP integrated with RES systems and subjected to non-convex system constraints. The two highly complex nonlinear conflicting objective functions namely non-convex fuel cost function and emission function are solved to attain optimum solution of operating cost and emission. The RES penetration over conventional dispatch function has also strengthened the system sustainability, and has helped in reduction of greenhouse gases emission and fuel dependency. The designed scheme of CSOA achieves faster convergence to optimum solutions while handling POZs, MFOs and losses constraints with tie-line restrictions. Additionally, by taking into account the multiple

Table 16
Flexible load demand cost analysis of CSOA comparing other approaches Test system-V.

Methods	Generation cost ($/h) mean cost	Computational time (s)
CSOA	**12 023.04**	**11.96**
DA [38]	2018.0762	12
CSA [39]	2021.5229	12.6
ALO [40]	2025.8236	14.5
ORCCRO [40]	2046.6344	17.2
BBO [41]	2058.5299	21
PSO [42]	2060.80	25
GA [43]	2073.8957	28

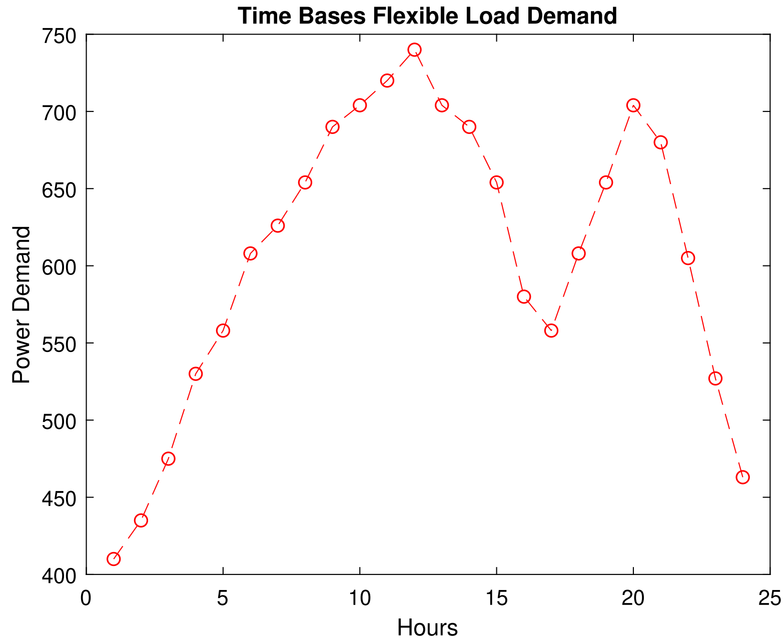

Fig. 8. Flexible dynamic load demand curve for Test System-V.

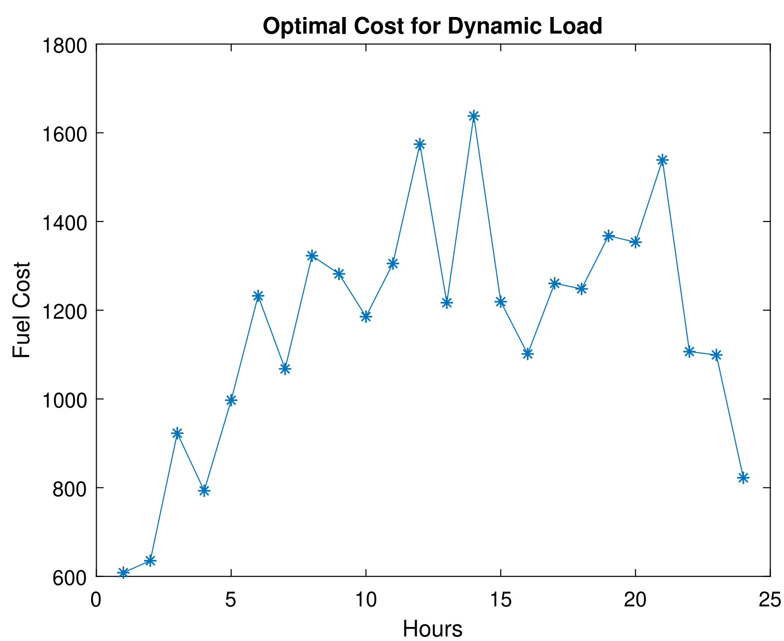

Fig. 9. Dynamic cost curve for Test System-V.

fueling, the designed scheme also assists the system operators and policy makers to utilize most available fuel with lower toxic emission characteristics. This would not only help in keeping the atmosphere clean, but also aids to lower the usage of imported fuels which further helps to stabilize the country economy. Furthermore, considering the numerical indicators of generation cost and computational efficiency of presented scheme, CSOA is more robust and supportively for complex MEEDP then other heuristic approaches reported in literature. Several practical constraints such as generation limit and load demand are also tackled to ensure protection of generating system contingencies. Moreover, this investigation has also provided solution for electric utilities to efficiently choose the power generating equipment and limit the toxic air emissions restricted by regulatory authorities such as clean air policies. Three case studies along with a special study with RES penetration have been considered for solving functions individually and simultaneously to demonstrate the capability of CSOA .

Despite the fact that this study provides satisfactory dispatch outcomes, there are some drawbacks. First, CSOA is a centralized approach and needs huge costly communication networks for adequate operations. Second, the capital cost for RES infrastructure and technological advancement is still limited. Third, the uncertainty in RES generations is not taken into account to its full extent. Therefore, in future we will incorporate hybrid distributed control systems to handles these limitations.

CRediT authorship contribution statement

Ijaz Ahmed: Conceptualization, Methodology, Software, Writing – original draft. **Muhammad Rehan:** Analysis, Investigation, Review of original draft. **Abdul Basit:** Visualization, Investigation, Software. **Saddam Hussain Malik:** Visualization, Investigation. **Um-E-Habiba Alvi:** Software, Validation. **Keum-Shik Hong:** Reviewing and editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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