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Multi-Objective Optimal Scheduling of a Microgrid Using Oppositional Gradient-Based Grey Wolf Optimizer

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Abstract: Optimal energy management has become a challenging task to accomplish in today's advanced energy systems. If energy is managed in the most optimal manner, tremendous societal benefits can be achieved such as improved economy and less environmental pollution. It is possible to operate the microgrids under grid-connected, as well as isolated modes. The authors presented a new optimization algorithm, i.e., Oppositional Gradient-based Grey Wolf Optimizer (OGGWO) in the current study to elucidate the optimal operation in microgrids that is loaded with sustainable, as well as unsustainable energy sources. With the integration of non-Renewable Energy Sources (RES) with microgrids, environmental pollution is reduced. The current study proposes this hybrid algorithm to avoid stagnation and achieve premature convergence. Having been strategized as a bi-objective optimization problem, the ultimate aim of this model's optimal operation is to cut the costs incurred upon operations and reduce the emission of pollutants in a 24-h scheduling period. In the current study, the authors considered a Micro Turbine (MT) followed by a Wind Turbine (WT), a battery unit and a Fuel Cell (FC) as storage devices. The microgrid was assumed under the grid-connected mode. The authors validated the proposed algorithm upon three different scenarios to establish the former's efficiency and efficacy. In addition to these, the optimization results attained from the proposed technique were also compared with that of the results from techniques implemented earlier. According to the outcomes, it can be inferred that the presented OGGWO approach outperformed other methods in terms of cost mitigation and pollution reduction.

Keywords: microgrid; multi-objective optimization; optimal scheduling; gradient-based grey wolf optimizer; renewable energy

1. Introduction

1.1. Literature Review

The demand for power has drastically increased in recent years, whereas fossil fuels are depleting at a fast rate. In this scenario, engineers, researchers, and scientists across the globe are looking for promising alternative energy resources that are not only renewable, but also environmentally friendly. Environmental pollution and the resultant global warming are two major concerns raised around the globe today. Fossil fuel-based traditional power plants that use coal, gas and other non-renewable energy sources are identified as the primary environmental pollutants. In this background, hybrid energy systems that combine wind, solar, hydro, and other renewable energy sources have gained attention in the past two decades, owing to its renewable nature and pollution-less energy production practices.

Further, these hybrid energy systems exhibit high efficiency and reliability. However, fluctuation in terms of both quality as well as quantity, as a result of environmental conditions, remains the primary disadvantage in renewable energy sources such as Photovoltaic solar cells, wind energy systems, etc. Since it is challenging to predict the fluctuations in PV and small Wind Turbines (WT) at the time of power generation, it becomes inevitable to integrate these sources with other reliable energy sources such as Fuel Cell (FC), Microturbine (MT), battery storage and so on, to ensure a constant supply of quality power. These hybrid systems can be relied upon as sustainable energy systems. In this background, the microgrid is one of the promising candidates that is not only energy-efficient, but also can integrate multiple number of pilot-level Distributed Energy Resources (DERs), such as microturbine (MT), Wind Turbine (WT), battery units, Fuel Cell (FC), photovoltaic (PV), and other energy sources. Though it is an advanced concept that was introduced in recent times, Microgrid (MG) has gained immense popularity owing to multiple advantages provided by the system. A microgrid can integrate different types of distributed RES to fulfil the local load requirements and connect or disconnect from the utility grid [1,2].

In literature, a PV-based 17-bus Low Voltage microgrid, connected with the grid, was analysed in the literature. This microgrid had a Wind Turbine as well as a Fuel Cell (FC) for the on-site production of hydrogen. The researchers optimally scheduled the storage of energy so as to provide energy at the right time and to ensure reserve provision [3]. In [3], the Harmony Search Algorithm was utilized to schedule the storage of energy during a 24-h horizon to mitigate the costs incurred upon operations. Further, the study also widely leveraged the hydrogen system under all operational scenarios, to balance the uncertainties that tend to arise from loads and renewable energy sources.

In [4], multi-objective PSO algorithm was proposed to elucidate multi-objective energy management problem in a grid connected microgrid. A simulation was carried out in a microgrid test system comprising a wind turbine, solar cell, battery, microturbine, and a diesel generator. Operating cost and pollutant emission were considered as objective functions. In order to investigate the performance of MOPSO, three different scenarios were tested in the simulation. In the study conducted earlier [5], NSGA II algorithm was applied to implement multi-objective optimal operation of a grid connected microgrid test system by considering operation cost and pollutant emission as objective functions. In [5], the uncertainty of the generation capacity of solar and wind power generating units and the uncertainty of load was considered to elucidate the multi-objective energy management problem. In literature [6], the researchers evaluated the bi-level optimal operation of a grid connected microgrid that contains loads, storage devices, and distributed energy resources. The upper level optimal model for distribution network dispatch was solved by using a multi-objective optimization approach by considering the microgrid's power loss and voltage profile as objective functions. A self-adaptive genetic algorithm was proposed to implement the optimal operation of the microgrid. The lower-level optimal model was developed by applying non-linear programming technique to seek the optimal daily operating scheme of different DGs in the microgrid. The microgrid operating cost was taken as objective function. In the study conducted by Xinhui Lu, the authors developed a multi-objective optimal dispatch model to be applied in the microgrid in grid-connected mode. This model holistically considered the costs incurred upon operations and environmental protection through the microgrid system [7]. The distribution generators, considered in this microgrid system, included Electric Vehicles (EVs), diesel engines, WTs, PV arrays, microturbines, etc. An improved PSO algorithm was developed to overcome the multi-objective optimal dispatch problem. In literature [8], a two-stage stochastic p-robust optimal energy trading management system was proposed to be applied in the microgrid. This system included a microturbine, diesel engine, PV and WT systems. Based on the components involved, the authors implemented a multi-scenario tree approach to develop different scenarios for unsure parameters such as WTs, loads, PV, and market-clearing prices. The discretization of all the probability density functions was accomplished via definite intervals. Then, the authors made use of a differential evolution clustering algorithm to mitigate the number of scenario sets to accomplish the general scenario.

A hybrid algorithm, integrating Gradient Boosting Decision Tree (GBDT) and Sandpiper Optimization Algorithm (SOA), was proposed by Prakash Arumugam [9] to achieve optimal energy management in MG systems under the grid-connected mode. This grid-connected microgrid had MT, WT, battery, and photovoltaic (PV) systems. The objective of the proposed technique was to mitigate the cost incurred upon fuel and other areas during operations and maintenance of grid-connected microgrid system and to reduce the hourly variations in power generation of the microgrid. The researchers listed state-of-charge for storage elements, power demand and renewable energy sources as some of the constraints faced in this research work. In the study conducted earlier [10], the authors proposed an energy management system on the basis of Grasshopper Optimization Algorithm (GOA) to find the optimal power generated by Distributed Generators in microgrid. This is crucial information when it comes to cost mitigation from total power generation. In this study, the researcher applied the proposed unit upon microgrid that had five generating units: industrial, commercial, feeding, and residential loads. Further, the study also made use of the Muddy Soil Fish Optimization Algorithm (MSFOA), a novel algorithm developed on the basis of the foraging pattern of fishes. The main aim of this algorithm is to reduce the overhead incurred upon production and mitigate the costs spent during the import of energy from the grid. Further, the study also considered the system constraints [11]. The researchers implemented the presented energy management system in a microgrid framework that had energy storage units, solar PV, diesel generators, and wind units. Further, numerous case scenarios for instance, isolation, and grid-tied scenarios were investigated under different aspects to prove the potentials of the presented MSFOA approach. In the study conducted earlier [12], a promising energy dispatch strategy was devised by the researchers for both the individual microgrid and the grid-connected ones. These microgrids were also inclusive of battery Energy Storage Systems (BESS), MT, WT, PV, FC, and a diesel generator. In this study, the researchers formulated Microgrid Energy Management (MGEM) mechanism as a mixed-integer linear programming technique. To achieve energy management in the microgrid, a novel multi-objective solution was proposed along with a demand response program. In [13], the authors incorporated a multi-objective Particle Swarm Optimization (PSO) technique to ensure energy resource management and optimal distribution of the resources in the proposed microgrid system. In this study, emission and operation cost were considered as objective functions. The researchers calculated the overall operational cost incurred from the microgrid and pollutant-induced emissions under three different scenarios. The microgrid was analyzed in detail earlier [14] as an energy management system when connected with primary power system. The study took parameters such as WT, PV, and load demand into consideration under probabilistic and deterministic conditions. Further, an Equilibrium Optimizer (EO) was also utilized to overcome the energy management problem. In this study, the authors considered operation cost, voltage deviation, and voltage stability index as objective functions. In the study conducted earlier [15], an optimization framework was proposed with three objectives for microgrid energy management in the case of smart homes and Demand Response (DR) programs. The proposed model was tested using an 83-bus distribution system with 11 microgrids. This study considered load demand variations and uncertainties present in the output power of Renewable Energy Sources (RESs). Further, a max–min fuzzy method was utilized to model the objective function as bi-objective and tri-objective models. In addition to these, the study also considered Peak-to-Average Ratio (PAR), emissions and operations cost as objective functions. Recently several optimization techniques were proposed to eliminate energy management problems in microgrids [16,17]. In [18], ANN-based backtracking search algorithm (ANN-BBSA) and ANN-based binary practical swarm optimization (ANN-BPSO) algorithm was implemented to elucidate multi-objective energy management problem in a virtual power plant, which was realized as a modified IEEE 14-bus system with five identical microgrids. In the study conducted earlier by the current study authors, the Local Energy Management System (LEMS) was proposed and implemented under Generalized Power Prediction Model (GPPM) to overcome the performance uncertainties for varying distributed generations of a microgrid [19]. In [20], the interior search algorithm was applied to solve the economic load dispatch problem in a microgrid which comprises diesel generators, fuel cells, and wind turbine. In this study [20], total operating cost was taken as the objective function. Table 1 shows the contributions made by research investigations in microgrid energy management. This table covers different aspects such as optimization algorithm, test system, Renewable Energy Sources (RESs), and storage technology.

Table 1. A review of optimization techniques in the energy management of a microgrid.

