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RESEARCH ARTICLE OPEN ACCESS

ENERGY MANAGEMENT OPTIMIZATION AND OPTIMAL CONTROL OF MICROGRID ENRICHED WITH RENEWABLE AND SUSTAINABLE DISTRIBUTED GENERATORS USING NATURE-INSPIRED METHOD

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ABSTRACT

One of most general nature-inspired meta-heuristic methods called Grey Wolf Optimization (GWO) inspired by grey wolves is applied to solve the energy management optimization (EMO) and optimal control (OC) problems of micro-grid (MG) impregnated with renewable and sustainable distributed generators (REDG). Our main goal is to minimize nonlinear objectives function of an electrical micro-grid taking into account a set of constraints. GWO method have been examined and tested on MG system composed of different types of DGs, such as wind turbines (WT), photovoltaic systems (PV), micro turbines (MT), fuel cells (FC), diesel electric generator (DEG), and loads with energy storage systems (ESS). The results are promising and show the effectiveness and robustness of proposed approach to solve the EMO and OC problems in different operational scenarios.

I. INTRODUCTION

The traditional electrical power system can be divided into three major categories: power generation, transmission and distribution systems [1]. The power plants are connected to the distribution network (DN) by transmission lines and the DN supplies electricity to all the loads in a given region. For a number of reasons, mainly technical and economic, individual power systems are connected together to form power pools. These regional or regional power grids operate independently, but are also interconnected to form a power grid. The rapid increase in the world population, digitalization and industrial evolution are the main causes of the growing demand for electricity.

In recent times, there has been a notable surge in the advancement and utilisation of RES [2]. A unique position is held by wind turbines among various energy sources. Indeed, wind energy is predicted to grow rapidly in many areas, but it can also have a substantial impact on the voltage and current quality in the network where it is injected because of its highly variable nature caused by large variations in wind speed [3].

Distributed generation (DG) has grown steadily during the last 20 years. Geographical and meteorological factors influence how DGs are integrated with RES, such as photovoltaic systems (PV) and small wind turbines (WTs). Moreover, the characteristics of their output powers are unpredictable and change over time. Conversely, non-renewable DGequipment, including fuel cells, micro turbines, diesel generators, and energy storage devices, possess a consistent output power and can be attached to any point within the DN [4], [5].

In a broader sense, the strategic utilization and effective management of DG units yield advantageous outcomes in terms of power quality enhancement, minimized power losses, improved reliability, and reduced emissions. To unlock the full potential of DG, an integrated approach encompassing coordinated operation and control alongside energy storage systems and controllable loads becomes imperative. This paves the way for the emergence of a ground-breaking paradigm known as micro-grids (MGs) [4], [6]. In essence, an

MG denotes a localized DN comprising a diverse array of DG units, controllable loads, and energy storage systems, which can operate either interconnected or islanded with the main distribution grid, thereby operating as a controlled entity [7], [8]. MGs represent as the pivotal element within contemporary power systems, embodying the essence of intelligent DN.

MGs are local DN comprising various DG units, controllable loads, and ESS that can operate either interconnected or isolated from the main distribution grid as a controlled entity. MGs represent the core of intelligent DN within modern power systems. In order to take full advantage of the operation of MGs, such as improved profitability and reduced dependence on the main network, it is important that the integration of DGs into MGs, and their relationship with the DN main upstream, helps to optimize the general operation of the system [9-11].

Energy management and optimal control are two closely related concepts that aim to optimize usage in a given system. Energy management refers to the overall management of energy within a system, seeking to minimize losses and maximize energy efficiency. This is a nonlinear optimization problem with constraints named optimal Energy and Operation Management (EOM). On the other hand, OC is a mathematical process that aims to optimize a system by adjusting the control variables according to certain conditions [12]. In the last 10 years, a very large number of mathematical methods has been applied to solve most important optimisation problems in power systems, such as optimal power flow (OPF), optimal reactive power dispatch (ORPD), economic dispatch (ED), optimal location and sizing of DG in DN, optimal control and optimal energy management of MGs, etc. Several methods have been proposed for determining the OEM of MG. An analytical approaches [13], [14] developed expressions to optimal energy management and online optimal control strategy of energy storage of MGs. A linear programming approach [15], [16] addresses the OEM problem of MG.

Recently, population-based methods have been widely used for OEM. Genetic algorithms [17-19] are frequently employed for EMO. A profit-maximizing approach was proposed by [20], while evolutionary programming [21], focused on reducing power losses and improving efficiency across various load models. A moth-swarm algorithm [22], are applied for OEM. Differential evolution algorithm were proposed by [23] to optimize or reduce the power losses in DN. Similarly, fore same purpose, backtracking search optimization [24] was applied to solve the OEM in microgrid, for the primary objective is the optimization of energy costs.

