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Optimal scheduling of distributed energy resources in microgrid systems based on electricity market pricing strategies by a novel hybrid optimization technique

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ABSTRACT

The upsurge in microgrid demand is an important aspect of imparting energy in future primarily because of the involvement of renewable energy sources, which alleviates the emission of toxic gases from fossil fuelled generators. The grid-connected mode of microgrid operation is the most economical and definitive mode of service wherein the grid is actively involved in the buying and selling of power prompting diminished generation cost of microgrid system. These cases, pertaining to two different low voltage microgrid systems, are applied consecutively for obtaining the generation cost of the systems and thus devise the cheapest strategy among them. The Grey Wolf Optimizer (GWO) is improvised by incorporating strategies from population-based Sine Cosine Algorithm (SCA) along with position updating methods of crows from Crow Search Algorithm (CSA) to form a hybrid modified Grey Wolf Optimizer Sine Cosine Algorithm Crow Search Algorithm (GWOSCACSA) algorithm. The implementation of the proposed technique produces a comprehensive generator cost reduction of the microgrid system. It was evident from the results that generation cost was minimum when Time of Usage (TOU) based market pricing strategy was considered. Further, it was also established that dynamic grid participation was reduced 47% in the system generation cost for the same scenario compared to the case when the grid was operating passively. The statistical analysis endorses the improvements of GWOSCACSA over other algorithms presented in the state-of-art-literature.

1. Introduction

The relevance of economical electric power generation can be considered indispensable for efficient and reliable power system operation. Optimal scheduling of fossil fueled generators is the pressing priority where utility engineers encounter challenges in bringing a trade-off between fuel cost and carbon emissions to suffice the consumer demand.

1.1. Economic load dispatch and relevance in the current power scenario

ELD problem is a multi-constrained, non-linear optimization problem, which is pivotal to power system planning and operation engineers. It primarily aims to allocate power generation to meet load demand with minimum cost while satisfying the system constraints of different generation units. Considering the prevailing condition of surge rise in power demand, enormous capital investment and running expenses of generating units coupled with limitation of fossil fuel reserves are confronted. This portrays ELD as an intimidating and complex issue for power engineers to be solved. Economic optimality can be ensured for a designated load demand by attaining minimum dispatching cost.

ELD problem works on the principle that all the generating units involved in delivering power to suffice the load demand will not incur the same cost to cater the same amount of load. Instead, some generating units may be more expensive for producing same amount of active power than the others. Therefore, this precisely makes optimal allocation of a given share of total demand more crucial to eventually lower the fuel cost. Thus, generated power is in accordance with the demand on the load side [1].

With respect to load demand, the ELD has been broadly classified as SELD, where the load is fixed throughout the day, and DELD, where the

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Nomenclature

List of Abbreviations

ELD	Economic Load dispatch
SELD	Static Economic load Dispatch
DELD	Dynamic Economic Load Dispatch
DERs	Distributed Energy resources
RES	Renewable energy sources
EMS	Energy Management System
GWO	Grey Wolf Optimizer
GW	Grey Wolves
GWOSCACSA	Grey Wolf Optimizer Sine Cosine Algorithm Crow Search Algorithm
RES	Renewable Energy Sources
ESS	Energy Storage Systems
EVBs	Electric vehicle batteries
ICA	Imperialist Competitive Algorithm
ISA	Interior search algorithm
PSO	Particle Swarm Optimization
AMPSO	Adaptive Modified Particle Swarm Optimization
MICA	Modified Imperialist Competitive Algorithm
EED	Economic Emission Dispatch
WOA	Whale Optimization Algorithm
MHSA	Modified Harmony search algorithm
PV	Photo Voltaic
MG	Micro Grid
DNO	Distribution Network Operator
EVB	Electric Vehicle Batteries
BESS	Battery Energy Storage Systems
GW	Grey Wolf
MG	Micro grid
LV	Low Voltage
MT	Micro turbine
FC	Fuel Cell
WT	Wind Turbine
VL	Variable Load
FL	Fixed Load
TOU	Time of Usage
CPP	Critical Peak Pricing
LMP	Locational Marginal Pricing

List of Symbols

F_g	Generator fuel cost
P_g	Active power output of generator
I_g	Binary symbol for ON/OFF generator status
C_{grid}	Total grid cost
MP	Market Price
u	Binary variable for charging
v	Binary variable for discharging
z	Binary variable for ON/OFF status of variable load
α, β, δ, ω	Type of grey wolves in GWO
t	Iteration time
$\overrightarrow{\rho}$ and $\overrightarrow{C}$	Regulation vectors
$\overrightarrow{\lambda}$	Distance between grey wolves and prey
$\overrightarrow{i}_1$ and $\overrightarrow{i}_2$	incidental vectors
dim	Dimension of the solution
rand	Random number

load demand changes from time to time. The former case is comparatively less complex and has limited constraints such as ramp rates, prohibited operating zones, etc. [2 3]. On the contrary, DELD has substantially more complex problems with additional constraints associated with the DERs and time periods [4]. EMS of microgrid systems are associated with the DELD bracket of cost reduction with startup, shut down times of DERs and charging/discharging state of energy storage systems as some of the crucial complex constraints that are to be faced while solving DELD.

1.2. Review of related research work

Numerous research work has been undertaken to obtain the most cost-efficient distribution of generation, which could have a great impact on the economy of the power generation process. The momentous rise in fuel price has propelled ELD problem as a necessary and relevant complex optimization issue in power network. Conventional computational methods, as mentioned in [5], could be applied but only in cases wherein the cost function is smooth, continuous, non-convex, and differentiable. However, when actual physical constraints as encountered in a real time power network are attempted to be incorporated in the optimization equation, it becomes non-smooth and convex, thereby stalling conventional methods [6]. Classical methods for optimization are being used for a prolonged time to solve ELD. Smooth ELD problems are frequently solved using iterative lambda method, gradient method, and dynamic programming [7]. In order to practically model an ELD problem efficiently, numerous constraints are necessary to be undertaken with high level of accuracy thereby making the objective function highly complex [8]. The nature of the cost curve-imposed limitations on the application of these algorithms. Despite being independent of the nature of the cost curve, dynamic programming is affected by dimensionality and consume huge time in large generating systems [9]. This led to an upsurge in the application of *meta*-heuristic algorithms, which could curb the non-linearity in ELD problem such as chaotic bat algorithm [10], Kinetic gas molecule optimization [11] Grey Wolf Optimization [12] and adaptive social acceleration constant-based particle swarm optimization [13]. Evolutionary algorithms, which are based on various processes that have led to the evolution of life, proved functional in such cases. Genetic Algorithm is an evolutionary technique based upon global search, deriving the idea from genetic and cell reproduction which is used as a powerful tool [14,15]. Daniel et al. [8] consider a time varying ELD problem by applying Levenberg Marquardt algorithm. Current electricity market scenario is marked by large, interconnected power systems and deregulated power markets. The authors in [16] have applied fuzzy based Ant Lion Optimizer for solving dynamic optimal power flow problem. Authors in [17] implemented 150 variations for different load in training the neural networks and applied lambda iteration method and Back Propagation Neural Network in optimal power flow problem. The most sought-after evolutionary methods of Differential Evolution and PSO are integrated for solving ELD by considering valve-point loading effects by authors in [18]. Similarly, authors in [19] have utilized Dragonfly Algorithm and Advanced Modified PSO is applied by authors in [20] to solve ELD problem. With respect to the current situation that is emphasizing microgrid, ELD problem and, specifically the dynamic type, is an important power system optimization problem for reliable and secured operation. The microgrid can be visualized as a cluster of DERs as well as loads restricted to a given geographical area [21]. The DERs comprises of fossil-fueled generator sets and RES conducive to the microgrid location. The DERs further includes ESS, which may be battery, fuel cells and micro turbines. The specification and uniqueness of each microgrid calls for independent modelling with specific constraints, thereby, making economic dispatch an intricate optimization problem to be handled by power engineers.

There are two pre-dominant modes of microgrid operation comprising of either islanded or utility connected. The utility mode of functioning is deemed to be more effective and resilient due to the microgrid ability to sell/buy power based on surplus/deficit power production of individual DERs. The reliability factor is enhanced in utility connected mode as it can reckon on the grid in case of DER collapse, i.e., averting an undesirable network shutdown. Microgrid are considered as focal aspect to deliver energy in future, where in the last decade has witnessed intense research in this area.

ICA and Matrix real coded Genetic algorithm were used by Chen et al. [22] and Kasei [23] for generator cost minimization in a grid connected microgrid. The efficacy of algorithms is verified by maneuvering variable loads, testing compact operating range and fluctuating pricing in electricity. Basu and Chowdhury [24] investigated both SELD and DELD problem with Cuckoo Search Algorithm, generating improved results compared to PSO and Differential Evolution. The microgrid specifically consisted to two wind turbines operational based on wind speed. Pareto-optimal front based economic-emission dispatch was performed by Moghaddam et al. using AMPSO in reference [25], and MICA on a utility connected microgrid system by Rabiee et al in [26]. Economic and emission dispatches and combined EED were evaluated using interior search algorithm (ISA) in [27], MHSA in [28] and WOA in [29] on a 3-unit islanded microgrid system supported with photo voltaic (PV) and wind system. Kumar et al. [30] have solved the problem of optimal energy generation scheduling with respect to the available RES by applying Artificial Fish Swarm Algorithm. The problem of load uncertainty existing in a Micro grid (MG) while proper scheduling of renewables is handled by modified particle swarm optimization algorithm by Gholami and Dehnavi [31]. Askarzadeh [32] professes a memory based genetic algorithm for cost minimization while optimal power sharing among DERs considering a smart grid structure. Further, two more scenarios were studied by authors in [33] for the mentioned test system by increasing the load demand to 10% of its existing value, including an energy storage device and connecting the microgrid to utility for the unilateral flow of power. Bahmani-Firouzi and Azizipanah-Abarghooee [34] have applied Improved Bat Algorithm has restorative measures to be adopted for optimal use of Battery Energy Storage. Sharma et al. [35] propose Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine for operational planning and energy cost minimization. The overall operational cost of a microgrid system is optimized by the application of GWO [36]. Sharma et al. [37] used a probabilistic approach to attend the uncertainty in load demand and RES outputs to minimize the generation cost of a MG system using WOA. Bishwajit and Bhattacharyya [38] employed a recently developed nature inspired algorithm for optimizing cost of generation of various renewable integrated small and large microgrid systems. The fitness functions of these microgrid systems were both unimodal and multimodal in nature. CSA outperformed both classical and ample number of metaheuristic algorithms in minimizing the generation cost of these microgrid systems.