Reference No.	Objectives	Control Algorithm	System Description	Storage Technology	RES	Year
[21]	Operation cost	Modified bat algorithm	Hybrid AC and DC microgrid	Battery	PV, WT, tidal	2021
[22]	Operation cost and Emission	Multi-Objective Particle Swarm Optimization (MOPSO)	Grid connected microgrid	Battery	PV, WT	2017
[23]	Operation cost, Emission	Binary Orientation Search Algorithm	Grid connected microgrid	Battery	PV, WT	2022
[24]	Operation cost	Θ-modified krill algorithm	Grid connected microgrid	Battery	WT, PV	2021
[25]	Decentralized energy management	HOMER Software	Islanded DC microgrid	Hydrogen, Battery	PV	2020
[26]	Hierarchical energy management Strategy	HOMER pro Software	Islanded DC microgrid	Hydrogen, BESS	PV	2019
[27]	Energy Management System	Hybrid automata algorithm	Islanded Microgrid	Hydrogen, BESS	PV, WT, biomass	2020
[28]	Multi-microgrids energy management	Preference-based multi-objective reinforcement learning (PMORL) technique	Grid connected Microgrid	Battery	PV, WT, tidal	2022
[29]	Optimal power flow with reactive power cost of MG as objective function	Generalized reduced-gradient (GRG) algorithm	Grid connected Microgrid	BESS	PV, WT	2020
[30]	Stochastic optimal energy management of MG with operation cost and emission as objectives	GAMS using CPLEX solver	Grid connected Microgrid	BESS, PHEV, TES	PV	2018
[31]	Energy Management System	NSGA-II	Grid connected Microgrid	Battery	PV, WT	2019
[32]	Energy Management System	Modified bat algorithm (MBA)	Grid connected Microgrid	BESS	PV, WT	2020
[33]	Energy Management System	Particle swarm optimization (PSO)	Grid conncted and autonomous Microgrid	BESS, PEV	PV, WT	2021
[34]	Energy Management in Microgrid	Mixed integer linear programing technique using CPLEX solver	Grid connected Microgrid with PV, FC, MT, battery	Battery	PV, WT	2019
[35]	Energy Management System of DC microgrid	Branch and reduce optimization navigator (BARON) algorithm	Microgrid with PV, FC, MT, DE, battery	Battery	PV, WT	2021
[36]	Stochastic energy management of smart microgrid	Quantum Particle Swarm Optimization (QPSO)	Grid connected Microgrid	Battery	PV, WT	2021

Table 1. *Cont.*

Reference No.	Objectives	Control Algorithm	System Description	Storage Technology	RES	Year
[37]	Energy management in microgrid	meta-dynamic-approach-based multiobjective flower pollination algorithm	Grid connected Microgrid	Battery	PV, WT	2021
[38]	Economic Emission Dispatch in Microgrid	Hybrid Modified version of GWO	3-unit RES integrated low voltage microgrid system	-	PV, WT	2021
[39]	Energy management System	Crow Search Algorithm	3,5,6,7,11, 38-units microgrid test system	BESS	PV, WT	2019
[40]	Energy management System	Modified version of artificial bee colony algorithm	Islanded Microgrid with stationary and the dynamic energy Bid	BESS	PV, WT	2020

1.2. Research Gap and Objective of the Paper

The authors conducted an extensive review of literature from which knowledgeable insights have been gained with regards to energy management challenges in dynamic systems and different test systems and entities. However, most of the research works conducted earlier emphasized the inclusion of specific multi-objective optimization algorithm to achieve energy management in dynamic test systems. These research studies were conducted on the basis of the Pareto front, utilizing multi-objective techniques and attained energy management. From the review of literature and comparative analysis conducted among two or more than two multi-objective energy management methods, the authors found a research gap that needs to be fulfilled. In the literature [41], the microgrid test considered single and multi-objective optimization to be implemented for the first case study. However, for the second and third case study, only single objective optimization was done for the optimal scheduling of the microgrid. In this current research study, we implemented the single and multi-objective optimization using the proposed optimization algorithm for the optimal scheduling of the microgrid for all the case studies considered. A comparison was made between the optimization results obtained by the proposed method and four other different optimization algorithms coded by us to find the better-compromised solution for less pollutant emissions and minimum generation cost.

In this research paper, we have proposed the Oppositional Gradient-based Grey Wolf Optimizer (OGGWO) for elucidating the multi-objective optimal scheduling of a grid connected microgrid. Opposition based learning is incorporated with the proposed algorithm in order to enhance the solution quality and convergence speed. The incorporation of the opposition-based learning encompasses the instantaneous consideration of an estimate and its equivalent opposite estimate so as to accomplish an enhanced approximation for the present candidate solution. Our proposed optimization algorithm utilized the advantages of the gradient feature that offers valuable information about the solution search space. This incorporation of the gradient feature explores the solution search space more perceptively with the consideration of the gradient direction in the problem search process and aids in attaining the global optimal solution. In order to enhance the exploration and exploitation capabilities of the proposed OGGWO algorithm, Gaussian walk and Levy flight techniques were incorporated, and the results were compared with the results obtained using EDNSGA-II, NSGA-II, GGWO, GWO, CSA, and PSO to prove the effectiveness of the proposed algorithm. GGWO, GWO, CSA, and PSO algorithms were coded by us for comparison purposes. The results of EDNSGA-II and NSGA-II were taken from the literature.

1.3. Contributions

The following is the list of contributions made by current research work for the state-of-the-art energy management system proposed in this study.

i. At first, OGGWO was implemented as an optimization tool to overcome the problem. Further, the efficiency and robustness of the proposed model were determined and contrasted against GGWO and conventional GWO.
ii. The authors compared the outcomes of the proposed method under three different scenarios to identify the optimization algorithm that produces the best compromised solution between generation cost and the emission of pollutants.
iii. Multi-objective optimization was carried out under all the case studies considered so as to find the best-compromised solution for the multi-objective energy management problem.

2. Problem Formulation

The primary objective behind the optimal operations of the microgrid, with Distributed Energy Sources (DERs) that include non-renewable and renewable energy sources, is to identify the optimal operating points of DERs to generate power during the scheduled horizon. The key aim of the optimal operations of the microgrid that is incorporated with DERs such as RESs and non-RESs is to find out the optimal operating points of DERs so that the power can be produced at the time of scheduled horizon. This objective should be met to reduce the cost incurred upon operations and reduce the emission rate in parallel. Thus, the current study aims at achieving two different and conflicting objectives together, i.e., emission reduction and mitigation of cost incurred upon operations.

In the current study, the authors propose a precise mathematical model to achieve short-term energy management so as to mitigate the costs spent upon operations and reduce the emission of pollutants in microgrid operations.

2.1. Objective Functions

As mentioned above, the current study considered the following objective functions such as operating costs and costs incurred upon reducing the pollution emissions.

2.1.1. Mitigation of Operating Cost

In Equation (1), the authors calculate the total operating costs incurred in a microgrid. In this equation, T corresponds to the total time taken, by the study, in terms of hours, whereas N_g denote the generation of energy and N_s correspond to storage units. Here, $U_i(t)$ corresponds to the status of i^{th} unit at time t (either it is switched on or off) $P_{Gi}(t)$ denote the output power amount of i^{th} storage unit whereas in case of j^{th} at time, t. The price of the energy rendered for i^{th} storage unit is denoted by $B_{Gi}(t)$ while it was $B_{Sj}(t)$ for j^{th} storage unit at time, t. $S_{Gi}(t)$ and $S_{sj}(t)$ denotes the costs involved during start-up or shut-down functions spent upon i^{th} storage unit and j^{th} storage unit respectively. Further, $P_{Grid}(t)$ and $B_{Grid}(t)$ denote the quantities of power that was exchanged with the offered market, at time, t [13].

$$\text{Min } f_1(X) = \sum_{i=1}^{T} \left\{ \begin{array}{c} \sum_{i=1}^{N_g} [U_i(t)P_{Gi}(t)B_{Gi}(t) + S_{Gi}|U_i(t) - U_i(t+1)|] - \ldots \\ \sum_{j=1}^{N_s} \left[U_j(t)P_{sj}(t)B_{sj}(t) + S_{sj}\left|U_j(t) - U_j(t+1)\right|\right] - (P_{Grid}(t)B_{Grid}(t)) \end{array} \right\} \quad (1)$$

2.1.2. Mitigation of Emission

For the next objective function, i.e., emission mitigation, a few components were considered such as carbon dioxide (CO_2), nitrogen oxides (NO_x), and sulphur dioxide (SO_2), i.e., atmospheric pollutants. Equation (2) shows the mathematical formulation for overall pollutant emission in kg [13]:

$$\text{Min } f_2(X) = \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N_g} [U_i(t)P_{Gi}(t)E_{Gi}(t)] + \sum_{j=1}^{N_s} [U_j(t)P_{sj}(t)E_{sj}(t)] + (P_{Grid}(t)E_{Grid}(t)) \right\} \quad (2)$$

$E_{Gi}(t)$ denotes the volume of pollution emitted by i^{th} generation unit, while for the j^{th} storage unit, it was denoted by $E_{sj}(t)$. In the case of volume of pollution at market, it was denoted by $E_{Grid}(t)$ at time, t. All the values are denoted in kg/MWh, respectively.

2.1.3. Constraints and Limitations

(a) Power Balance constraints

$$\sum_{k=1}^{N_k} P_{LK}(t) = \sum_{i=1}^{N_g}[P_{Gi}(t)] + \sum_{j=1}^{N_s}[P_{sj}(t)] + (P_{Grid}(t)) \tag{3}$$

Here, P_{LK} corresponds to K amount at load level, whereas N_k denotes the whole count of load levels available in the grid.

(b) Ramp Rate Constraints

This constraint occurs as a result of fluctuations in output power. It can be either an increasing fluctuation or vice versa in DGs. The following is the equation used to describe the constraint [13]:

$$R^i_{down}.\Delta t \leq P(h)^i - P(h-1)^i \leq R^i_{up}.\Delta t \tag{4}$$

Here, R^i_{down} denotes the ramp-down of i^{th} DG output power whereas R^i_{up} correspond to ramp-up of i^{th} DG output power. Further, Δt denotes the time step taken, in terms of hours.

(c) Inequality constraints

All the units considered in this study have both upper, as well as lower thresholds for their power generation capacity. The units include DGs, storage units, and the market [13].

$$\begin{aligned} P_{Gi,min}(t) \leq P_{Gi}(t) \leq P_{Gi,max}(t) \\ P_{sj,min}(t) \leq P_{sj}(t) \leq P_{sj,max}(t) \\ P_{Grid,min}(t) \leq P_{Grid}(t) \leq P_{Grid,max}(t) \end{aligned} \tag{5}$$

Equation (6) covers the limitations of charging and discharging rates of the storage unit.

$$\begin{aligned} SOC_{sj}(t) = SOC_{sj}(t-1) + P_{chg/Dchg}(t) \\ 0 \leq |P_{chg/Dchg}(t)| \leq P_{CDSj,max} \end{aligned} \tag{6}$$

Here, $SOC_{sj}(t)$ denotes the charging amount of the storage unit at current time and $SOC_{sj}(t-1)$ denotes the charging amount of the storage unit at previous time. $P_{chg/Dchg}(t)$ corresponds to the charging (discharging) amount at t^{th} hour while the maximum charging (discharging) rate is denoted by $P_{CDSj,max}$.