Local swarm intelligence methods have been applied to solve the OEM. PSO [7], [25], addresses OEM taking into account load variations in DN. Similar, Zhang et al., [26] use also PSO for EMO, while artificial bee colony [27-29] focuses on loss reduction with multiple DG sources. Ant colony optimization [29-30], aim to minimize OEM incorporating uncertainty in statistical cost estimation and demand response. Kamarposhti et al. [31] use also ACO to enhancing reliability and cost efficiency for sustainable energy systems by solving the OEM problem in microgrid. Nature-inspired and bio-inspired methods, including grey wolf optimization [32], cuckoo search [33], ant lion optimization [34], bacterial foraging-based algorithm [35], firefly algorithm [36] and [37] are used to solve the OEM. Whale optimization algorithm [38], dragonfly algorithm [39], glowworm swarm optimization [40], [41], crayfish optimization algorithm [42], dolphin echolocation algorithm, cuttlefish algorithm [43], greylag goose optimization [44], are used for OEM for losses and enhancing voltage in MG.

Physical approaches like gravitational search algorithms [45], [46] address optimized operation of microgrid and optimal power flow by reducing power losses, and gas emissions while improving power quality. Wind driven optimization [47] also target for gas emission optimization in microgrid. Kamel et al. [48] use archimedes optimization algorithm for solving the energy management problem in smart inter-connected micro-grids. Population-based algorithms like shuffled frog leaping [49], [50], colliding bodies optimization [51], teaching learning-based optimization [52], harmony search [53], and sine-cosine algorithm [54] are applied to solve EMO of MG in various objectives such as power loss reduction and voltage enhancement. In [55], authors combined GA with linear programming for sizing and energy management optimization of hybrid system. Moradi and Abedini [56], combined GA with methods like PSO for energy management optimization in DN. Similarly, Kouba and Sadoudi **[**57**],** addressed EMO by merging fuzzy logic with GA. Kumar et al. [58] use flying foxes optimization algorithm and deep attention dilated residual convolutional neural network for energy management optimization in smart grid system with RES and ESS.

Hybrid optimization methods like PSO and GSA [59], hybrid GWO and PSO [60], hybrid sperm swarm optimization and gravitational search algorithm have been proposed by Kamel et al. [61] to optimize for energy management optimization of power systems. These multi-objective approaches focus on minimizing costs, network losses, and improving the voltage profile. In recent year, hybrid evolutionary-swarms [62], hybrid evolutionary-bio-inspired algorithms [63], hybrid evolutionary-physical-inspired algorithm [64], hybrid swarm and physical-inspired algorithms [65], hybrid nature-inspired and swarm algorithms [66] and hybrid swarms intelligences algorithms [67] are used to optimize the energy management in DN and MGs.

II. PROBLEM FORMULATION

II.1 OBJECTIVE FUNCTION

In general, the EMO problem can be presented as follows [68]:

$$\begin{aligned} \min\ f(x,u) &= \sum_{t=1}^{NT} \cos t^{t}\left(x^{t},u^{t}\right) \\ &= \min_{u} \sum_{t=1}^{NT}\sum_{i=1}^{NG}\left[B_{Gi}\left(P_{Gi}^{t}\right)+MP^{t}P_{Grid}^{t}\right] \end{aligned} \tag{1}$$

Subject to

$$h(x,\ u)=0 \tag{2}$$

$$g(x,\ u)\le 0 \tag{3}$$

$f(x,u)$ is the cost function throughout the planning horizon. $h(x,u)$ and $g(x,u)$ are, respectively, the set of nonlinear equality and inequality constraints.The active power exchanged with the grid at time t is denoted by P^t_{Grid}. NT and NG are the total count of time and DGs, including storage; P^t_{Gi}, $B_{Gi}(P^t_{Gi})$ and MP^t are, respectively, the active power output, the bid of i^{th} DG and the electricity exchange price between the MG and grid at time *t* [69]. The state and control variables, x and u, are defined as follows

$$x^t = P^t_{Grid} \tag{4}$$

$$u^t = \left[P^t_{Gi}, P^t_{G2}, \ldots . P^t_{GNG}\right] \tag{5}$$

II.2 CONSTRAINTS

II.2.1 POWER BALANCE CONSTRAINTS (PBC)

For each time interval t, the total output power of the DGs, energy storage devices and utility must cover the total demanded load in the MG. As a result, the power balance constraint can be represented as follows:

$$\sum_{i=1}^{NG} P^t_{Gi} + P^t_{Grid} = \sum_{D=1}^{ND} P^t_{L_D} \tag{6}$$

P_{L_D} is the quantity of the Tenth loads level and ND is the total number of loads levels.