Considering the uncertainty in wind power furcating, a non-dominated sorting genetic algorithm II was used by Sarshar et al. [39] as an optimization tool to perform multi-objective energy management of a microgrid system. The impact of network reconfiguration was studied by Kavousi-Fard et al. [40] to conduct dynamic scheduling on a microgrid system. Network reconfiguration helped in altering the local power flow and reducing the active power loss. Optimum allocation for the cooperative operation of multi-coupled microgrids was proposed in reference [41], where the microgrid alliance contributes to the day ahead exchange of energy with the grid and by penalizing the microgrids, deviations from their commitments are limited. The authors in [42] carried out a coordinated energy dispatch approach where the upper level provides an optimum energy exchange schedule in between MGs and Distribution Network Operator (DNO), while the lower level ensures sufficient monitoring of supply and demand. Through the current plan, the authors not only maintain an economic equilibrium of supply–demand but also increase the use of distributed Microgrid systems for renewable energy. Alharbi et al. [43] proposed a detailed and novel framework for the operation and planning of the BESS based on repurposed EVBs. A novel linearized BESS sizing model was developed to achieve optimum design and operation decisions for the BESS. Lai [44], developed a new distributed scheme for a master–slave-categorized dc microgrid network with inadequate bandwidth connectivity to integrate the voltage of multiple DER to the optimum level. In addition, the authors also achieved optimum load distribution for economical operation. Reconfiguration of MG with PV and wind system is done with islanding constraints to achieve objectives of minimization of total operation cost of microgrid. The authors have considered fuel cost, reliability cost, cost of purchasing power from the mains, and switching cost as the system objectives [45]. Oskouei et al. [46] have investigated the effect of wind energy inception on a grid connected energy system by mixed integer non-linear programming method on a modified 6 bus and 24 bus test system. Inception of renewables to grid structure is investigated by accounting for PV panel, wind power and load demand as uncertainties and applying time-varying acceleration coefficients particle swarm optimization algorithm [47]. Hemmati et al. [48] analyzed the concept of smart distribution systems on IEEE 33-bus distribution test system by minimization of system costs. The authors have considered purchased power cost, switching costs, power loss cost for executing demand response. Oskouei et al. [49] analyzed the uncertainties related to electricity markets by proposing a hybrid stochastic approach.

1.3. Identifying the research gap and choice of hybrid GWOSCACSA in the current work

A detailed in-depth literature review performed above highlights the innovative research going on with respect to MG energy management problems considering various objectives. However, it was also noticed that most of the research was based on the time of usage (TOU) method of electricity market pricing, and a few were based on TOU with tax. As far as the literature survey performed by the authors, it was noticed that the articles lacked a fair comparative analysis on two or more methods of electricity market pricing, nor did they mention the reason of choosing TOU over the others.

Coming to the choice of the optimization tool, recent literature also establishes the merits of algorithms such as GWO, SCA and CSA in tackling multi-modal and complex optimization problems. Hybrid and modified metaheuristic algorithms are improvised with logical alterations or exhibit the nature the various algorithms involved to amalgamate and form the hybrid. This is the reason that hybrid and/or modified optimization techniques yield better quality solutions than the original one. The meticulous foraging ability of GWO in a large search space is its outstanding facet and it avoids premature convergence, it has lesser number of control parameters, and it gives the same accurate result consistently even after many trials. SCA has the prominent feature of extra ordinary exploration potential and its toggling between sine and cosine functions generates an adequate trade-off between diversification and intensification process. While CSA, on the other hand, has the prominent feature of exploitation potential, which ensures handling enormous population size with ease and results in rapid convergence. The authors in the current work thus proposed a hybrid of these three algorithms as GWOSCACSA which would ensure adaptation of the best attributes of all the three thereby delivering optimal solutions.

1.4. Research contribution of the article

The novel contribution of this article, which bridges the research gap among the various literature, consulted and cited above, can be listed as follows:

i. Three different types of electricity market pricing are formulated.

Table 1
Various market pricing strategies.

Strategy	Mathematical equation	Brief Explanation	Ref.
1	$C_{grid} = \sum_{t=1}^{T} FP^{*}P^{t}_{grid}$	FP is fixed price of electricity with which microgrid buys or sells power from utility depending on the value of P_{grid}	NA
2	$C_{grid} = \sum_{t=1}^{T} MP^{t*}P^{t}_{grid}$	Unlike FP, MP changes depending on the TOU throughout scheduling period T	[25 26 39]
3	$P_{buy} = \sum_{t} MP^{t*}P^{t}_{grid}$ if $P^{t}_{grid} > 0$ $P_{sell} = \sum_{t} (1 - tax)^{*}MP^{t*}P^{t}_{grid}$ if $P^{t}_{grid} < 0$ $C_{grid} = P_{buy} + P_{sell}$	Here selling price is measured as a taxable multiple of MP. The tax is fixed by the utility as on what percentage of MP, the utility wishes to buy back the power from microgrid	[34 35 36 37]

ii. All these market pricing strategies are incorporated on two different LV MG systems in turns, and the generation cost is evaluated for every strategy.
iii. A comparative analysis among the generation costs is performed to sort out the cheapest and most convenient strategy among the four.
iv. A novel hybrid GWOSCACSA is proposed to evaluate the generation cost.
v. The generation cost is also evaluated using GWO, GWOSCA and GWOCSA.
vi. Statistical analysis among the various optimization techniques is done to test the robustness of the hybrid GWOSCACSA.

1.5. *Organization of research work*

The research article begins with the introduction to research problem and literature review followed by Section 2 specifying the problem formulation. Section 3 highlights the implementation of the proposed hybrid algorithm in the current problem. Section 4 gives a detail account of simulation results, with the work being concluded in section 5.

2. Microgrid energy management formulation

The mathematical equation comprising of the generation cost incurred by the DERs, and the electricity market price charged by the utility, are given by equation (1):

$$Min\sum_{t}\sum_{g}[F_{g}(P^{t}_{g})I^{t}_{g} + SU^{t}_{g} + SD^{t}_{g}] + C_{grid} \tag{1}$$

where the symbols *F*, *P* and *I* denotes the fuel cost, active power output and ON/OFF status of the generators *g* respectively. It is a binary symbol with value 1 or 0 where 1 means the generator is ON for that particular time period t and 0 means the generator is OFF. *SU* and *SD* stands for start-up and shut down costs of generator *g*. C_{grid} is the total cost incurred by the grid throughout the day.

The total cost incurred by the grid varies according to the various electricity market pricing strategies available in various regions of the world. These pricing strategies normally changes with the change in load demand throughout the day. Fixed pricing (FP) strategy is not affected by the change in load demand. The price of electricity in this strategy remains the same throughout the day. Time of Usage (TOU) is a type of electricity market pricing where the electricity market prices change on hourly basis with rise and fall in load demand. This is the most widely followed market pricing strategy in the world. TOU with tax, Critical Peak Pricing (CPP) and two settlement payment system are some of the other prevalent market pricing strategies. Unlike TOU, where the selling price and the cost price of electricity remains unchanged, in TOU with tax system, the utility buys the excess electricity from the MG with a tax affected price. The tax is levied on the selling price by the utility. This is expressed as Strategy 3 in Table 1 below.

CPP is a medium of managing electricity demand even under compact demand–supply balance [50 51]. It primarily targets load reduction in a more dynamic way in the comparatively few expensive hours. CPP enhances electricity prices to austere levels at peak hours on the critical days proclaimed earlier. As a result of CPP strategies the people may respond in a sensible way with respect to electricity usage such as turning off air conditioners at home or diminishing electricity consumption.

The day-ahead market provides the status about the plants scheduled to run on the following day but it does not provide information about the plant which will eventually run on the following day. This is judged on the basis of real-time data and frequently it is observed that if a plant is scheduled to run in the day-ahead market than it is positively discharged in real-time. The impetus of real-time market is to dispense regional transmission units to adapt to economic dispatch based on alterations in demand forecast between the 24 h ahead time frame and the 1 h ahead time frame. It is, therefore, feasible that a generating unit would clear a certain quantity in the day-ahead market and a different quantity in the real-time market. The existing Locational Marginal Pricing (LMP) will eventually regulate the complete generator payments for both day-ahead and real-time markets. This payment process is called the "*two settlement system*"[52].

This paper considers evaluating the generation price of two MG test systems considering the FP, TOU and TOU with tax-based strategy. These strategies are formulated and displayed in Table 1.

The objective function, equation (2), is subjected to some necessary constraints related to various sections of the microgrid considered, given by equations (3–13).

$$\sum_{t}\sum_{g}P^{t}_{g} + P^{t}_{grid} = FL^{t} + \sum_{d}\sum_{t}L^{t}_{d} \tag{2}$$

Constraints for the grid:

$$-P^{max}_{grid} \leqslant P^{t}_{grid} \leqslant P^{max}_{grid} \tag{3}$$

Constraints for generators:

$$P^{min}_{g} \leqslant P^{t}_{g} \leqslant P^{max}_{g} \tag{4}$$

$$T^{on,t}_{g} \geqslant ONT_{g}(I^{t}_{g} - I^{t-1}_{g}) \tag{5}$$

$$T^{off,t}_{g} \geqslant OFFT_{g}(I^{t-1}_{g} - I^{t}_{g}) \tag{6}$$

Constraints for energy storage system [40]:

$$P^{t}_{g} \leqslant P^{t,dch,max}_{g}u^{t}_{g} - P^{t,ch,min}_{g}v^{t}_{g} \tag{7}$$

$$P^{t}_{g} \geqslant P^{t,dch,min}_{g}u^{t}_{g} - P^{t,ch,max}_{g}v^{t}_{g} \tag{8}$$

$$u^{t}_{g} + v^{t}_{g} \leqslant 1 \tag{9}$$

$$T^{t,ch}_{g} \geqslant CT_{g}(u^{t}_{g} - u^{t-1}_{g}) \tag{10}$$

$$T^{t,dch}_{g} \geqslant DT_{g}(v^{t}_{g} - v^{t-1}_{g}) \tag{11}$$

Constraints for the adjustable loads (for MG test system 2) [40]:

$$AL^{min}z^{t}_{d} \leqslant AL \leqslant AL^{max}z^{t}_{d} \tag{12}$$

$$\sum_{t\in[STd,\ ETd]} AL_d^t = ALE_d \tag{13}$$

$$T_d^{on} \geqslant OT_d(z_d^t - z_d^{t-1}) \tag{14}$$

Equation (2) states the conservation of energy. At any given period of time, the sum of the active power delivered by the DERs and the utility should suffice the total loads (both fixed and variable) during that period. Equation (3) marks the operating range of the power to be purchased from or sold to the utility. Equations (4–6) states the operating time and range of the conventional fossil fuelled generators. The constraints for optimally scheduling the energy storage system are stated in equations (7–11). Symbols 'u' and 'v' are binary variables showing the charging/discharging status of the battery. Equations (12–14) states the operating constraints of the variable loads for the residential microgrid test system. Like u and v, symbol 'z' is a binary variable stating the ON/OFF status of the adjustable or variable loads.

The fitness function stated in equation (1) is minimized by a proposed GWOSCACSA algorithm which is discussed in the succeeding section.

3. Hybrid optimization algorithms

This paper implements GWO and hybrid GWO-SCA-CSA, or GWO-SCACSA, for optimal scheduling and energy control on microgrid systems. The hybrid algorithm is established through mathematical formulations as given in the following section.