3. Oppositional Gradient-Based Grey Wolf Optimizer

Mirjalili et al. (2014) proposed GWO inspired from the hunting behavior of grey wolves [41]. In general, there are four types of wolves, such as the Alpha, followed by Beta, Delta, and finally Omega [42]. In a pack of wolves, Alpha is the dominant wolf and is the decision-maker for the whole pack, while the rest of the members in the pack must obey the alpha's commands and decisions. Further, only the alphas breed in the pack. The second position is occupied by Beta wolves, which act as a mediator between the alpha wolf and the rest of the wolves. It helps the alpha wolf and becomes the first choice of nominee for alpha, in case an Alpha wolf dies or is too old for swarm management. Though beta wolves control other wolves of the swarm, it fulfils the order of Alpha wolf. Hierarchically, Omega is the least ranked grey wolf [43] and follows the rest of the high-ranking wolves. Those wolves that are not categorized as the other three, i.e., Alpha, Beta, or Omega fall under the category Delta Wolf. Deltas tend to manage the Omega wolves, while at the same time it also helps the Alpha wolf and Beta wolves.

It is important for an algorithm to ensure there is equilibrium between exploration and exploitation skills so that the exploration can be achieved. GWO continues to look for solution space through constant upgradation of the position of dominated wolves such as Alpha, Beta, and Delta. Two new features have been added to the traditional GWO algorithm in this study, which resulted in Oppositional Gradient-Based Grey Wolf Optimizer (OGGWO). The first feature is the adoption of a novel procedure that uses gradient data to improve the algorithm's exploitation as well as exploration skills. In most of the optimization challenges, the gradient tends to render the critical information with regards to the shape of the solution space. This is done by measuring the steepest slope at every point in the solution space. Afterwards, the particles are transferred to a nearby local optima using gradient information, while at the same time, an appropriate exploration capability is also maintained. GWO is heavily empowered by such updating operators. It results in the efficient searching of solutions in solution space and enhances the exploration potentials of the algorithm to side-step local optima. Opposition Based Learning (OBL) is one of the powerful optimization tools to enhance the convergence speed of numerous heuristic optimization techniques [44]. The successful implementation of OBL involves the evaluation of population at both the opposite site and current site in the same generation so that a better candidate solution can be obtained for the given problem. The concept of OBL has successfully been applied in various meta-heuristics to enhance the convergence speed. The concept of opposite number needs to be defined to explain OBL [44]. A novel procedure is incorporated to update the formulations for Omega wolves in OGGWO algorithm as shown in (7) and (8).

Both Gaussian walks as well as Levy Flight (LF) are added as second features to the existing traditional GWO. These random walks enhance the random nature of the presented OGGWO model and empower it for exploration. Though self-similar clusters (or trajectories) are created by Levy Flight and Gaussian walks, significant differences are found between their structures [45]. Gaussian walk produces a minor, but dense cluster that contains numerous small steps and executes the same number of iterations, such as with clusters [46]. Having been randomly chosen, these methods improve the proposed OGGWO model's exploration capability by helping the algorithm avoid local optima. In this case, OGGWO switches randomly between Gaussian walk, as well as LF and make use of both the methods [46]. Figure 1 shows the flowchart of the proposed Oppositional Gradient-based Grey Wolf Optimization algorithm. The following formulations are used in OGGWO to upgrade the Omega wolves' position in the solution space at the time of closing every iteration as shown in (12) and (13).

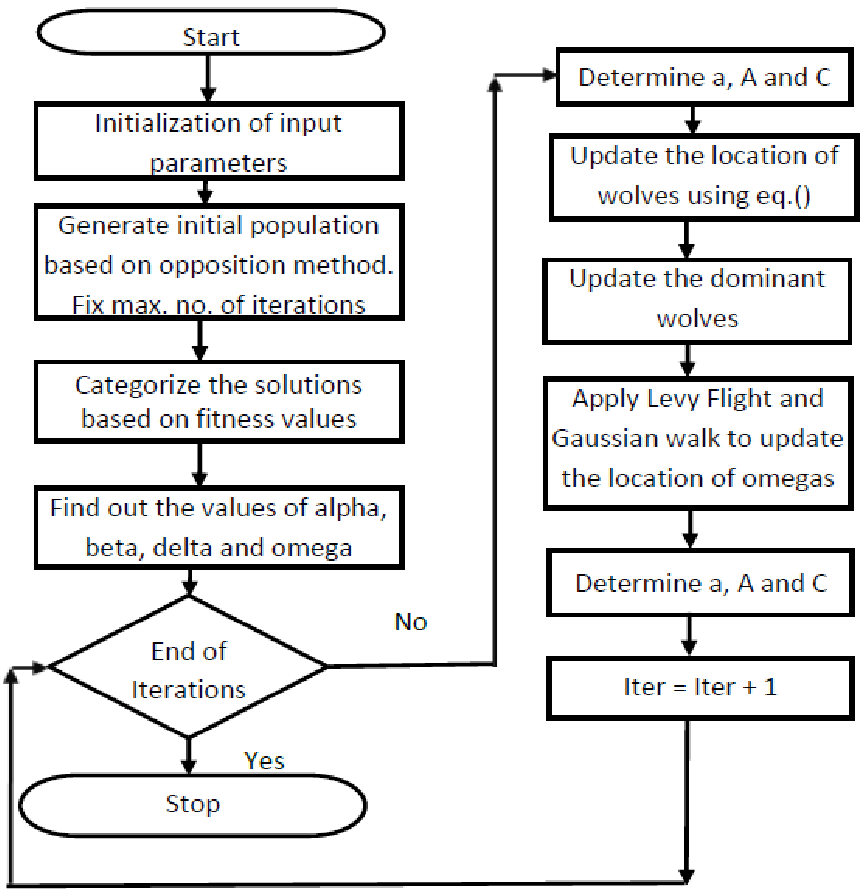

Figure 1. A flowchart of the Oppositional Gradient-based Grey Wolf Optimizer.

Step 1: The position of grey wolves (search agents) is randomly initialized in the search space. This step further fixes the number of iterations, followed by population size (number of wolves).

Step 2: For each search agent, the fitness value is determined as it denotes the distance between prey and the wolf.

Step 3: The opposite points are initialized and used to generate the opposite population so as to calculate the fitness values of every individual population.

Step 4: Sorting is executed for both current and opposite populations (pop and opop respectively), in line with their fitness values

Step 5: The n_P number of the fittest solution is selected out of a combination of current and the corresponding opposite population.

Step 6: Based on fitness values, three solutions are found such as best (a), second-best (b) and finally, the third best (d). These solutions correspond to alpha, beta and delta category wolves, respectively.

Step 7: Based on Equation (7), the position of the grey wolves is modified.

$$X_W^i(t+1) = \gamma \frac{\partial f^{Min}}{\partial X^i}. \leq \frac{\partial f}{\partial X_w^i}(t) < \gamma \frac{\partial f^{Max}}{\partial X^i} \; for \; i = 1, \ldots, m \; and \; w = 1, \ldots, n, \tag{7}$$

$$X_W^i(t) - rand(0,1)\lambda^i(t)\left(\frac{\partial f}{\partial X_w^i}(t)\right), \; Otherwise, for \; i = 1, \ldots, m \; and \; w = 1, \ldots, n, \tag{8}$$

Here, i corresponds to the index of decision variables in an optimization problem. On the contrary, n denotes the count of grey wolves. $\frac{\partial f^{Max}}{\partial X^i}$ and $\frac{\partial f^{Min}}{\partial X^i}$ correspond to the highest positive and the least negative slopes, at every dimension, during every iteration of the algorithm. Further, γ corresponds to a continuous parameter that is calculated as (0,1]. As per the formulation given above, λ^i is updated using Equation (9) as given herewith.

$$\lambda^i(t) = \frac{0.1\left[Ub^i - Lb^i\right]}{\max\left(\left|\frac{\partial f^{Min}}{\partial X^i}\right|, \left|\frac{\partial f^{Max}}{\partial X^i}\right|\right)} \tag{9}$$

Here, LB corresponds to Lower Bound, whereas UB denotes the Upper Bound of the problem. This results in the following equation straightforwardly.

$$\left|\lambda^i(t)\frac{\partial f}{\partial X_w^i}(t)\right| \geq 10\left(Ub^i - Lb^i\right) \tag{10}$$

The gradient of the problem in few optimization problems may remain unknown. This is attributed to the non-differentiability of objective function or discrete features possessed by decision variables. In order to overcome these issues, the following equation is presented.

$$\frac{\partial f}{\partial x} = \frac{[f(t) - f(t-1)]}{[X(t) - X(t-1)]} \tag{11}$$

Step 8: The fitness value is updated based on the modified position of grey wolves.

Step 9: Alpha, beta and delta values are updated

Step 10: The position of omega wolves is updated using the Equations (12) and (13) that employ Gaussian walk and Levy flight.

$$\begin{gathered} X_{W,new}^i = X_W^i + KGaussian(|\vartheta_i|, \sigma) - \left(\xi \times \vartheta_i - \xi' \times X_W^i\right), \\ for \; i = 1, \ldots, m \; and \; w = 1, \ldots, n, \end{gathered} \tag{12}$$

$$\begin{gathered} X_{W,new}^i = X_W^i + X_W^i Levy(\eta), \\ for \; i = 1, \ldots, m \; and \; w = 1, \ldots, n, \end{gathered} \tag{13}$$

Here, the best solution is denoted by ϑ_i whereas $|\sigma|$ correspond to the standard deviation of Gaussian distribution. The Gaussian parameter is changed by OGGWO as $\sigma = |K \times (x_i - BP)|$, while it also reduces the length of steps at the time of iterations by fixing $= \frac{\log(l)}{l}$. Here, l corresponds to the number of iteration. Further, $X_{W,new}^i$ corresponds to the new position of the wolves, whereas

X_W^i denotes the current position. In addition to these, ξ' and ξ denote random numbers in (0,1]. Equation (14) denotes the calculation for Levy flight.

$$Levy(x) = \frac{[0.01 \times \sigma \times r_1]}{|r_2|^{\frac{1}{\beta}}} \tag{14}$$

Here, the random numbers are denoted by r_1 and r_2 between (0, 1]. β corresponds to constant, which is equal to 1.5. In Equation (13), σ is computed with the help of following equation.

$$\sigma = \left[\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})/(\frac{\Gamma(1+\beta)}{2}\beta[2^{\frac{(\beta-1)}{2}}])\right]^{1/\beta} \tag{15}$$

Step 11: The opposite population is created out of the current population using the jumping rate.