3.1. Grey wolf optimization & its amendments

GWO is a population-based and naturally inspired metaheuristic algorithm [53]. It comes under the swarm intelligence-based algorithm category and formulated based on the behavior of GW in catching the prey. In the pack of GW, based on the managing strength of the set of wolves, they behave as leaders, subordinates to the leaders in decision-making, and the followers to the above. These characteristics are well-defined in the GWO algorithm by assuming α-group as leaders, β-group as subordinate to the α-group, δ-group as followers to the α and β groups, and finally ω-group as the rest of the GW involving in passing the information from the boundaries to the other groups.

This strategy is formulated as a mathematical model for finding the optimal solution and formed the GWO algorithm. It considers encircling, hunting, attacking, and searching the prey as main phases and expressed as follows:

3.1.1. Encircling prey

The mathematical model of encircling the prey by GW can be derived from Fig. 5. It shows that the proper adjustment of distances between the prey and wolf will result in the position update of the wolves within the search space. This can be derived from equations (15, 16).

$$\vec{\lambda} = \left|\vec{C}.\vec{\chi}_p(t) - \vec{\chi}(t)\right| \tag{15}$$

$$\vec{\chi}(t+1) = \vec{\chi}_p(t) - \vec{\rho}.\vec{\lambda} \tag{16}$$

where: present iteration denoted by 't'; $\vec{\rho}$ and $\vec{C}$ are regulation vectors; $\vec{\lambda}$ gives the distance between the GW and prey, and ;$\vec{\chi}_p$ and $\vec{\chi}$ are the position vectors of prey and GW respectively.

The values of the regulation vectors depend on the distance between the GW and the prey. These can be expressed by equations (17,18).

$$\vec{\rho} = 2\vec{a}.\vec{i}_1 - \vec{a} \tag{17}$$

$$\vec{C} = 2.\vec{i}_2 \tag{18}$$

where: $\vec{i}_1$and $\vec{i}_2$ are the incidental vectors in [0, 1], and; $\vec{a}$ decreases from 2 to 0 linearly. The incidental vector provides the flexibility in moving the GW randomly using equation (15), (16) within the search space.

3.1.2. Searching (Exploration) and attacking (Exploitation) the prey:

The value of $\vec{\rho}$ in equation (17) determines the searching or attacking nature of the GWs. As $\vec{a}$ decreases from 2 to 0 linearly, range of $\vec{\rho}$ in the range of [-2a, 2a]. Hence, $\vec{\rho} < 1$ characterizes the GW converges towards the prey and diverges to explore for the prey if$\vec{\rho} > 1$. The exploration phase further considers a function $\vec{C}$ as given in equation (18) to emphasize/deemphasize the prey position due to the environmental effects. This factor improves the avoidance for the local optima, and exploration ability even in the final iterations of the GWO algorithm.

In exploration phase, α, β, and δ GWs diverge from each other and they will converge towards the prey in exploitation phase. Hence, the hunting nature of different wolf groups can be found by equations (19–22),

$$\vec{\chi}_1 = \vec{\chi}_\alpha(t) - \vec{\rho}_1.\vec{\lambda}_\alpha \tag{19}$$

$$\vec{\chi}_2 = \vec{\chi}_\beta(t) - \vec{\rho}_2.\vec{\lambda}_\beta \tag{20}$$

$$\vec{\chi}_3 = \vec{\chi}_\delta(t) - \vec{\rho}_3.\vec{\lambda}_\delta \tag{21}$$

$$\vec{\chi}(t+1) = \frac{\vec{\chi}_1 + \vec{\chi}_2 + \vec{\chi}_3}{3} \tag{22}$$

where: $\vec{\lambda}_\alpha$, $\vec{\lambda}_\beta$, and $\vec{\lambda}_\delta$are the distance between the α, β, and; $\delta$is the wolf group. These can be calculated by equation (23)

$$\left.\begin{aligned} \vec{\lambda}_\alpha &= \left|\vec{C}_1.\vec{\chi}_\alpha - \vec{\chi}\right| \\ \vec{\lambda}_\beta &= \left|\vec{C}_2.\vec{\chi}_\beta - \vec{\chi}\right| \\ \vec{\lambda}_\delta &= \left|\vec{C}_3.\vec{\chi}_\delta - \vec{\chi}\right| \end{aligned}\right\} \tag{23}$$

Therefore, in GWO algorithm,α, β, and δgroups update their positions using equation (19–21) and update the position of the prey using equation (22).

3.2. Modified Grey wolf Optimizer

The lowest in the hierarchy of grey wolves are the ω group, which endorse the δ wolves in the hunting pattern [54]. Therefore, the algorithm is modified as provided in the equation (24).

$$\left.\begin{aligned} \vec{\lambda}_\alpha &= \left|\vec{C}_1.\vec{\chi}_\alpha - \vec{\chi}\right| \\ \vec{\lambda}_\beta &= \left|\vec{C}_2.\vec{\chi}_\beta - \vec{\chi}\right| \\ \vec{\lambda}_\delta &= \left|\vec{C}_3.\vec{\chi}_\delta - \vec{\chi}\right| \\ \vec{\lambda}_\omega &= \left|\vec{C}_4.\vec{\chi}_\omega - \vec{\chi}\right| \end{aligned}\right\} \tag{24}$$

The location of the wolves during hunting can be modelled as provided in equation below. It is modified to include the ω group of wolves by equation (25).

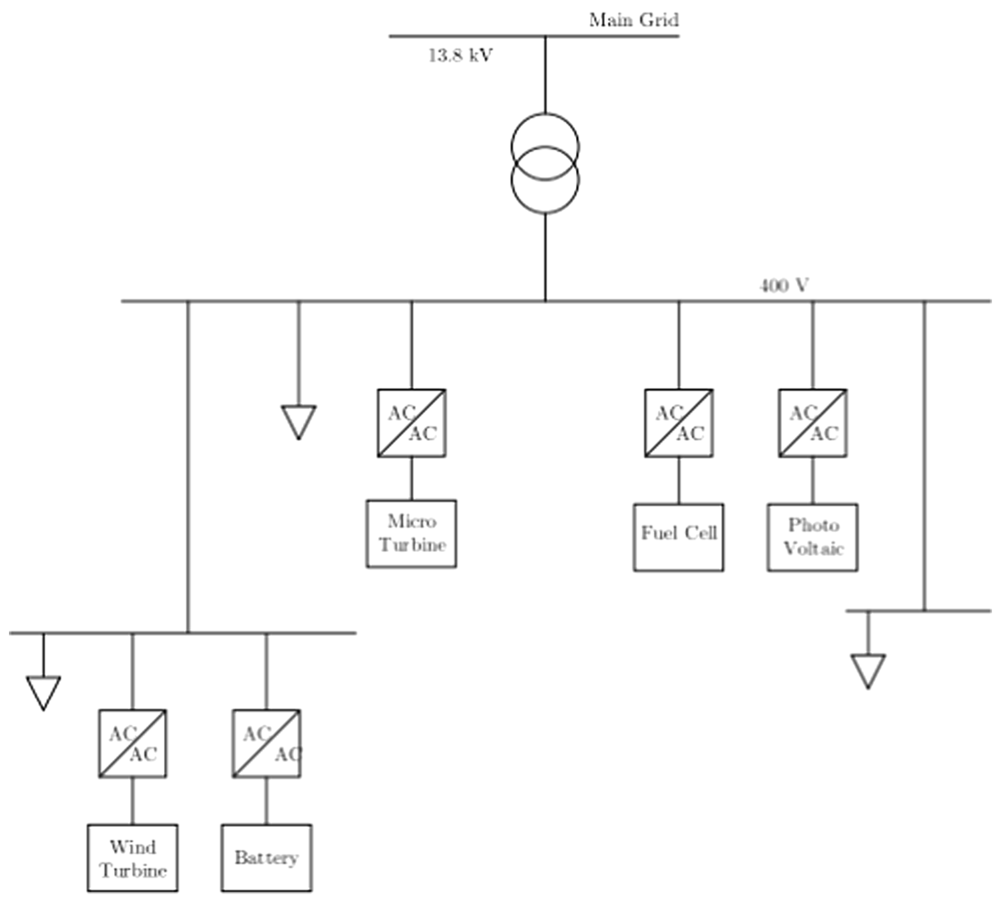

Fig. 1. Subject Microgrid overview [39].

Table 2
DER parameters [39].

	Min	Max
MT	6	30
FC	3	30
BAT	−30	30
GRID	−30	30

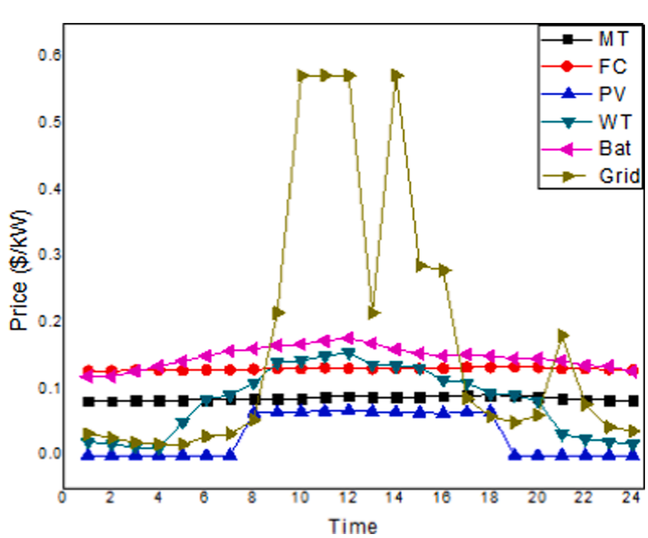

Fig. 2. Hourly pricing of DERs and utility [39].

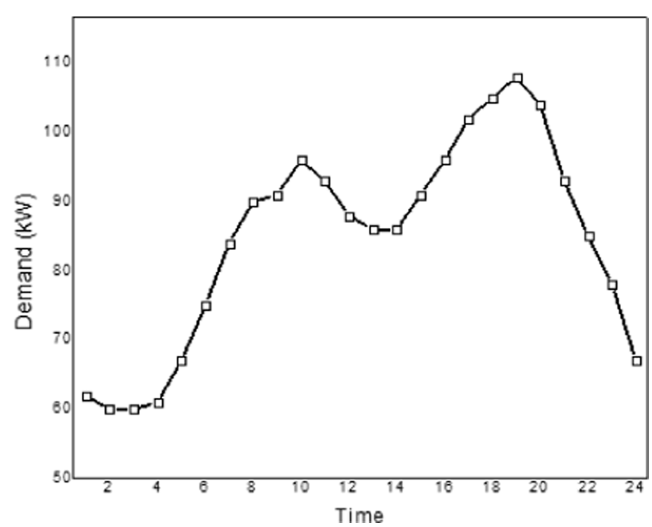

Fig. 3. Load demand for MG test system 1 [39].

$$\left.\begin{array}{l}\overrightarrow{\chi}_1 = \overrightarrow{\chi}_\alpha(t) - \overrightarrow{\rho}_1.\overrightarrow{\lambda}_\alpha \\ \overrightarrow{\chi}_2 = \overrightarrow{\chi}_\beta(t) - \overrightarrow{\rho}_2.\overrightarrow{\lambda}_\beta \\ \overrightarrow{\chi}_3 = \overrightarrow{\chi}_\delta(t) - \overrightarrow{\rho}_3.\overrightarrow{\lambda}_\delta \\ \overrightarrow{\chi}_4 = \overrightarrow{\chi}_\omega(t) - \overrightarrow{\rho}_4.\overrightarrow{\lambda}_\omega\end{array}\right\} \tag{25}$$

The iterative procedure is updated and presented in the next step as provided by equation (26).