Step 12: The n_P number of the fittest solution is selected after integrating the current and the opposite populations.

Step 13: The steps 3–7 are repeated until the maximum number of iterations is achieved.

Step 14: The best solution is achieved as the output.

As per the steps discussed above, the leading framework remains the same in both GGWO and OGGWO. However, significant changes are made in the latter. For example, OGGWO leverages a mix of original and gradient-based operators to update the position of wolves more than the conventional GWO operators. Further, a new function is also added in OGGWO to determine the gradient's objective function at every point in the solution space [47]. In addition to the above, Gaussian walk and Levy Flight have been incorporated in OGGWO to increase randomness during the closure of every iteration. This phenomenon significantly increases both exploration and exploitation capability, as long steps and short steps shift the particles in solution space.

4. Fuzzy Logic-Based Collection of the Finest Compromise Solution

In general, it is important to select the optimal compromise solution out of the available options prior to making any decisions. In this study, a fuzzy membership approach was used by the author to identify the optimal compromised solution [48]. In j^{th} objective function, f_j of individual k is characterized by a membership function μ_j^k, owing to the indefinite characteristic of the conclusion of the decision maker as denoted herewith.

$$\mu_j^k = \begin{cases} 1 & f_j \le f_j^{min} \\ \frac{f_j^{max} - f_j}{f_j^{max} - f_j^{min}} & f_j^{min} < f_j < f_j^{max} \\ 0 & f_j \ge f_j^{max} \end{cases} \tag{16}$$

Here, f_j^{max} corresponds to the highest value of the j^{th} fitness function. In addition to this, its least value is denoted by f_j^{min} among the rest of the non-dominated solutions. The calculation is done for normalized membership function μ^k that is applicable for each non-dominated solution k.

$$\mu^k = \frac{\sum_{j=1}^{N} \mu_j^k}{\sum_{k=1}^{r} \sum_{j=1}^{N} \mu_j^k} \tag{17}$$

Here, r corresponds to the whole number of non-dominated solutions. The highest value, i.e., μ^k is achieved by the best compromise solution.

5. Modeling of the Microgrid

In the case of applying DGs individually, it creates multiple problems. So, it is suggested to follow a systematic approach so that generation, as well as associated loads, is considered as either the microgrid or sub-system to avoid the challenges involved in it and leverage the true potentials of DGs. In parallel, the DGs in the microgrid can be combined together and analyzed about the exploitation of renewable energy sources in huge quantities regarding economy, technology, and environment within the target system. These insights help in making knowledge-based decisions and manage the operations in a better manner. In addition to this, Distribution Generation is a compendium of a vast range of prime mover technologies that include fuel cells, gas turbines, micro turbines, solar PV, IC engines, and wind power. Such RES-based technologies are cost-efficient and emit fewer pollutants, contradicting a huge economy [17]. For instance, Fuel Cells generate electricity out of oxygen and hydrogen, whereas water vapor is the only emission from this source. Having said so, natural gas and other fuel reformation emit NOx and CO_2. Fuel cells are comparatively more efficient than microturbines, in terms of emission, which incurs heavy costs. In the current research work, the researchers considered a commonly-known LV microgrid based on the study conducted earlier that included various types of DGs such as PV, WT, MT, low-temperature Fuel Cell (PAFC), and storage devices such as lead-acid batteries [38]. The authors assumed that the active power, produced by whole DG sources, stands as unity power, while at the same time, it does not request or produce reactive power. Furthermore, a power exchange link is also used between utility (LV network) and the mentioned microgrid for the purpose of energy trading at different hours in a day, in line with the decisions taken by the MGCC (Microgrid Central Controller).

6. Results and Discussion

As per the literature [41], the current study considered a microgrid test system with a distributor and a few DGs such as Wind Turbine (WT), Fuel Cell (FC), Photovoltaic panel (PV), Microturbine (MT), and battery. The model, suggested in this study, has two objective functions, such as whole emission of the pollutants and microgrid costs, which include the costs incurred upon power generation and start-up/shut-down costs of units. The chosen problem was rectified through three different scenarios such as main case, secondary case, and third case. In the main issue, the whole set of units were dispatched based on their original drawbacks. In the second case, photovoltaic (PV), as well as Wind Turbine (WT) functions were assumed to be at its maximum output (Max-Ren). For the final case, the utility was considered as an unconstraint unit which can exchange energy with the microgrid without any limits (WLE). The microgrid was expected to meet the total load demands as predicted in [41]. One prime residential area, one feeder with light usage commercial consumers, along with one industrial feeder that supplies power to a small workshop in a typical day was considered. The total energy demand of the day considered was 1695 kWh.

In addition to these, the energy price difference for a real-time market was sourced from the literature [41] for the day considered. In order to ensure flawless microgrid operations, three DG units with WT, PV, and MT were used. The optimization algorithm has the ability to assign these units with on and off states, when there is a power dispatch problem, considering both objectives. Likewise, the on/off state was regarded as 1 for the utility in all cases, since the microgrid was operated in grid-connected mode. To analyze the overall impact of PAFC and battery upon grid operations and to leverage the optimal benefits out of the resources, the on state was selected with an intention for relevant units. From the study conducted earlier, both minimum as well as maximum generation limits were taken for DG sources [41]. Further, the same source was also used to provide the bid coefficients, in terms of Euro cents per kWh. In order to perform the data analysis in a rapid fashion, all the units in the current research work were considered to function under electricity mode only. The microgrid is preferred for installation since it has a salient feature, i.e., the ability to combine multiple sorts of renewable energy sources together.

Microgrid forecasts are highly important for actual operations since this information can be utilized to prepare the systems to be flexible and appropriate. Since it is impossible to execute the renewable energy operations in a conventional manner, it is easy to predict its behavior. Thus, microgrid system efficiency can be enhanced with the help of forecasted information. An expert prediction model was used in the current research work to evaluate the power outputs from PV and WT. From the literature [41], the daily maximum power output from PV and WT values were extracted. Further, the authors used the same study to source information on both daily load power, as well as energy market price in a typical microgrid.

In order to validate the efficacy of the proposed optimization algorithm, simulation was conducted for 50 trial runs to migrate the cost incurred upon operations. The current study considered population size (50) and 1000 maximum iterations as its controlling parameters. Tables 1 and 2 show the characteristics of 5 DG sources which generate electricity in the microgrid. Through the common coupling point, the microgrid either shares surplus energy or demands additional energy from the utility. The whole set of units that include the macrogrid (utility), are able to function within their power limits, while it can meet the requirements in parallel.

Table 2. An optimal generation schedule for Case-I.

Hour	MT	FC	PV	WT	ESS	Grid
1	16.17	30	0	8.84	−30	36.99
2	19.74	26.98	0	10.62	−4.79	7.45
3	6	22.01	0	8.01	−20.05	44.03
4	6.75	30	0	12.44	−12.38	24.19
5	8.68	23.02	0	12.01	−19.98	43.27
6	25.28	0	0	13.56	−18.13	54.29
7	25.02	23.9	0	12.03	−25.57	48.62
8	0	30	0	13.37	2.34	44.29
9	27.39	27.03	0.17	15.19	−27.23	48.45
10	29.99	30	2.04	19.34	29.05	−14.42
11	30	29.51	8.03	24.26	26.18	−24.98
12	29.18	28.03	9.72	22.03	11.03	−11.99
13	30	29.86	11.03	19.2	−29.98	25.89
14	0	30	8.91	24.09	29.13	−6.13
15	30	30	8.44	24.99	27.24	−29.67
16	22.48	24.66	3.99	19.98	−20.23	45.12
17	30	30	1.98	23.47	−29.98	46.53
18	30	0	0	18.98	9.81	46.21
19	30	22.19	0	19.01	1.02	35.78
20	30	30	0	22.31	−0.59	22.28
21	17.99	19.79	0	12.99	6.94	35.29
22	1.02	28.93	0	21.08	27.98	5.99
23	22.05	0	9	13.09	−8.16	42.02
24	0	0	0	20.11	29.41	17.48

6.1. Case I: Operation of Distributed Energy Sources with Specified Limits

The first test case, considered in this study, was the operation of all DGs and grids within the specified limits as represented in [41]. Table 2 shows the optimal generation schedule for 24 h to minimize both cost and emission levels. From Table 3, it can be understood that the majority of the load demands, during the first few hours of the day, was met by fuel cells present inside the grid and utility through the common coupling point. This is attributed to fewer bids of relevant units than the rest of the others for a specific period. Since the demand increased for high number of utility bids in the next few hours, the DG units enhanced their output power based on the priorities such as low cost and low emission level.

Further, the microgrid regulatory controller sequentially supplied the units and exported the energy from the microgrid, which in turn increased the revenue and reduced the net emission for a specific period under study. On the other hand, the battery was charged for the first few hours a day, especially when the low cost is charged during this period. When the load curve achieved the highest value in the later hours of the day, the discharge action was executed. When RESs such as solar and wind are deployed, it emits less pollutants, whereas the operating cost increases. In other terms, these energy sources are economically unviable due to which the energy generated from these sources needing to be confined to a limit based on emission/economic limitations.

Table 3 shows the analytical outcomes of optimization algorithms and compares the results achieved for the main case. Based on the results attained, in terms of best and worst solutions, it can be inferred that the proposed optimization algorithm accomplished an excellent outcome for cost and emission objectives. Further, it also attained faster convergence characteristics. In addition to this, the proposed algorithm proved to have another advantage for optimization, based on the statistical indices of average and standard deviation.

Table 3 shows the SD values attained by the proposed algorithm for cost and emission objectives, which were 2.55 and 4.72, respectively, which infers that the proposed algorithm is an excellent choice for optimization. In order to showcase the performance of the proposed OGGWO algorithm, Figures 2 and 3 portray the convergence characteristics held by OGGWO, as well as the rest of the optimization algorithms for the best solution and for every single objective. The illustrations show that the proposed method achieved the minimum value for cost objective function after 705 iterations and remained unchanged thereafter. On the other hand, the GWO algorithm converged at 713 iterations. With regards to emission objective function, the proposed method reached the minimum value at 734 iterations, whereas GWO algorithm required 745 iterations for convergence.