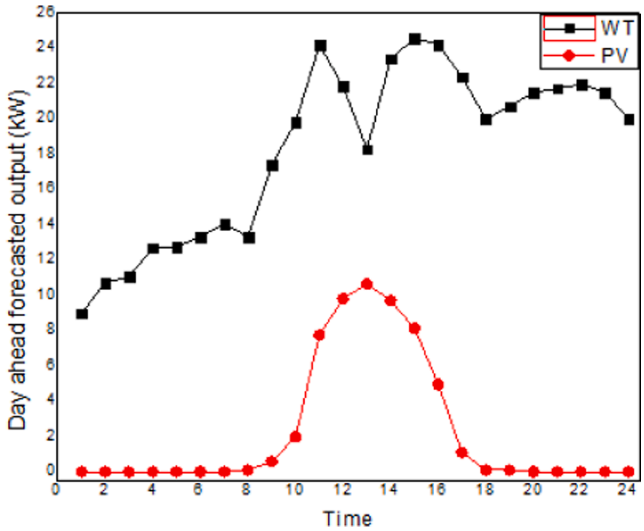

Fig. 4. Day ahead forecasted RES output [39].

Table 3
Least generation cost ($) obtained by algorithms after 30 trials.

Algorithms	Strategy 1	Strategy 2		Strategy 3
		Active	Passive	
WOA **[S]**	214.0505	132.1927	194.6928	141.3660
SCA **[S]**	214.1415	132.8717	192.4850	141.7147
DE **[S]**	214.5699	133.0705	194.4115	143.6395
GWO **[S]**	214.8640	132.4026	193.5009	140.1940
MGWOSCA **[S]**	214.5753	130.7019	193.1836	138.4744
MGWOCSA **[S]**	214.0133	130.4714	191.1856	138.4515
GWOSCACSA **[P]**	**213.9960**	***129.7663***	**190.2848**	**138.2857**

Note: Bold indicates best attained value; Bold italics indicates best strategy; S: Studied; P: Proposed.

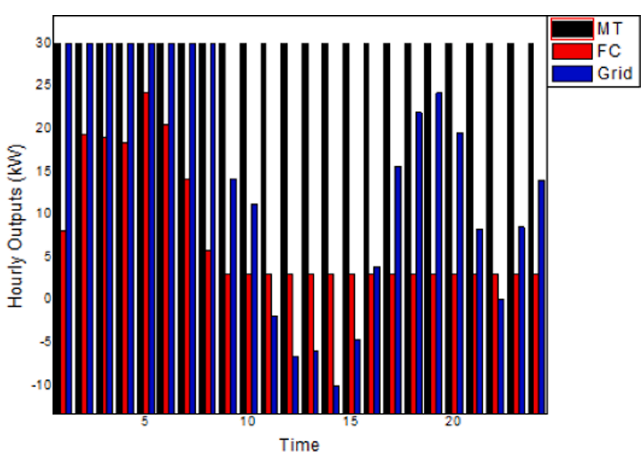

Fig. 5. Hourly output of DERs by MGWOSCA for Strategy 1.

$$\left.\begin{aligned} \vec{\chi}'_3 &= \frac{\vec{\chi}_3 + \vec{\chi}_4}{2} \\ \vec{\chi}(t+1) &= \frac{\vec{\chi}_1 + \vec{\chi}_2 + \vec{\chi}'_3}{3} \end{aligned}\right\} \quad (26)$$

3.3. *Sine cosine algorithm*

SCA is a popular optimization method which implements trigono-

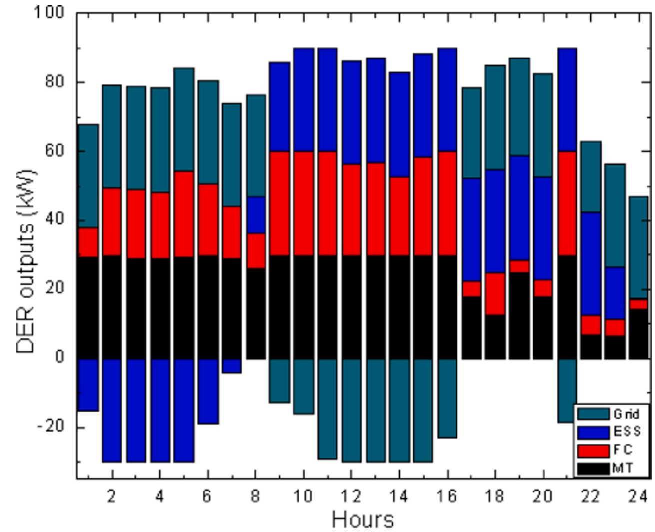

Fig. 6. Hourly outputs of DERs when least generation price was obtained with GWOSCACSA.

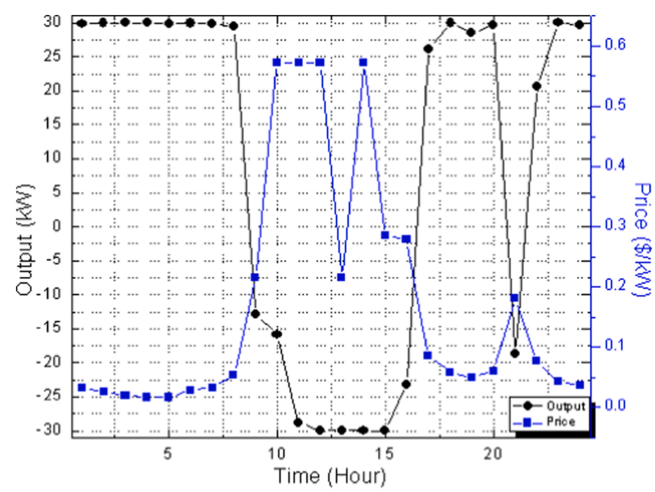

Fig. 7. Grid hourly output (kW) vs. Electricity market price for strategy 2 by GWOSCACSA.

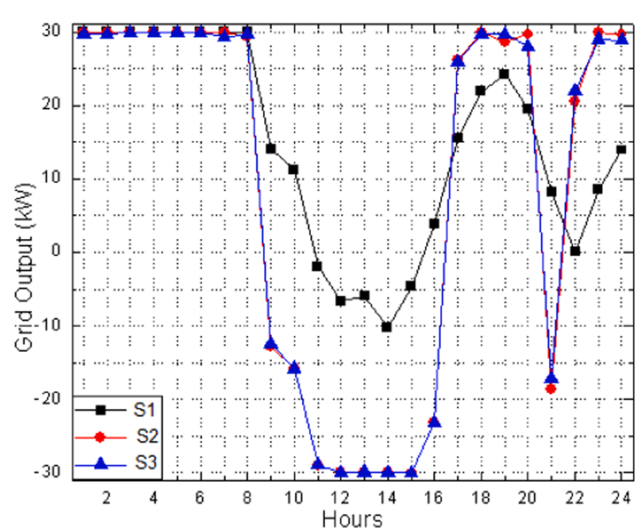

Fig. 8. Grid hourly output when least generation costs were obtained by GWOSCACSA.

Table 4
DER parameters for residential microgrid system [40]

Dispatchable Generators	Range (MW)	Bids ($/kW)	Min Up time (h)
G1	0.8/2	0.157	3
G2	0.8/3	0.154	3
G3	0.5/2.5	0.194	3
G4	0.5/2.5	0.218	3
Grid	±1	Table 5	24

Table 5
Fixed loads, Non dispatchable power and electricity market price for test system 2 [40].

Fixed Loads (kW)	Non Dispatchable generator (kW)	Electricity Market Price ($/kW)
2972	416.5	0.23
2990.575	416.5	0.19
3009.15	416.5	0.14
3038.87	416.5	0.12
3083.45	416.5	0.12
3380.65	213.5	0.13
3529.25	416.5	0.13
3603.55	304.5	0.14
3715	416.5	0.17
3640.7	721	0.22
3715	1347.5	0.22
3603.55	1379	0.22
3529.25	913.5	0.21
3343.5	553	0.22
3362.075	416.5	0.19
3380.65	304.5	0.18
3454.95	416.5	0.17
3343.5	416.5	0.23
3492.1	304.5	0.21
3603.55	416.5	0.22
3715	304.5	0.18
3454.95	304.5	0.17
3343.5	213.5	0.13
3492.1	143.5	0.12

Table 6
Variable load parameters [40].

Loads	Range (kW)	Total Energy (kWh)	Consumption hours (h)	Min Up time (h)
L1	0/80	320	11–14	1
L2	0/80	320	15–19	1
L3	20/80	240	16–19	1
L4	10/50	300	1–24	24
L5	20/60	300	13–24	12

metric functions to intensify and diversify the search space. This helps the optimization tool in yielding a better-quality solution and not getting stuck in local minima. Mathematical formulation of SCA is given by equation (27) according to reference [55],

$$X_{dim}^{iter+1} = \begin{cases} X_{dim}^{iter} + rand_1 * sin(rand_2) * \left|rand_3 * Pos_{dim}^{iter} - X_{dim}^{iter}\right|, & rand_4 < 0.5 \\ X_{dim}^{iter} + rand_1 * cos(rand_2) * \left|rand_3 * Pos_{dim}^{iter} - X_{dim}^{iter}\right|, & rand_4 \geq 0.5 \end{cases} \tag{27}$$

where: *dim* denotes the dimension of the solution set comprising of decision variables, and;X_{dim}^{iter+1} is the solution generated by implementation of SCA. During successive iteration, the position of solution from the destination point is varied and is given as *Pos*. The indication about the direction of the solution is guided by random number $rand_1$, while $rand_2$ highlights the displacement inclined towards or away from the

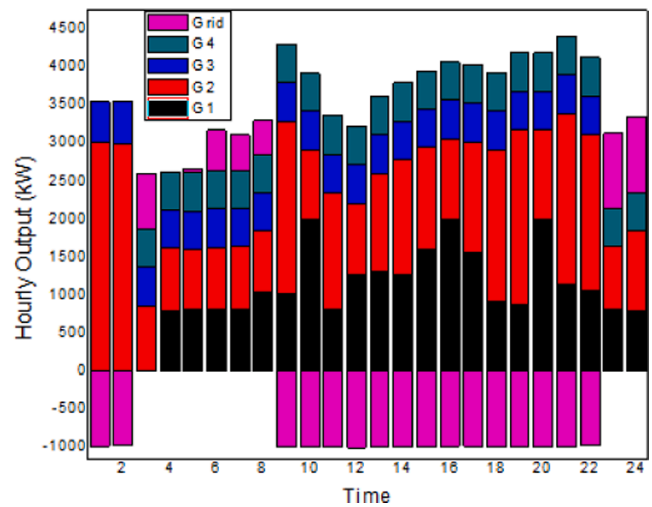

Fig. 9. Hourly outputs of DERs when only FL were considered during Strategy 2 by GWOSCACSA.