By applying the fuzzy logic based approach as discussed in Section 4, the global best compromise solution was attained by the proposed algorithm to mitigate the operating cost and emission.

Figure 4 shows the pareto-fronts of respective trade-off objectives, obtained by various methods, used for comparison and the best-compromised solution. The figure infers that the proposed algorithm was effective in elucidating the non-linear multi-objective optimization problem since the Pareto optimal fronts of non-dominated solutions were distrusted in a good manner. In addition to this, the computational time consumed by the proposed algorithm to mitigate both emission, as well as operating cost, was lesser. This reveals the quality of the proposed algorithm. The optimization results amply corroborate the ability of the proposed algorithm to tackle the issues associated with equality and inequality that tend to happen in energy management challenges.

Table 3. A statistical comparison of simulation results for case-I.

Optimization Algorithm	Parameter	Cost Euro	Emission Kg
EDNSGA-II [41]	Min Cost	148.67	1230.66
	Min Emission	163.97	1175.99
	BCS	158.81	1212.7
	Std Dev	2.9	5.08
NSGA-II [41]	Min Cost	165.49	1236.5
	Min Emission	173.77	1199.08
	BCS	168.27	1216.54
	Std Dev	3.15	7.08
PSO	Min Cost	168.15	1241.29
	Min Emission	176.04	1203.12
	BCS	171.38	1220.07
	Std Dev	4.28	8.14
CSA	Min Cost	167.38	1239.86
	Min Emission	175.42	1202.18
	BCS	170.46	1219.14
	Std Dev	4.06	7.99
GWO	Min Cost	161.14	1234.08
	Min Emission	170.78	1195.64
	BCS	164.26	1214.31
	Std Dev	3.09	6.87
GGWO	Min Cost	147.39	1228.14
	Min Emission	162.04	1173.67
	BCS	157.13	1212.03
	Std Dev	2.71	4.88
OGGWO	Min Cost	146.44	1226.71
	Min Emission	161.28	1172.48
	BCS	156.31	1211.28
	Std Dev	2.55	4.72

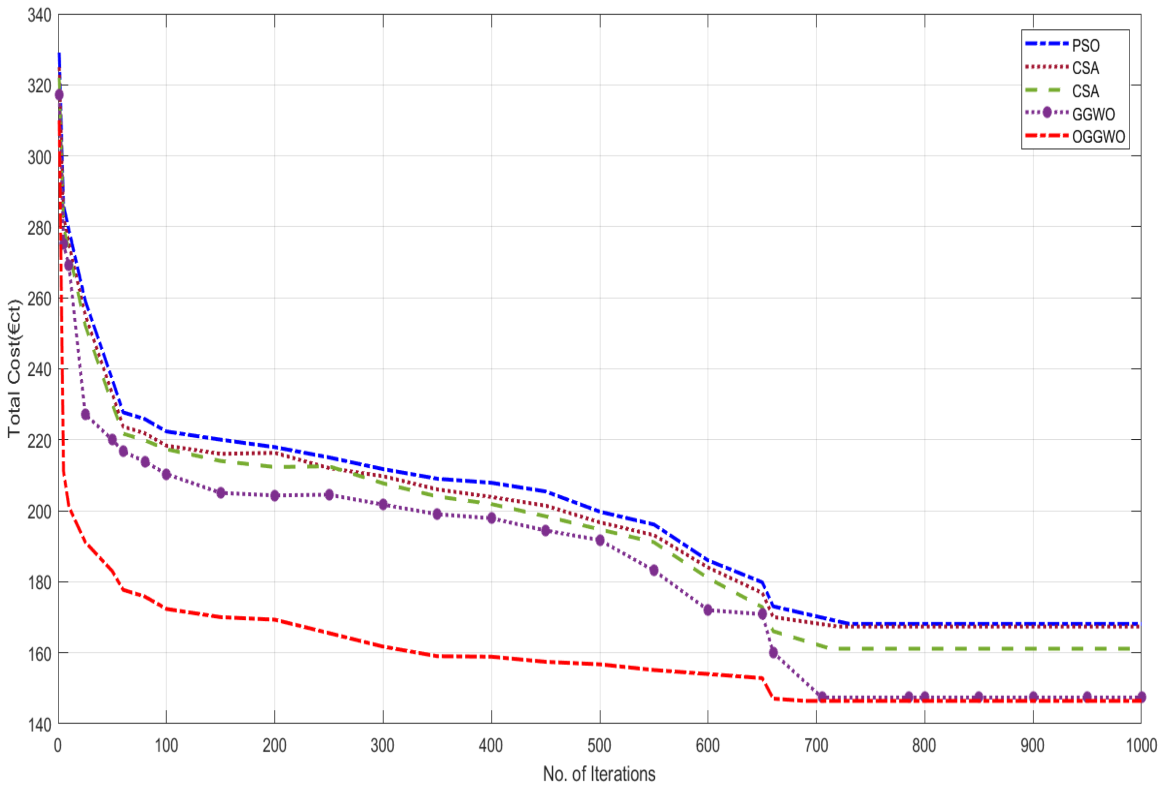

Figure 2. The cost convergence characteristic for Case-I.

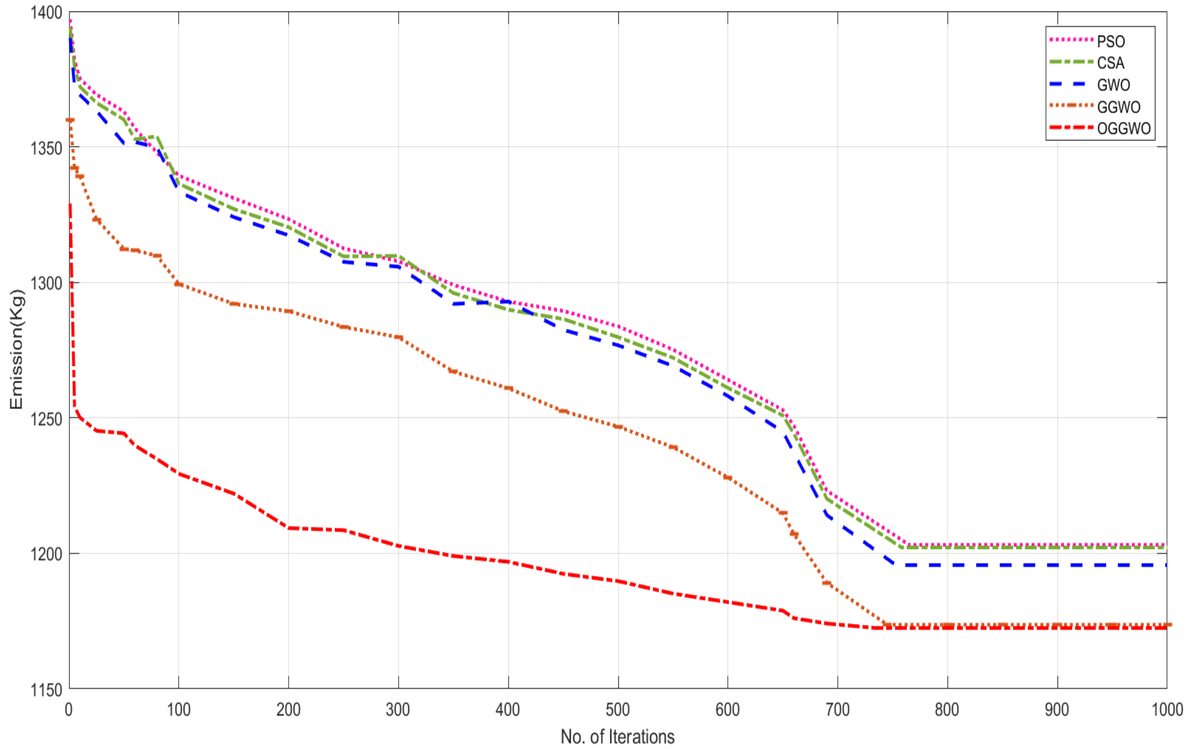

Figure 3. The emission convergence characteristic for Case-I.

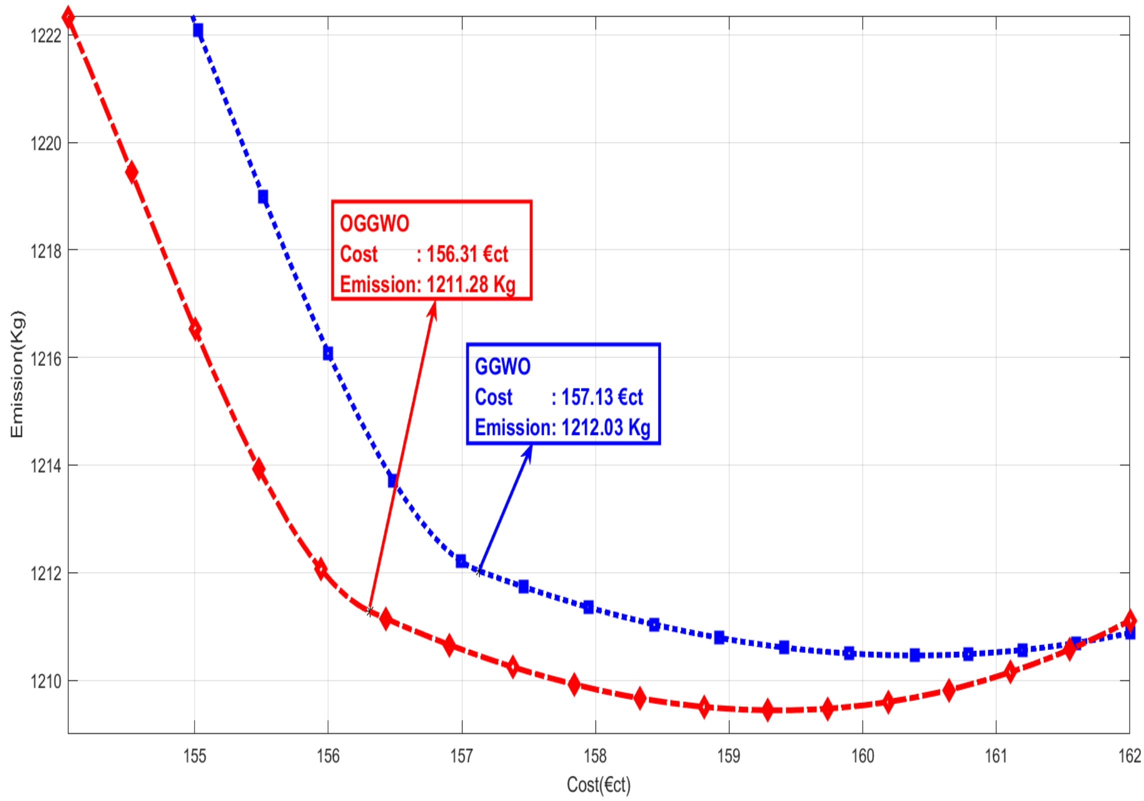

Figure 4. The emission cost trade-off characteristic for Case-I.

6.2. Case II: Operation of Renewable Energy Sources at Maximum Limits

Both PV, as well as WT, was considered to operate at maximum power in this case for every hour, whereas the rest of the sources considered such as grid, battery, MT, and FC were operated at permitted levels, as per the literature [41]. Table 4 shows the comparison of statistical performances of OGGWO and the rest of the optimization algorithms for each objective. When the results achieved by GWO were compared for each objective with the proposed OGGWO algorithm, the outcomes inferred that the GWO algorithm was deficient and its performance was inconsistent. For instance, Table 5 shows the performance of the proposed algorithm with regards to the multi-objective optimization and allocation of optimal power to units. The table implies that heavily-performing units must be leveraged to attain economic and emission objectives simultaneously. As per this inference, both the battery, as well as PAFC, is suggested to be extensively used, whereas the rest of the units are to be used as and when required. In the case of light load requirements, i.e., during the first few hours of the day, surplus energy can be exported to the macrogrid. However, if the load requirement is high, the reverse option is preferred. So, utility-supplied energy plays an important role in sustainable operations.

In the second scenario, an assumption was made that RESs such as WT and PV produce the highest amount of power for every hour in a day. On the other hand, the other generators such as a battery, PAFC, MT, and utility function in normal mode, similar to their behavior found in the primary case. In this scenario, the proposed algorithm was again incorporated and validated for the multi-objective optimization problem. The results were attained and inferred through a comparison with that of the other algorithms. Table 5 compares the statistical performances of the algorithms discussed earlier. In this comparison, every single objective underwent 50 trials.

From the table, it can be inferred that the multi-objective optimization problem was appropriately handled by the proposed algorithm while it also ensured a minimum diversity for every objective and trial, compared with other optimal solutions. The total operation cost of the microgrid was increased in the second scenario when compared with the main case. However, the net emission was reduced compared to the previous case. This is attributed to the fact that when RESs penetrate heavily into the grid network, it reduces the net emission. However, it incurs high costs upon the operations for a specific period under study.

Table 4. A statistical comparison of simulation results for case-II.

Optimization Algorithm	Parameter	Cost Euro	Emission Kg
EDNSGA-II [41]	Min Cost	190.6	NA
	Min Emission	NA	1162.4
	BCS	NA	NA
	Std Dev	NA	NA
PSO	Min Cost	194.24	1205.29
	Min Emission	203.15	1168.12
	BCS	198.57	1184.89
	Std Dev	5.98	7.63
CSA	Min Cost	193.38	1203.14
	Min Emission	201.08	1166.58
	BCS	196.78	1183.28
	Std Dev	5.79	7.58
GWO	Min Cost	189.73	1200.23
	Min Emission	198.29	1160.25
	BCS	192.04	1179.27
	Std Dev	4.76	6.64
GGWO	Min Cost	187.13	1197.38
	Min Emission	202.87	1158.03
	BCS	190.48	1177.49
	Std Dev	4.43	4.63
OGGWO	Min Cost	186.27	1210.24
	Min Emission	201.89	1156.79
	BCS	188.23	1175.82
	Std Dev	4.26	4.46

Table 5. An optimal generation schedule for Case-II.

Hour	MT	FC	PV	WT	Battery	Grid
1	29.98	0	0	9.15	−28.13	51
2	17.22	16.89	0	10.84	−16.93	31.98
3	6.75	21.56	0	11.56	−18.31	38.44
4	23.15	3	0	12.68	−20.89	43.06
5	6.23	19.23	0	13.29	−29.98	58.23
6	26.99	3.73	0	13.41	−25.12	55.99
7	26.86	24.91	0	14.78	−24.89	42.34
8	6.91	25.99	0	13.95	−14.98	58.13
9	0	30	0.45	19.12	24.31	17.12
10	30	30	2.29	19.25	27.45	−12.99
11	30	30	8.02	24.11	30	−29.13
12	29.98	0	10.23	22.43	29.92	−4.56
13	0	21.56	10.75	18.79	−5.99	40.89
14	30	30	10.18	24.12	23.11	−31.41
15	0	0	9.78	24.87	19.23	37.12
16	30	30	5.09	24.92	−29.98	35.97
17	24.35	28.15	0.56	23.12	−26.99	52.81
18	11.98	20.03	0	20.54	18.22	34.23
19	29.95	30	0	20.79	−29.98	57.24
20	29.95	3.56	0	22.59	−8.34	56.24
21	30	30	0	22.34	−30	40.66
22	27.98	0	0	23.89	29.73	3.4
23	19.98	19.45	0	22.57	−19.23	35.23
24	8.78	20.12	0	20.61	−20.48	37.97

The convergence characteristics for operating cost and emission, attained by OGGWO, GGWO, GWO, CSA, DE, and PSO are shown in Figures 5 and 6, respectively. These figures infer that the proposed OGGWO algorithm possesses stable and quick convergence characteristics to find the optimal solution. Figure 7 showcases the distribution of non-dominant solutions, which infers the Pareto optimal fronts of OGGWO and GGWO algorithms. The figure implies that the proposed OGGWO algorithm is a promising candidate to overcome the multi-objective energy management problem compared to the rest of the optimization techniques. In addition to the above, the proposed OGGWO algorithm ensured the distribution of non-dominated solutions in the best manner. It also assured that the solutions are feasible for large-scale standard test systems.

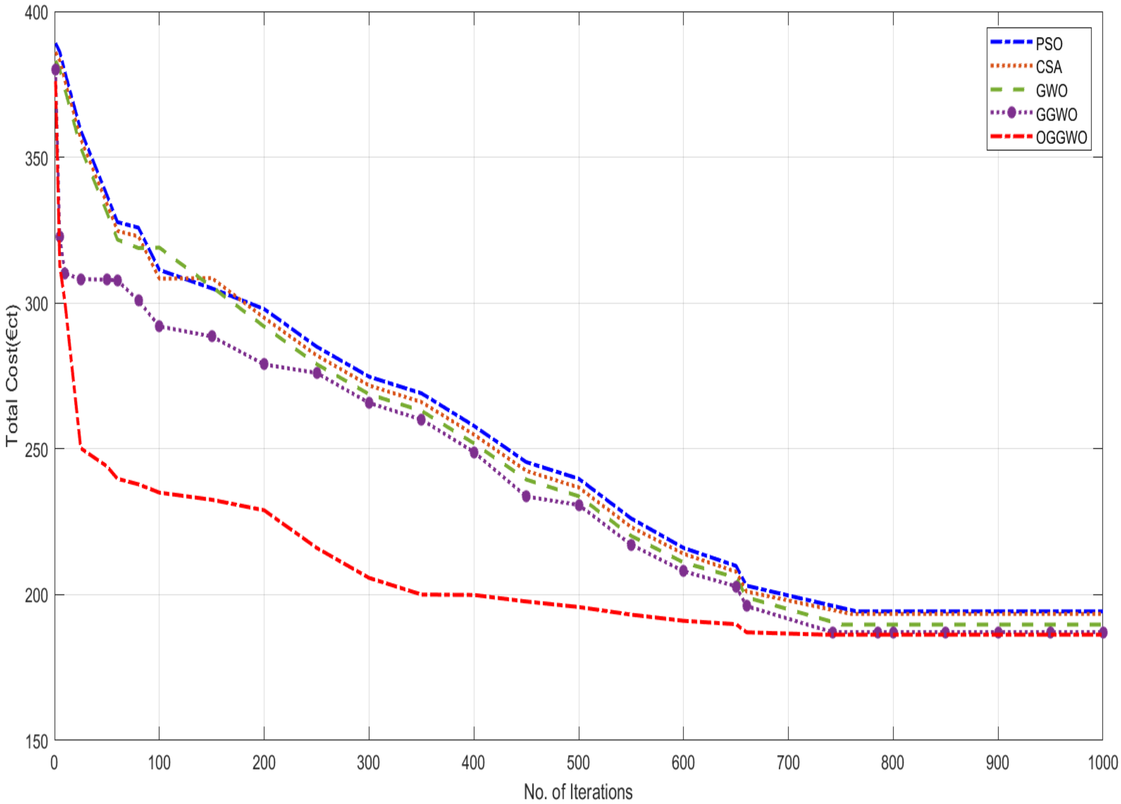

Figure 5. The cost convergence characteristic for Case-II.

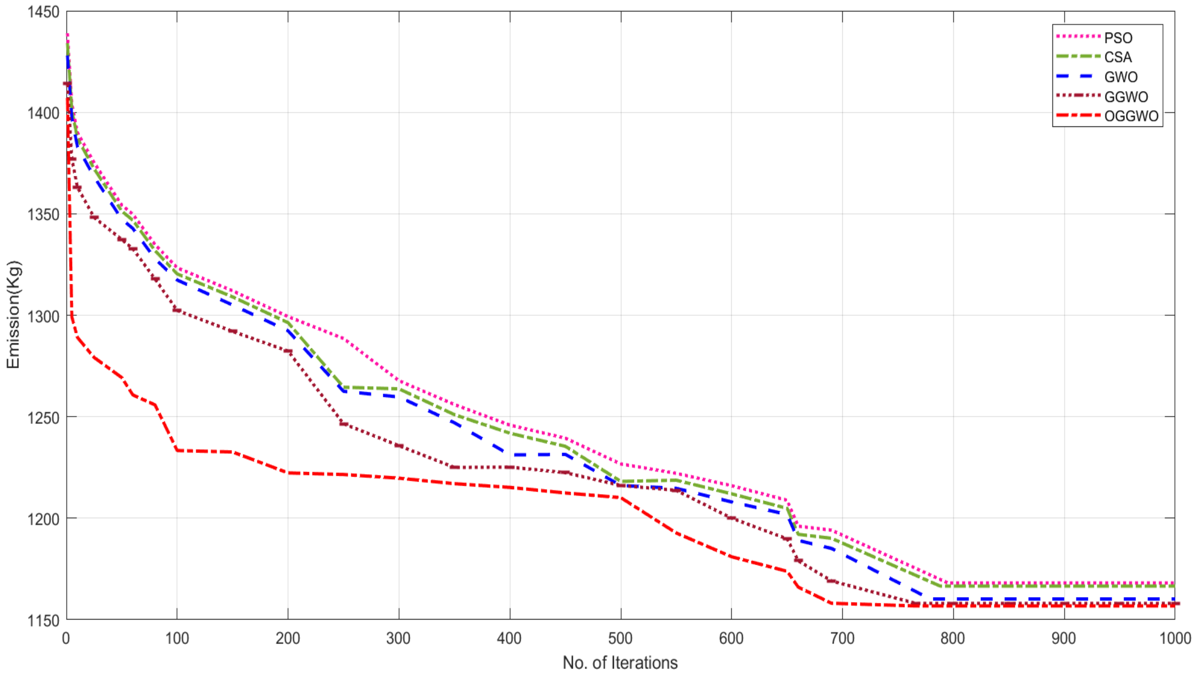

Figure 6. The emission convergence characteristic for Case-II.