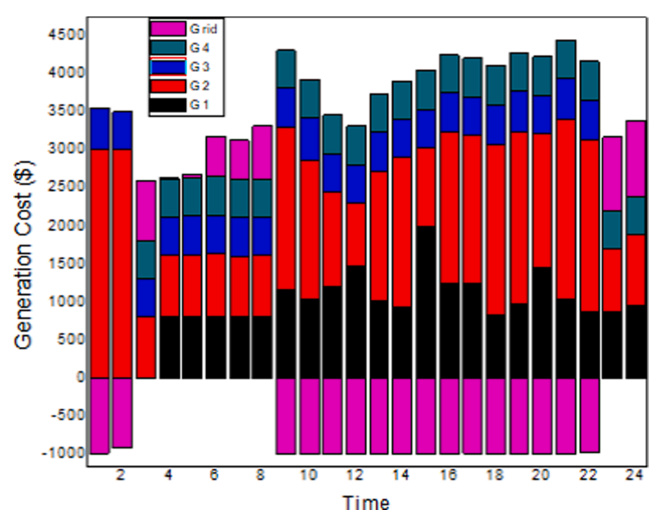

Fig. 10. Hourly outputs of DERs when (FL + VL) were considered during Strategy 2 by GWOSCACSA.

Table 7
Generation cost obtained using algorithms for test system 2 for various strategy (Notes: FL = Fixed Load; VL = Variable Loads).

Algorithms	Strategy1 ($)		Strategy2 ($)		Strategy3 ($)	
	FL	FL + VL	FL	FL + VL	FL	FL + VL
MGWOSCA **[S]**	11557.01	11781.12	11208.68	11466.95	11496.54	11738.39
MGWOCSA **[S]**	11502.32	11720.57	11206.90	11416.49	11486.62	11723.34
GWOSCACSA [P]	**11488.59**	**11719.98**	***11180.58***	***11403.75***	**11483.01**	**11721.98**

Note: Bold indicates best attained value; Bold italics indicates best strategy; S: Studied; P: Proposed.

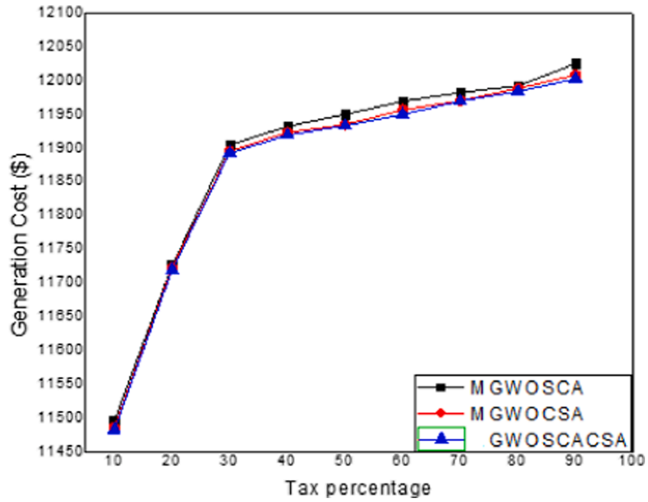

Fig. 11. Generation cost for various tax percentage using hybrid algorithms.

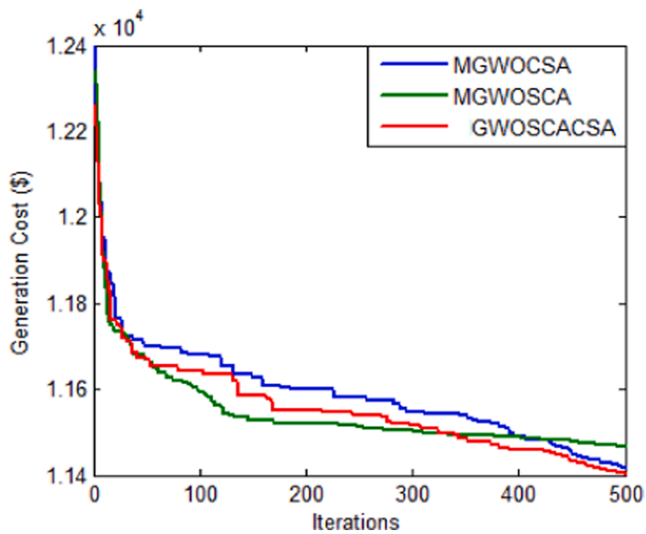

Fig. 12. Convergence curve characteristics for strategy 2 (FL + VL).

destination. Random number $rand_3$ acts as a weight factor and $rand_4$ provides the transition between the sine and cosine function during each iteration.

3.4. Crow search algorithm

CSA follows two probabilistic strategies depending on the behavior of a crow from a flock as described by authors in [56]. As per the first strategy, crow '*j*' without having the idea that it is being tracked by another crow '*i*' from the flock, hides its food as per its memory, which is later stolen by crow '*i*'. The second possible case is crow '*j*' possess the knowledge that its being tracked by crow '*i*' and hence flies away to a random position to hide its food. Mathematically, these two cases are represented by equation (28),

$$X^{i,iter+1} = \begin{cases} X^{i,iter} + rand_i \times fl^i \times (mem^{j,iter} - X^{i,iter}) & rand_j \geqslant AP^j \\ any\ random\ position & otherwise \end{cases} \tag{28}$$

In above equation (28), random numbers are generated with uniform distribution between 0 and 1 and is given as $rand_i$ and $rand_j$. The flight length of ith crow in the search space is denoted asfl^i. During the iterative process in search space an occurrence of 'Case 1′ will cause memory update of crow 'i' as given in the equation (29).

$$mem^{i,iter+1} = \begin{cases} X^{i,iter+1} & if\ f(X^{i,iter+1})\ is\ better\ than\ f(mem^{i,iter}) \\ mem^{i,iter} & otherwise \end{cases} \tag{29}$$

being f(.) the value of the fitness function.

3.5. Modified GWOSCACSA

Hybrid MGWO-SCA-CSA, called here GWOSCACSA, is modelled by incorporating the advantageous properties of SCA [55] and CSA [56] in various stages of MGWO [54]. Mathematically, the distance of the wolves while hunting is altered using SCA equations and the strategy of CSA is used to modify the position updating procedure of MGWO by equation (30).

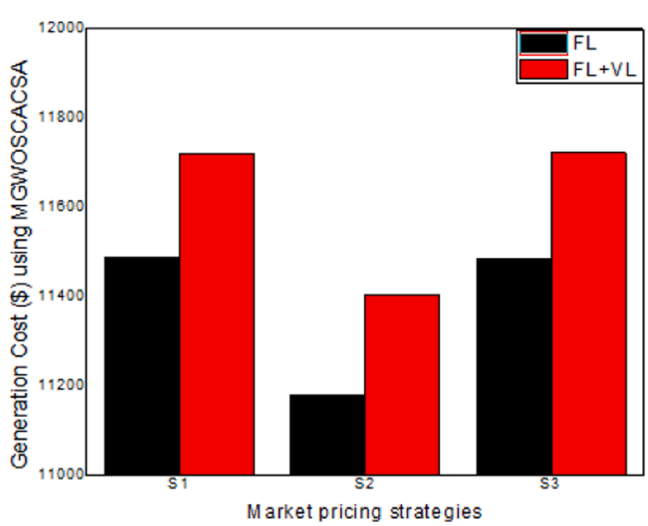

Fig. 13. Difference in generation cost considering only FL and both FL and VL.

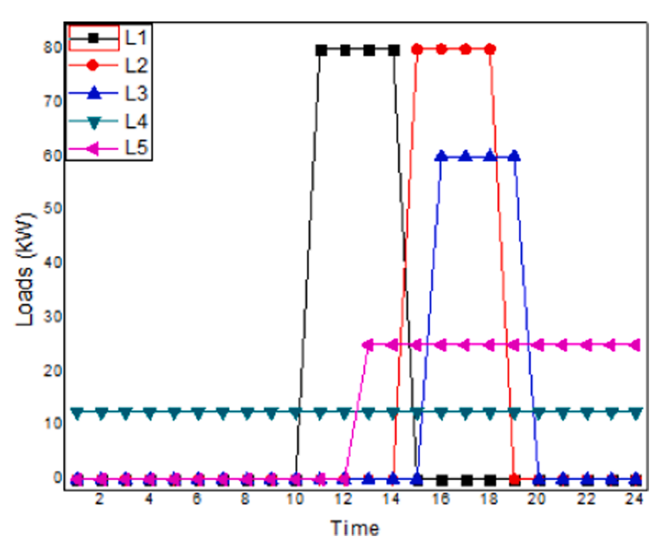

Fig. 14. VL distribution when least cost was obtained during Strategy 2.

Table 8
Statistical analysis of results obtained for Strategy 2 of electricity market price.

Test System	Algorithms	Minimum ($)	Maximum ($)	Average ($)	Hits	SD	Time (s/iter)
1	MGWOSCA	130.7019	133.8542	131.8052	13/20	1.5426	0.89
	MGWOCSA	130.4714	132.8736	131.0720	15/20	1.0672	1.09
	GWOSCACSA	**129.7663**	130.5730	129.8470	17/20	0.2483	0.8
2	MGWOSCA	11466.9471	11473.7830	11468.9979	14/20	3.2140	1.36
	MGWOCSA	11416.4927	11422.7302	11418.9877	12/20	3.1351	2.07
	GWOSCACSA	**11403.7511**	11408.9989	11404.8007	16/20	2.1537	1.13

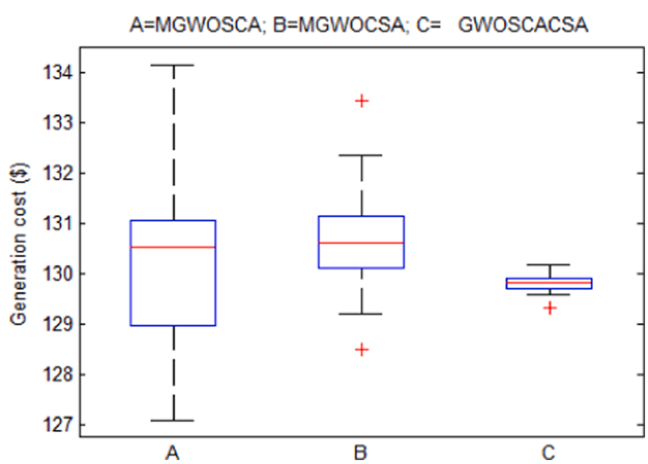

Fig. 15. Box plot for Strategy 2 (Active grid/Test System 1).

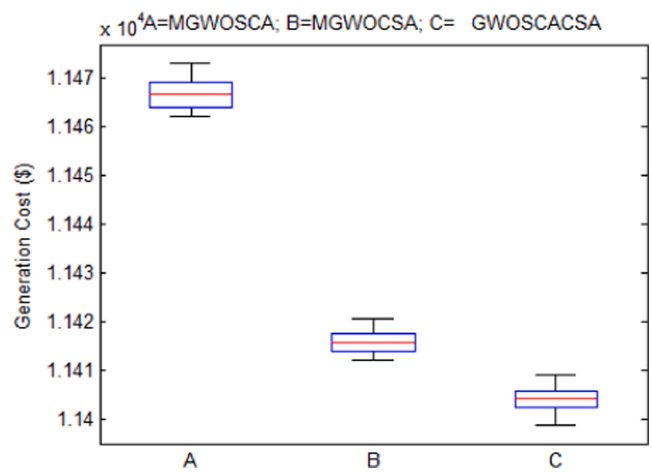

Fig. 16. Box plot for Strategy 2 (FL + VL/Test System 2).

$$\left.\begin{array}{l} \vec{\lambda}_{\alpha} = \begin{cases} rand^{*}sin(rand)\left|\vec{C}_{1}.\vec{\chi}_{\alpha} - \vec{\chi}\right| & if\ rand > 0.5 \\ rand^{*}cos(rand)\left|\vec{C}_{1}.\vec{\chi}_{\alpha} - \vec{\chi}\right| & otherwise \end{cases} \\ \vec{\lambda}_{\beta} = \begin{cases} rand^{*}sin(rand)\left|\vec{C}_{2}.\vec{\chi}_{\beta} - \vec{\chi}\right| & if\ rand > 0.5 \\ rand^{*}cos(rand)\left|\vec{C}_{2}.\vec{\chi}_{\beta} - \vec{\chi}\right| & otherwise \end{cases} \\ \vec{\lambda}_{\delta} = \begin{cases} rand^{*}sin(rand)\left|\vec{C}_{3}.\vec{\chi}_{\delta} - \vec{\chi}\right| & if\ rand > 0.5 \\ rand^{*}cos(rand)\left|\vec{C}_{3}.\vec{\chi}_{\delta} - \vec{\chi}\right| & otherwise \end{cases} \\ \vec{\lambda}_{\omega} = \begin{cases} rand^{*}sin(rand)\left|\vec{C}_{4}.\vec{\chi}_{\omega} - \vec{\chi}\right| & if\ rand > 0.5 \\ rand^{*}cos(rand)\left|\vec{C}_{4}.\vec{\chi}_{\omega} - \vec{\chi}\right| & otherwise \end{cases} \end{array}\right\rangle \quad (30)$$

Thereafter χ_1, χ_2, χ_3 and χ_4 are calculated by equation (25). The position updating step of GWOSCACSA follows that of CSA according to equation (31):

The parameter AP acts as decisive variable to consider all the α, β, δ and ω wolves for updating process or to rely on the alpha (leader) wolf only. AP is a probabilistic value changes in every iteration using equation (32).

$$AP = 1 - \left(\frac{1.01^{*}iter^{3}}{Max\_iter^{3}}\right) \quad (32)$$

Authors in [57] and [58] have utilized the proposed hybrid approach in solving single objective and bi-objective fitness functions related to microgrid systems and gained superior quality results than various others algorithms involved. This is also a motivational point for the authors to implement this hybrid algorithm as the optimization tool for solving the market pricing problem of microgrid systems.

$$\left.\begin{array}{l} \vec{\chi}_{(t+1)} = \vec{\chi} + fl^{*}rand^{*}\left\{\left(\left(\vec{\chi}_{1} - \vec{\chi}\right) + \left(\vec{\chi}_{2} - \vec{\chi}\right) + \left(\vec{\chi}'_{3} - \vec{\chi}\right)\right\}\Big/3 \quad if\ AP > rand \\ \vec{\chi}_{(t+1)} = \vec{\chi} + fl^{*}rand^{*}\left(\vec{\chi}_{1} - \vec{\chi}\right) \quad otherwise \end{array}\right\} \quad (31)$$

3.6. Analogy relating hybrid GWOSCACSA with the energy management problem

If T is the time period for optimal scheduling, D is the number of DERs involved in powering the microgrid system on which the energy management is to be performed, and N is the number of search agents of the population, then the matrix depicting the population is shown in equation (33), wherein every search agent of the population follows the system constraints mentioned in equations (2) to (14).

$$S = \begin{bmatrix} S^1_{1,DER1}, & S^2_{1,DER1}, \cdots S^T_{1,DER1}, & S^1_{1,DER2}, & S^2_{1,DER2}, \cdots S^T_{1,DER2} \cdots S^1_{1,DER\ D}, & S^2_{1,DER\ D}, \cdots S^T_{1,DER\ D} \\ S^1_{2,DER1}, & S^2_{2,DER1}, \cdots S^T_{2,DER1}, & S^1_{2,DER2}, & S^2_{2,DER2}, \cdots S^T_{2,DER2} \cdots S^1_{2,DER\ D}, & S^2_{2,DER\ D}, \cdots S^T_{2,DER\ D} \\ S^1_{3,DER1}, & S^2_{3,DER1}, \cdots S^T_{3,DER1}, & S^1_{3,DER2}, & S^2_{3,DER2}, \cdots S^T_{3,DER2} \cdots S^1_{3,DER\ D}, & S^2_{3,DER\ D}, \cdots S^T_{3,DER\ D} \\ & & \cdots\cdots\cdots\cdots & & \\ & & \cdots\cdots\cdots\cdots & & \\ S^1_{N,DER1}, & S^2_{N,DER1}, \cdots S^T_{N,DER1}, & S^1_{N,DER2}, & S^2_{N,DER2}, \cdots S^T_{N,DER2} \cdots S^1_{N,DER\ D}, & S^2_{N,DER\ D}, \cdots S^T_{N,DER\ D} \end{bmatrix} \quad (33)$$

The position of the wolves is depicted by particles in the population matrix which acts the control variables. The distance of wolves from the prey is taken as the fitness value for the objective function. Considering the proposed work as a constrained minimization approach, the position of search agent with least fitness function value is the best solution among all search agents in the search space and is termed as χ_α.

4. Test system results

Two study the effect of the aforementioned market pricing strategy, two microgrid test systems were considered, and the generation cost were minimized for both. The results and discussion are detailed in this section.

4.1. Test system 1

Test system 1 is a LV grid-connected microgrid powered by a MT, a FC, a battery as ESS and RES, e.g., PV system and WT, as shown in Fig. 1. Their specifications are detailed in Table 2.

The hourly bidding of all the DERs, including electricity market price, are displayed in Fig. 2. The forecasted value of load demands is shown in Fig. 3, while that of PV and wind outputs are shown in Fig. 4. The generation cost was minimized using four different optimization algorithms. All of them were executed for 500 iterations and the number of search agents was fixed as 80 for all. Flight length (*fl*), a parameter that occurs in MGWOCSA and GWOSCACSA, was set at 2. These assumptions were done according to reference [48].

Table 3 shows the best possible generation cost obtained using the various aforementioned optimization techniques for different strategies of electricity market pricing. The basic inferences that be concluded from the table are:

- The maximum generation cost was obtained during strategy 1. This strategy marks the fixed price of electricity market price. Since the fixed price of electricity was not available in the literature, it was calculated by evaluating the overall mean of hourly electricity price. When C_{grid} is fixed, the grid is allowed to operate only after the rest of the DERs deliver their maximum capacity. This hinders the grid from buying power from the microgrid, which increases the generation cost.
- It can be seen that the least generation cost of the microgrid system was realized by the proposed algorithm when the second strategy of electricity market pricing was considered, and the grid was actively participating. It was also observed that for the same strategy of market pricing, when the grid was made to passively participate, i.e., grid cannot buy power from the microgrid system or mathematically lower limit of grid is fixed at 0 kW, in the transaction mechanism, the generation cost rose to 47% from \$129 to \$190. This steep rise was primarily due to the reason that the grid was not allowed to purchase electricity from the MG system when load demand was less.
- Strategy 3 is the situation when the grid purchases power from the microgrid on a taxable charge. The tax is levied upon the electricity market price, as shown in equation (1c). The tax was considered to be 10% according to references [19-22], and the generation cost was minimized. Proposed modified GWOSCACSA reduced the generation cost to \$138 for this scenario.

Table 9
Wilcoxon's analysis for the results obtained using proposed GWOSCACSA.

Test system	Strategy	Minimum	Maximum	Average	SD	Variance	Hits	p-value (x 10^{-5})
1	1	213.9960	216.8736	214.4276	1.0542	1.1113	17/20	2.2956
	2	129.7663	130.5730	129.9680	0.3584	0.1284	17/20	3.5593
	3	138.2857	139.0567	138.4399	0.3164	0.1001	16/20	2.9259
2	1	11719.9799	11725.7320	11721.1303	2.3606	5.5725	16/20	2.9259
	2	11403.7511	11408.9989	11404.8007	2.1537	4.6382	16/20	2.9259
	3	11721.9805	11722.6073	11722.1372	0.2785	0.0775	15/20	3.5593

Fig. 5 shows the hourly output of MT, FC and grid while GWOSCACSA was utilized for cost reduction in generation for the 1st strategy of market pricing. It is to be noted that the generation cost was highest during this strategy. This is because when the electricity price is anchored, utility is allowed to operate only after the rest of the DERs deliver their maximum or minimum capacity according to their bid prices. It is clear from the figure that since the bid price of MT is less than that of FC (from Fig. 2), the output of MT was fixed at the maximum operating limit whereas for most of the hours the output of FC was fixed at its least permissible value. The left of the load demand, if any, was to be supplied by the grid. This finally led to the anomaly, which incurred a 65% rise in the generation cost compared to strategy 2.

Fig. 6 shows the hourly output of the DERs when the least generation cost ($130 approx.) was obtained by proposed GWOSCACSA during active participation of grid of strategy 2. The charging and discharging of battery, buying and selling power by the grid and economical sharing of loads by MT and FC all within their permissible limits can be realized from Fig. 6.

Fig. 7 shows the complementary behavior of grid with the electricity market price in minimizing the active power production cost of the system for strategy 2 using the proposed approach. It can be seen clearly that when the electricity price is more, then the grid buys power from the MG system. On the contrary, during the hours when electricity market price is low, then the grid sells power to the microgrid. This buy and sell economical interaction between the utility and the microgrid is the sole cause of a least generation cost during this strategy

Fig. 8 shows the participation of the grid for all the 3 strategies when generation cost was evaluated using proposed GWOSCACSA algorithm. The more power the grid buys from the system, the less the generation cost of the system will be. It is clear from this figure that the grid showed least participation in buying power from the microgrid during the first strategy compared to the other two.

4.2. Test system 2

An appraisal of test system 2 consisting of both dispatchable and non-dispatchable distributed generators, which supply power to the system. is accounted for in this work. It comprises of a LV utility connected residential microgrid system. Traditional generators driven by fossil fuels include the dispatchable generators, while generators fed by renewable sources comprises the non-dispatchable type. In the later one, power output cannot be scheduled. The distinctive aspects of the dispatching generators are provided in Table 4.