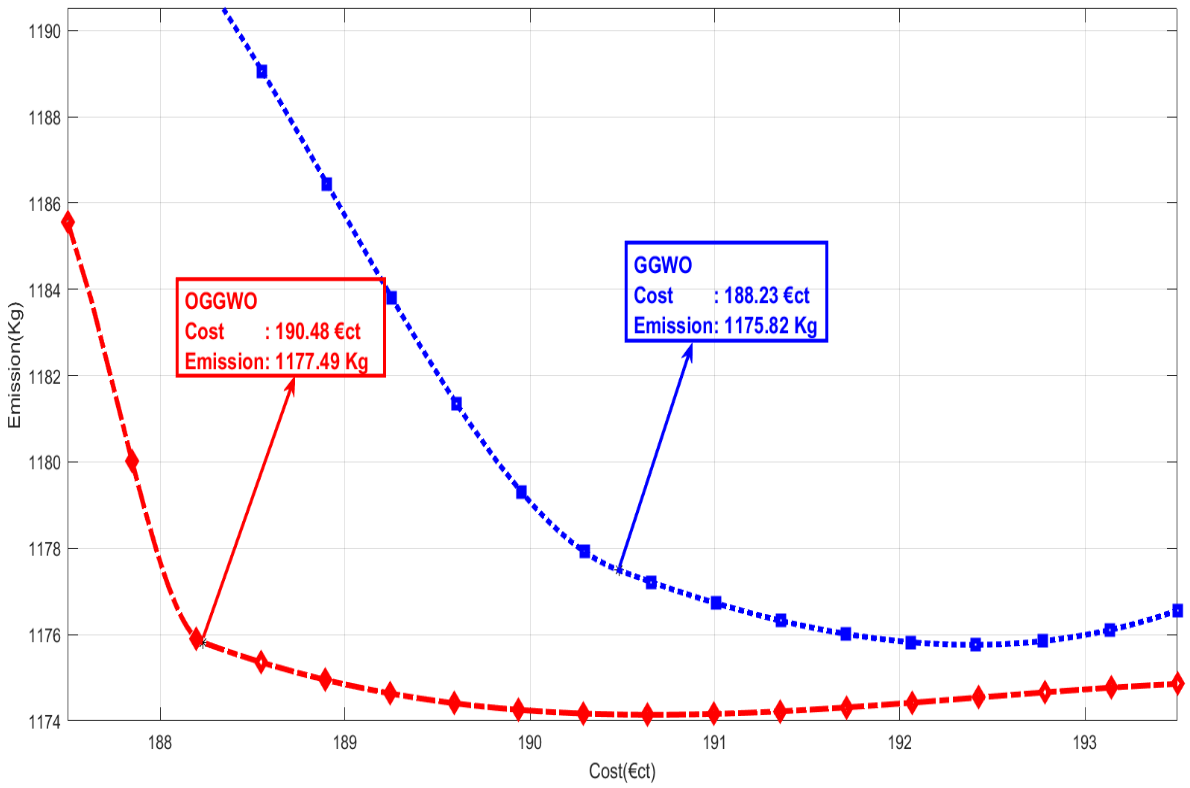

Figure 7. The emission cost trade-off characteristic for Case-II.

6.3. Case III: Unlimited Power Exchange between LV and MV

The overall set of DG units function as per their power limits in the third scenario. In this case, the utility behaves as an unconstraint unit whereas energy exchange occurs between utility and microgrid irrespective of the limitations. The data required to overcome the multi-objective optimization issue such as real-time market prices, technical specifications of DGs, and load curve remains unaltered. Like the earlier cases, evolutionary-based optimization algorithms were utilized in this case as well to resolve operation management issues found in the microgrid. The simulation results were collected from the experimentation.

Table 6 shows the simulation results for the third case, which was attained to mitigate the operation cost and emission. As per the results, both operating costs, as well as the emission rate of the microgrid, were reduced more than in than the basic scenario, under a few conditions such as allowing unlimited power exchange and economic and environmental objectives. When the second and third scenarios were compared for optimization, in terms of costs and emission, the results infer that the total cost of operation was reduced in the third scenario, while the net emission rate was reduced in the second scenario. Table 7 compares the statistical results of OGGWO and other optimization algorithms, pertaining to every single objective. The comparative analysis results infer that GGWO was deficient and its results were more inconsistent than for the proposed OGGWO algorithm.

One of the significant observations in the third scenario is that during the first few hours of the day, the utility occupied the top position in meeting load demands inside the grid. On the contrary, the energy was purchased from the microgrid in bulk quantities at peak times. Regarding both objectives, when the grid experienced a shortage in power generation, both WT and PV were started; otherwise, both were triggered in the case of requirement for more energy to be exported to the macrogrid. Other DGs such as battery and FC produced the maximum electricity for the majority of the hours in a day under study, whereas MT generated the highest power between 9.00 to 17.00 h.

Figures 8 and 9 show the convergence characteristics of OGGWO, GGWO, GWO, CSA, DE, and PSO for operating cost and emission. The proposed OGGWO achieved a fast and smooth convergence characteristic curve towards reaching the optimal solution. The proposed algorithm successfully overcame the optimization problem for the third time, whereas minor differences can be found in optimal solutions for both the objective functions. Figure 10 represents the trade-off characteristics between operating cost and emission for OGGWO and GGWO which revealed the efficiency of OGGWO in elucidating multi-objective energy management problems. Further, the comparative analysis conducted between the Pareto fronts of the proposed OGGWO algorithm and GGWO algorithm showcases that the former afforded the least and was well-distributed than the latter one. The simulation outcomes established the superiority of the proposed OGGWO in managing equality and inequality issues that occur in energy management problems.

Table 6. A statistical comparison of simulation results for case-III.

Optimization Algorithm	Parameter	Cost Euro	Emission Kg
EDNSGA-II [41]	Min Cost	127.3	NA
	Min Emission	NA	1506.9
	BCS	NA	NA
	Std Dev	NA	NA
PSO	Min Cost	133.12	1552.48
	Min Emission	142.39	1512.83
	BCS	137.03	1530.25
	Std Dev	3.78	9.83
CSA	Min Cost	132.28	1549.28
	Min Emission	140.59	1511.35
	BCS	135.25	1528.94
	Std Dev	3.59	9.64
GWO	Min Cost	126.74	1545.85
	Min Emission	135.38	1505.37
	BCS	132.06	1526.12
	Std Dev	2.61	8.57
GGWO	Min Cost	125.13	1556.29
	Min Emission	140.56	1503.32
	BCS	130.27	1522.48
	Std Dev	2.34	6.69
OGGWO	Min Cost	124.46	1556.73
	Min Emission	139.59	1502.68
	BCS	129.06	1520.83
	Std Dev	2.18	6.52

Table 7. An optimal generation schedule for Case-III.

Hour	MT	FC	PV	WT	Battery	Grid
1	6	0	0	4.97	−13.99	65.02
2	12.23	3.18	0	0.34	−10.99	55.24
3	0	0	0.27	10.98	−29.23	77.98
4	0	0	0	5.65	−13.99	69.34
5	0	0	0	11.98	−30	85.02
6	0	3	0	13.21	−28.23	87.02
7	0	3.25	0	12.99	−25.12	92.78
8	6	0	0	8.28	−17.23	92.95
9	30	30	0.13	18.12	−15.29	28.04
10	30	30	1.68	19.23	29.76	−14.67
11	30	29.99	7.13	23	30	−27.12
12	30	30	9.89	22.23	30	−34.12
13	30	0	11.03	16.02	27.03	1.92
14	9.56	9.32	2.99	7.94	9.89	46.3
15	30	30	8.07	24.29	18.99	−20.35
16	11.23	11.28	1.86	8.75	8.76	53.12
17	29.74	3.93	1.03	22.27	−30	75.03
18	0	0	0	18.99	−30	116.01
19	6.93	15.24	0	12.96	−20.12	92.99
20	7.12	3	0	15.38	−21.11	99.61
21	30	30	0	20.03	29.89	−16.92
22	0	0	0	22.34	−29.99	92.65
23	0	3.23	0	8.03	12.02	54.72
24	0	0	0	20.01	−30	76.99

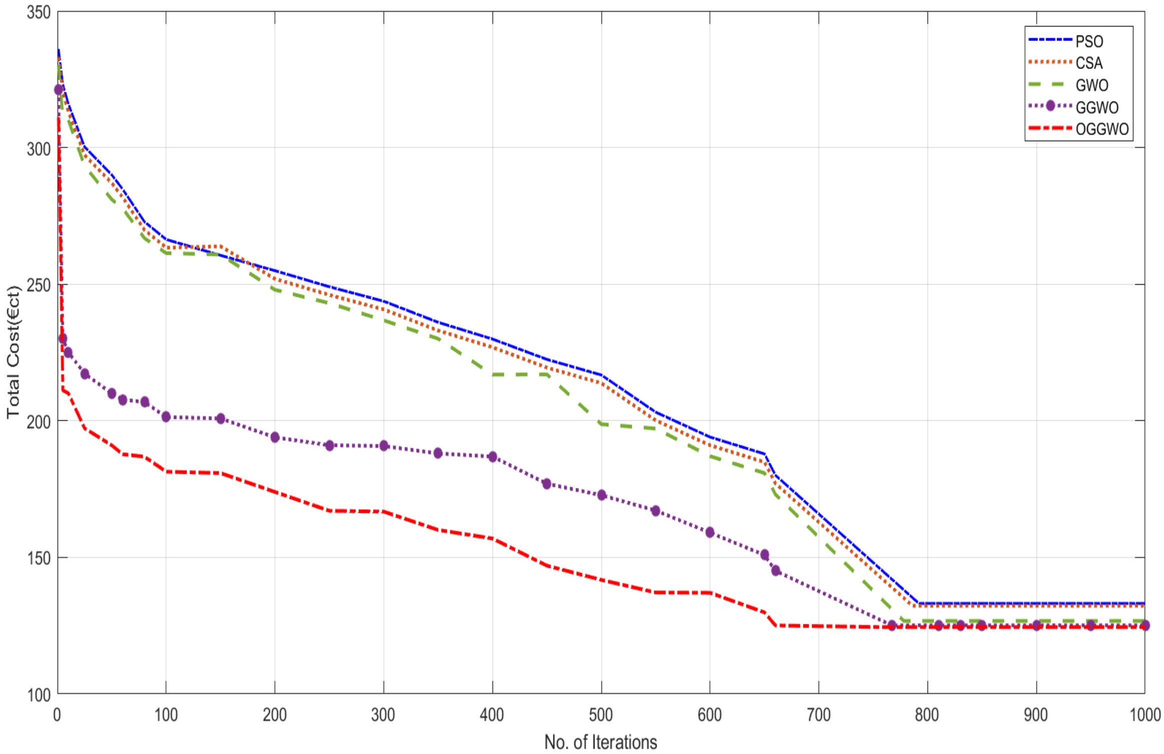

Figure 8. The cost convergence characteristic for Case-III.