Table 5 demonstrates the electricity market value, power return and the fixed load assigned to the non-dispatchable generators. The type of load which consumes power only for a distinct period of time during a day are categorized as variable load (VL). VL includes water pump, air conditioners, etc.

Table 6 shows the attributes of the variable loads. The population size and maximum number of iterations implemented to minimize the generation is the same as in MG test system 1.

Table 7 presents the generation costs for all the strategies obtained using the hybrid algorithms. The least generation cost for MG test system 2 was obtained by proposed GWOSCACSA when strategy 2 of electricity market pricing was considered. Involvement of VL for strategy 2 yielded a 2% rise in the generation cost compared to the case when only FL were considered. Like the previous test system, the maximum cost was obtained during strategy 1.

Figs. 9 and 10 show the hourly output of DERs when GWOSCACSA minimized the generation cost of the residential MG system using strategy 2 of electricity market pricing. The ON/OFF time of the DERs can be seen to be maintained in these figures. Acquiring power from a MG set can play a pivotal part in diminishing the cost of generation. This is seen to have fulfilled from Figs. 9 and 10.

As a depth of research, the generation cost was evaluated for various tax percentages to study its effect in the generation cost of the system. The pattern observed in the rise in generation cost, when the tax percentage was gradually increased from 10 to 90%, is shown in Fig. 11. There was steep rise in the generation cost from 10 to 30% and thereafter there was a steady rise. This primarily happened because as the tax percent increased the difference between buying and selling price increased which hindered the grid from actively and freely participating in the buying and selling of electricity. The study was done considering both FL and VL.

The convergence curves of the hybrid algorithms for strategy 2 (FL + VL) is shown in Fig. 12.

Fig. 13 shows the difference between the generation costs by proposed GWOSCACSA when only FL or FL + VL were considered. For all the strategies, it was obvious that since the load increased with the inclusion of VL, the generation cost of (FL + VL) will be more than only FL. Also, if it is considered the difference in generation cost among the strategies, the pattern was same as observed in test system 1. The max generation cost was obtained during strategy 1 while the least was obtained during strategy 2.

Fig. 14 shows the VL distribution within their specified operating hours, as mentioned in Table 6. The minimum operating time of all the loads, as mentioned in Table 6, can be seen to have maintained by the algorithms while delivering the least generation cost of the microgrid test system.

4.3. Statistical analysis

All the algorithms were run for 20 individual trials during all strategies of electricity market pricing strategy. To make the analysis easier and less complicated, only the best strategy was considered for statistical analysis. Table 8 shows an investigation of statistical results based on the best, worst, mean and standard deviation described after 20 executions of the algorithm. It can be clearly seen that GWOSCACSA consumes less time. the reason behind this can be explained as follows. Table 8 shows that the amalgamation of three conventional algorithms to make a hybrid algorithm consume minimum time in yielding a better quality results than other algorithms. It is to be noted that the three algorithms are incorporated altogether in various stages of the conventional grey wolf algorithm and not one by one. The movement directions and speed of the wolves are improved using position update equations of SCA. This maintains a proper balance between exploration and exploitation and prevents the algorithm from getting stuck in local minima. The involvement of the feature of CSA in the position updating strategy ensures population diversity, to further improve the search ability and performance of the algorithm. Especially, when solving complex optimization problems, parallelizing the algorithm is an effective way to improve the efficiency and accuracy of the algorithm. However, some time is consumed once while coding the algorithm, but it is a one-time affair. Once the algorithm is coded, proposed GWOSCACSA yields better quality solutions than other hybrids and conventional algorithms.

From the data reported in Table 8, box plots were created and displayed in Figs. 15 and 16 for test system 1 and 2 respectively.

The potency of the algorithm is further justified through the Wilcoxon's signed-rank test which is based on choice of two alternative hypothesis wherein H_0 taken as hypothesis that states that the five algorithms are no different and H_1 hypothesis states that the ways are different, where $\alpha = 0.05$, being α the significance level. Table 9 provides the mean average, worst and best solutions obtained by the of objective function. The standard deviation is studied by the GWO-SCACSA method. In cases that 'p-value' < 0.05 in every test systems, then the Wilcoxon's signed rank test is proved and the null hypothesis is rejected according to reference [59].

Table 5 shows that proposed hybrid algorithm consumes less than a second to complete one iteration during strategy 2 of test system 1. Whereas for Test system 2, when loading was increased along with constraints such as ON/OFF time of DERs and VL, the time taken per iteration rose to 1.13secs. This along with the fact that the algorithm yields the best result 75–85% of time as displayed in Table 9, corroborates the robustness of the algorithm.

5. Conclusions

This paper has been focussed on shrinking the generation cost generation of a LV grid-connected microgrid system reinforced by RES. In a nutshell, it can be concluded that the TOU based electricity market pricing economizes generation cost of an MG system when grid is participating actively in buying and selling power. The detailed significant findings of the study are listed below:

a. The generation cost of the MG system was minimum when the second strategy of electricity market pricing was considered with the active participation of the grid. The dynamic nature of the electricity market price complements the progressive change in the load demand to buy and sell power from the MG, which cooperates in reducing the generation cost of the system. However, for the same strategy and passive participation of the grid, the generation cost rose to 47% than earlier because in passive involvement, the grid can only sell power to the MG and cannot buy from it.
b. The generation cost of the MG system was maximum when the first strategy of electricity market pricing was implemented because the fixed price of the electricity emphasized the utilization of grid only after the rest of the DERs delivered their maximum/minimum capacity. Hence the selling of power by the MG was very less.
c. In the third strategy of electricity market pricing states that selling price is a taxable percentage of ME. The tax is set by the grid itself. In that case, the amount with which the microgrid buys power from the grid is more than the amount with which the microgrid sells power to the grid. This leads to a rise in generation cost compared to the second strategy. It was seen that 10% tax incurs the minimum cost for this strategy but not as minimum as strategy 2.
d. The hybrid approach of GWOSCACSA provided the improved results in the objective of generation cost reduction for the microgrid system. This is also accomplished with minimal computational time due to improved convergence. The algorithm has also been verified to demonstrate best statistical results when it is compared with other algorithms, satisfying the constraints considered. These attributes of the proposed algorithm justify its robustness and makes it a suitable choice to tackle multifarious complex power system optimization.

For future scope of research work, the generation cost on any microgrid system can be evaluated using all the three strategies depending upon the availability of data to test the robustness and dependency on the grid compared to the DERs comprising the system.

CRediT authorship contribution statement

Bishwajit Dey: Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Saurav Raj:** Visualization, Investigation. **Sheila Mahapatra:** Supervision, Software, Validation. **Fausto Pedro García Márquez:** Writing - review & editing.

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.

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Appendix

Table A1 shows the statistical investigation of the proposed algorithm on benchmark functions.

Figs. F1–F15 shows the convergence characteristics of the best obtained values. This table also consists of the mean value (F_{mean}), standard deviation (FSD) as given in (a1) and (a2). The proposed technique performance is validated by comparison with other algorithms with homogeneous parameters considering a population size of 100 and number of iterations as 1000.

$$F_{mean} = \frac{\sum_{i=1}^{N} f_i}{N} \tag{a1}$$

$$F_{SD} = \frac{\sum_{i=1}^{N} (f_i - F_{mean})^2}{N} \tag{a2}$$

where 'N' is the total number of individual runs, here it is considered as 30.

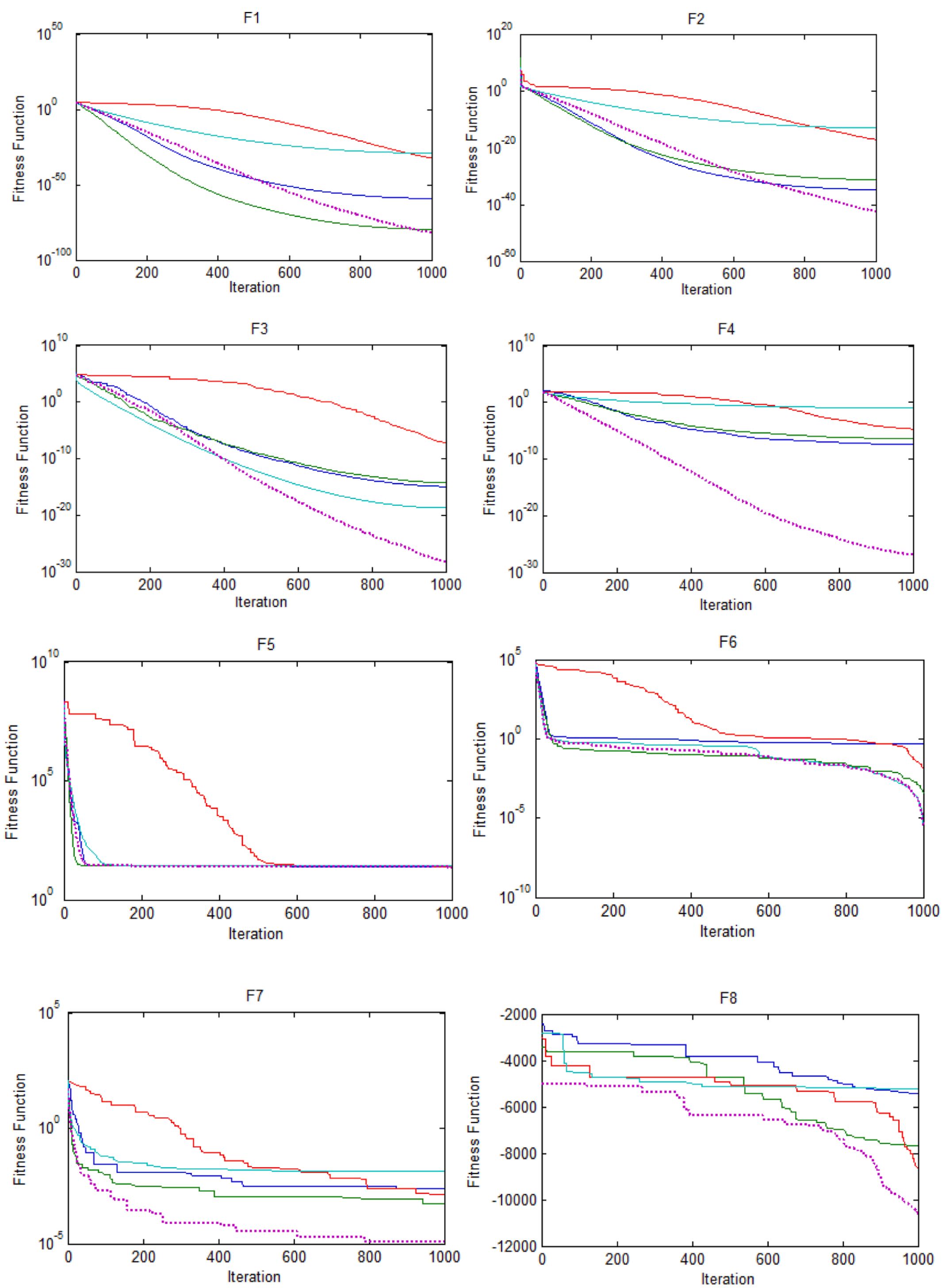
Table A1
Statistical Analysis of benchmark functions.

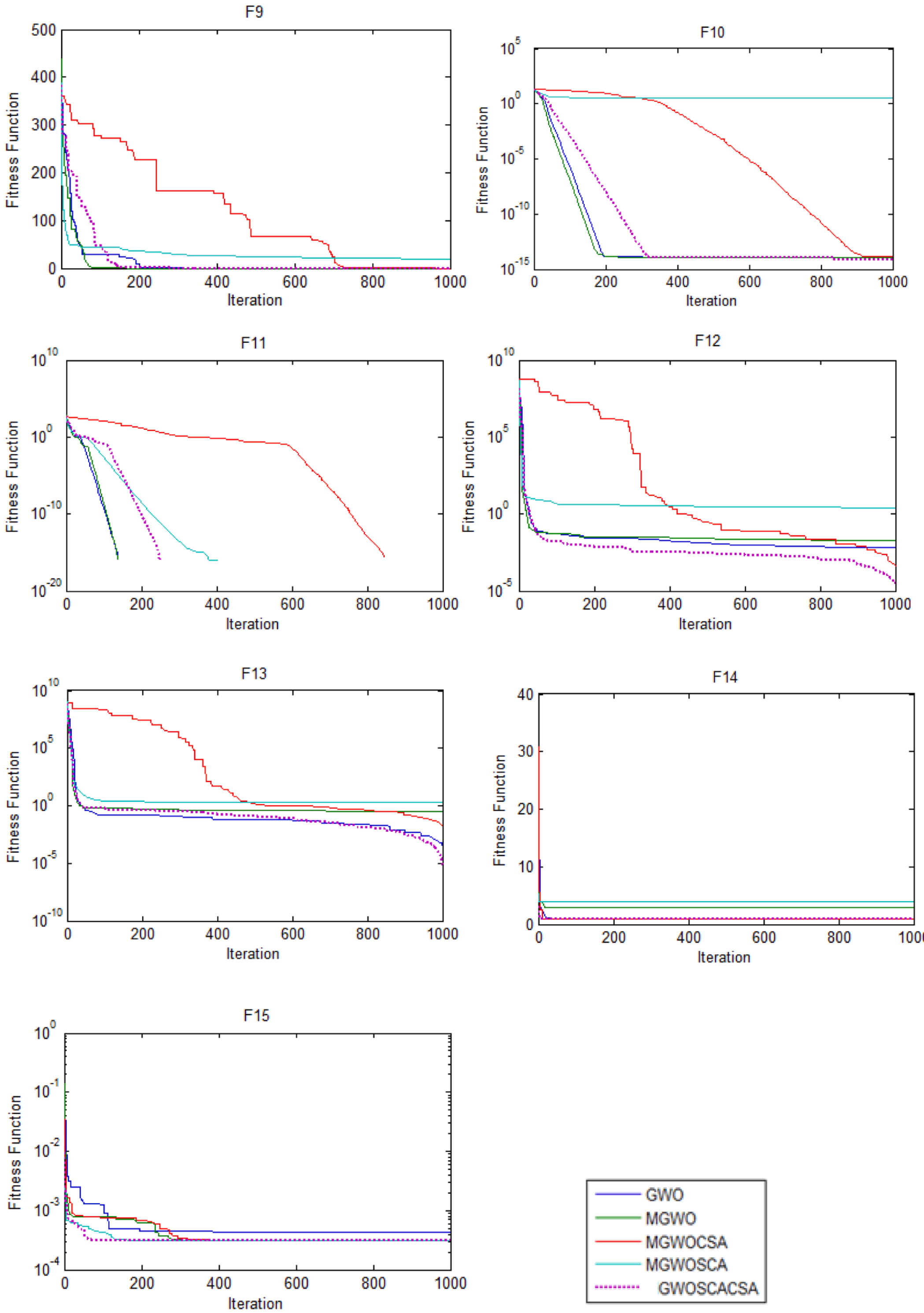
Benchmark Functions	f_{min} / Range	Algorithms	Mean Value	SD
F1	0	GWO	$9.5165x10^{-60}$	0.014251
$f_1(x) = \sum_{i=1}^{n}x_i^2$	[-100,100]	MGWO	$2.5824x10^{-80}$	0.004520
		MGWOSCA	$9.1657x10^{-30}$	0.000521
		MGWOCSA	$4.2860x10^{-33}$	0.000125
		GWOSCACSA	**$1.3738x10^{-82}$**	**0**
F2	0	GWO	$2.2464x10^{-35}$	0.042510
$f_2(x) = \sum_{i=1}^{n}\lvert x_i\rvert + \prod_{i=1}^{n}\lvert x_i\rvert$	[-10,10]	MGWO	$7.5184x10^{-32}$	0.017458
		MGWOSCA	$1.5567x10^{-13}$	0.015214
		MGWOCSA	$1.2511x10^{-17}$	0.007858
		GWOSCACSA	**$3.1709x10^{-43}$**	**0.000852**
F3	0	GWO	$1.1493x10^{-15}$	56.502145
$f_3(x) = \sum_{i=1}^{n}\left(\sum_{j-1}^{i}x_j\right)^2$	[-100,100]	MGWO	$5.4293x10^{-15}$	41.552512
		MGWOSCA	$1.8839x10^{-19}$	8.152452
		MGWOCSA	$5.288x10^{-8}$	11.754125
		GWOSCACSA	**$4.5113x10^{-29}$**	**0.088120**
F4	0	GWO	$4.0643x10^{-8}$	1.020152
$f_4(x) = max_i\{\lvert x_i\rvert, 1\leqslant i\leqslant n\}$	[-100,100]	MGWO	$4.0237x10^{-7}$	0.584512
		MGWOSCA	0.0989	0.125458
		MGWOCSA	$1.846\ x10^{-5-}$	0.222521
		GWOSCACSA	**$1.0872x10^{-27}$**	0.009459
F5	0	GWO	25.2275	52.012511
$f_5(x) = \sum_{i=1}^{n-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	[-30, 30]	MGWO	27.0586	11.012532
		MGWOSCA	27.0568	9.020949
		MGWOCSA	24.8876	5.225121
		GWOSCACSA	**22.4315**	**1.845254**
F6	0	GWO	0.5016	0.000001
$f_6(x) = \sum_{i=1}^{n}([x_i + 0.5])^2$	[-100,100]	MGWO	$3.1603\ x10^{-6}$	0.000001
		MGWOSCA	$3.9856\ x10^{-6}$	0
		MGWOCSA	0.0134	0
		GWOSCACSA	**$3.4321\ x10^{-4}$**	**0**
F7	0	GWO	0.0026	0.027849
$f_7(x) = \sum_{i=1}^{n}ix_i^4 + random\ (0,1)$	[-1.28, 1.28]	MGWO	$5.6768\ x10^{-4}$	0.029452
		MGWOSCA	0.0131	0.001202
		MGWOCSA	0.0014	0.004589
		GWOSCACSA	**$1.1729\ x10^{-5}$**	**0.002321**
F8	-418.982×5	GWO	$-5.3780\ x10^3$	1252.021202
$f_6(x) = \sum_{i=1}^{n} - x_i sin(\sqrt{\lvert x_i\rvert})$	[-500, 500]	MGWO	$-7.6616\ x10^3$	784.051212
		MGWOSCA	$-5.1823\ x10^3$	210.001200
		MGWOCSA	$-8.6602\ x10^3$	241.994519
		GWOSCACSA	**$-1.0610\ x10^4$**	**27.911001**
F9	0	GWO	0	21.021521
$f_9(x) = \sum_{i=1}^{n}[x_i^2 - 10cos(2\pi x_i) + 10]$	[-5.12,5.12]	MGWO	0	9.094502
		MGWOSCA	19.4655	10.457508
		MGWOCSA	0	2.825245
		GWOSCACSA	**0**	**1.521452**
F10	0	GWO	$1.1546\ x10^{-14}$	0.091921
$f_{10}(x) = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}cos(2\pi x_i)\right)$	[–32,32]	MGWO	$1.1546\ x10^{-14}$	0.045215
		MGWOSCA	3.5745	0.025002
		MGWOCSA	$1.5099\ x10^{-14}$	0.026023
$+20 + e$		**GWOSCACSA**	**$7.9936\ x10^{-15}$**	**0.004959**
F11	0	GWO	0	0.008781
$f_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n}x_i^2 - \prod_{i=1}^{n}cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[-600,600]	MGWO	0	0.006121
		MGWOSCA	0	0.002151
		MGWOCSA	0	0.002951
		GWOSCACSA	**0**	**0.000100**
F12	0	GWO	0.0065	0.017850
$f_{12}(x) = \frac{\pi}{n}\{10sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2[1 + 10sin^2(\pi y_{i+1})]$	[-50,50]	MGWO	0.0193	0.010019
		MGWOSCA	2.4148	0.002325
$+(y_n - 1)\} + \sum_{i=1}^{n}u(x_i, 10, 100, 4)$		MGWOCSA	$3.9245\ x10^{-4}$	0.001723
		GWOSCACSA	**$3.0041\ x10^{-5}$**	**0.000052**
$y_i = 1 + \frac{x_i + 1}{4}$				
$u(x_i, a, k, m) = \begin{cases} k = (x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < a \end{cases}$				
F13	0	GWO	$7.3609\ x10^{-6}$	0.001312
$f_{13}(x) = 0.1\{sin^2(3\pi x_1) + \sum_{i=1}^{n}(x_i - 1)^2[1 + sin^2(3\pi x_i + 1)]$	[-50,50]	MGWO	0.2942	0.000214
$+(x_n - 1)^2[1 + sin^2(2\pi x_n)]\} + \sum_{i=1}^{n}u(x_i, 5, 100, 4)$		MGWOSCA	1.9717	0.000220
		MGWOCSA	0.0198	0.000091
		GWOSCACSA	$3.6339\ x10^{-4}$	0
	1	GWO	0.9980	2.153159
	[-65,65]	MGWO	2.9821	0.784992
		MGWOSCA	3.9683	0.452991

(*continued on next page*)

Table A1 (*continued*)

Benchmark Functions	f_{min} / Range	Algorithms	Mean Value	SD
F14		MGWOCSA	0.9980	0.149990
$f_{14}(x) = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2}(x_i - a_{ij})^6}\right)^{-1}$		**GWOSCACSA**	**0.9980**	**0.005966**
F15	0.00030	GWO	4.2463×10^{-4}	0.007812
$f_{15}(x) = \sum_{i=1}^{11}\left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4}\right]^2$	[-5,5]	MGWO	3.0749×10^{-4}	0.004111
		MGWOSCA	3.0749×10^{-4}	0.000235
		MGWOCSA	3.0749×10^{-4}	0.000179
		GWOSCACSA	**3.0749×10^{-4}**	**0**





Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijepes.2021.107419.

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