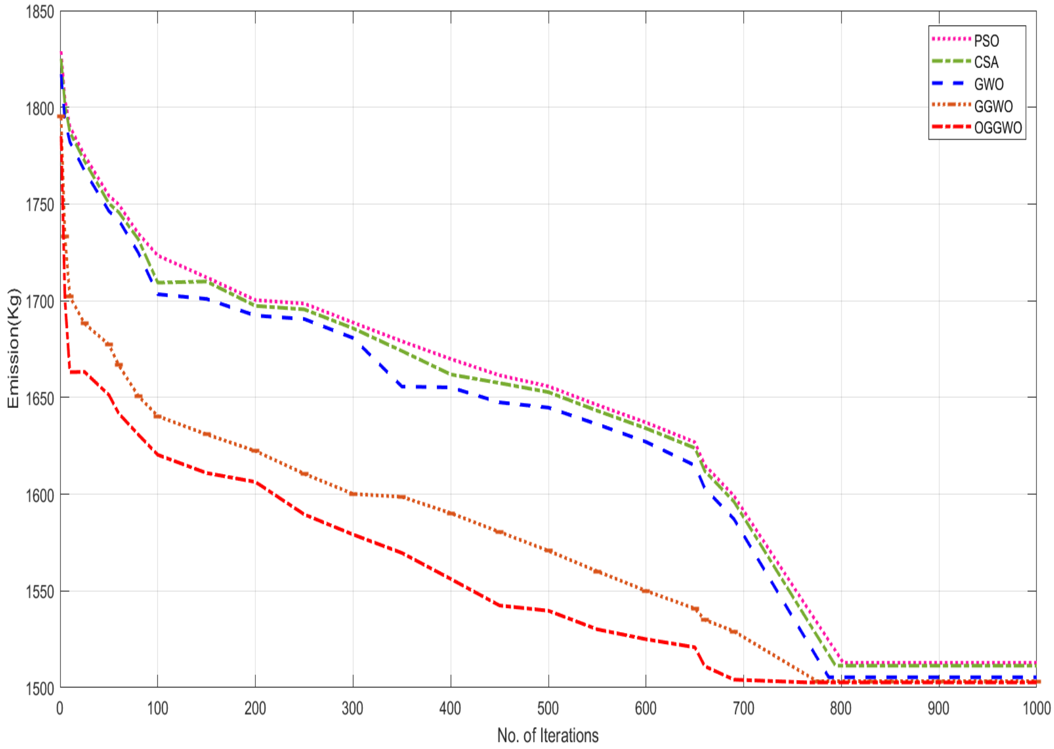

Figure 9. The emission convergence characteristic for Case-III.

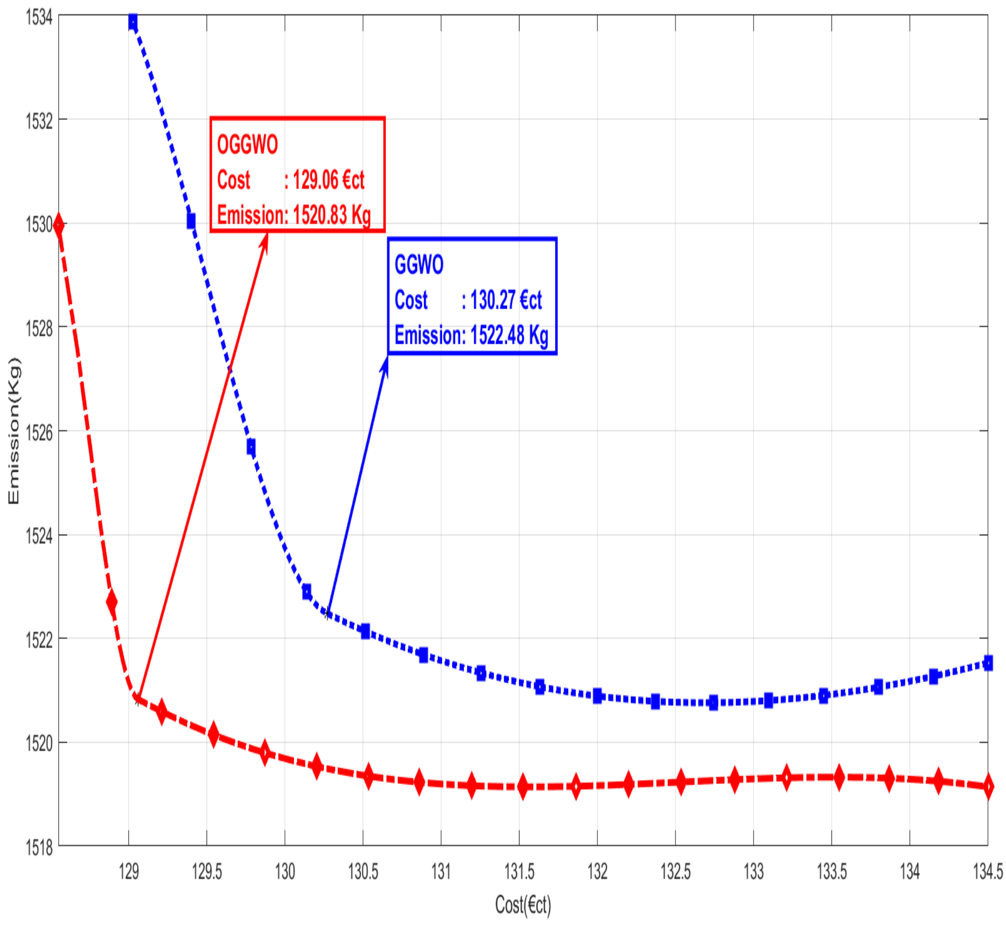

Figure 10. The emission cost trade-off characteristic for Case-III.

7. Conclusions

Environmental pollution is a significant threat to humanity and other living beings on earth. Across the globe, there is a tremendous increase observed in environmental pollution due to unsustainable and environmentally-harmful human activities. The very existence of human beings on earth is being questioned these days, whereas the measures taken to curb the environmental pollution will only decide the fate of human beings. Traditional power plants, fueled by fossil fuels to produce energy remain the primary source of environmental pollution. Different corrective measures are being taken these days, such as the utilization of advanced technologies, the prevalent implementation of renewable energy sources into the power sector, and the appropriate utilization of energy. These initiatives may curb environmental pollution in the coming years. Microgrids with different RESs such as PV, WT, battery, and so on enact an important role in curbing the environmental pollution caused during conventional energy generation methods. In this background, a novel algorithm has been proposed in this study, i.e., the Oppositional Gradient-based Grey Wolf Optimizer (OGGWO). The proposed algorithm was validated under three different scenarios to establish its effectiveness. A typical microgrid was used as a test system loaded with a battery, FC, WT, MT, and PV. The microgrid was connected with the utility grid, as well as for power exchange as decided by MGCC. Further, the researchers proposed a multi-objective formulation encompassing both emission and operational costs under equality and inequality constraints. The application results were retrieved on a 24-h horizon, whereas the results were compared with other existing techniques. The results establish that the proposed technique outperformed other algorithms and produced excellent results. Further, the results of the proposed algorithm were also compared against GGWO and different optimization algorithms. Based on the comparison results, it can be inferred that the OGGWO algorithm is capable of avoiding premature convergence. The proposed optimization algorithm can also be applied to solve the optimal sizing and placement of FACTS devices in distribution systems.

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Abbreviations

ANN	Artificial Neural Network
BARON	Branch and Reduce Optimization Navigator
BBSA	Backtracking search algorithm
BESS	Battery Energy Storage System
BPSO	Binary Particle Search Algorithm
CSA	Cuckoo Search Algorithm
DER	Distributed Energy Resources
DG	Distributed Generator
DR	Demand Response
DSM	Demand Side Management
EDNSGA-II	Economic Dispatch based Non-Dominated Sorting Genetic Algorithm
EO	Equilibrium Optimizer
EV	Electric Vehicle
FC	Fuel Cell
GAMS	General Algebraic Modeling System
GBDT	Gradient Boosting Decision Tree
GGWO	Gradient based Grey Wolf Optimizer
GOA	Grasshopper Optimization Algorithm
GPPM	Generalized Power Prediction Model
GRG	Generalized reduced-gradient

GWO	Grey Wolf Optimizer
LEMS	Local Energy Management System
LF	Levy Flight
LV	Low Voltage
MBA	Modified Bat Algorithm
MG	Microgrid
MGCC	Microgrid Central Controller
MGEM	Microgrid Energy Management
MOPSO	Multi-Objective Particle Search Algorithm
MSFOA	Muddy Soil Fish Optimization Algorithm
MT	Microturbine
MV	Medium Voltage
NA	Not Available
NSGA-II	Non-Dominated Sorting Genetic Algorithm
OBL	Opposition Based Learning
OGGWO	Oppositional Gradient based Grey Wolf Optimizer
PAFC	Phosphoric Acid Fuel Cell
PAR	Peak-to-Average Ratio
PMORL	Preference-based multi-objective reinforcement learning
PSO	Particle Search Algorithm
PV	Photovoltaic
QPSO	Quantum Particle Search Algorithm
RES	Renewable Energy Sources
SOA	Sandpiper Optimization Algorithm
WT	Wind Turbine

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