II.2.2 POWER GENERATION CAPACITY CONSTRAINTS

For stable operation, the active power output of each unit including the utility, is limited as follows:

$$P^t_{Gi,\min} \le P^t_{Gi} \le P^t_{Gi,\max} \tag{7}$$

$$P^t_{Grid,\min} \le P^t_{Grid} \le P^t_{Grid,\max} \tag{8}$$

$P^t_{Gi,\min}$, $P^t_{Grid,\min}$, $P^t_{Gi,\max}$ and $P^t_{Grid,\max}$ are, respectively, the minimum and maximum active powers of the i^{th} DG, and the utility at time *t*.

II.2.3 RESERVE SPINNING CONSTRAINTS (RSC)

The RSC is necessary to maintain the reliability of the system, due to the power fluctuations of the renewable and the load fluctuations. To satisfy the RS, the following inequality constraint must be satisfied [70]:

$$\sum_{i=1}^{NG} P^t_{Gi,\max} + P^t_{Grid,\max} = \sum_{D=1}^{ND} P^t_{L_D} + R^t \tag{9}$$

Where, R^t is the spinning reserve programmed at time *t*. In an MG, the RSC is considered by adding an additional value to the total power demand, which should be supplied by the DG units. It should be noted that the maximum power (not the operating point) of the energy sources is considered in the above equation.

II.2.4 ENERGY STORAGE LIMITS (ESL)

Since there are certain limits to the charge and discharge rate of storage devices during each time interval, the following equation and constraints can be expressed as

$$\begin{gathered} W_{ess,t} = W_{ess,t-1} + \eta_{charge} P_{charge} \Delta t - \frac{1}{\eta_{dicharge}} P_{dicharge} \Delta t \\ \begin{cases} W_{ess,\min} \le W_{ess,t} \le W_{ess,\max} \\ P_{charge,t} \le P_{charge,\max} \quad and \quad P_{dicharge,t} \le P_{dicharge,\max} \end{cases} \end{gathered} \tag{10}$$

$W_{ess,t}$ and $W_{ess,t-1}$ are the amount of energy stored in the battery at time t and t-1, respectively; $P_{charge}(P_{decharge})$ is the charge (discharge) rate allowed for a defined period of time Δt; $\eta_{charge}(\eta_{decharge})$ is the efficiency (yield) of the battery during the *charging* (discharging) process; $W_{ess,\min}$ and $W_{ess,\max}$ are the lower and upper limits of the amount of energy stored inside the battery; and $P_{charge,\max}(P_{dicharge,\max})$ is the maximum rate of charge (discharge) of the battery during each interval time Δt [29].

II.2.4 CALCULATION OF ACTIVE POWER FROM (TO) THE GRID

The active power from (to) the utility is considered as a dependent variable. The grid power is calculated as

$$P^t_{Grid} = \sum_{D=1}^{ND} P^t_{L_D} - \sum_{i=1}^{NG} P^t_{Gi} \tag{11}$$

The obtained P_{Gi}^{t} we check whether or not satisfies the constraint in (8). Therefore, the $P_{Grid,\lim}^{t}$ is defined as:

$$P_{Grid,\lim}^{t} = \begin{cases} P_{Grid,\max}^{t} & si\ P_{Grid}^{t} > P_{Grid,\max}^{t} \\ P_{Grid,\lim}^{t} & si\ P_{Grid,\lim}^{t} < P_{Grid,\min}^{t} \\ P_{Grid}^{t} & si\ P_{Grid,\min m}^{t} \le P_{Grid,\min}^{t} \le P_{Grid,\max}^{t} \end{cases} \tag{12}$$

The new extended function to be optimized when the penalty factor multiplied by the square of the difference between the actual value and the limit value of the dependent variable is

$$\min_{u} F_p = \min_{u} \sum_{t=1}^{NT} \cos t^{t}\left(x^{t}, u^{t}\right) + \lambda_p \left(P_{Grid}^{t} - P_{Grid,\lim}^{t}\right)^2 \tag{13}$$

Where λ_p is the penalty factor.

II.3 BIDS CALCULATION OF DISTRIBUTED GENERATION

Depending on the cost function of the units, if any, the market price feedback and the need to make some profit, necessary for the annual depreciation of the installation cost, the DG bids are considered quadratic, as shown in (14) [9].

$$B_{Gi} = a_i P_{Gi}{}^{2} + b_i P_{GI} + c_i \tag{14}$$

II.3.1 MICRO-TURBINE AND FUEL CELL

The MT and FC bids in (\$/h) can be calculated as follows [5], [71]:

$$B_G = C_{fuel} \frac{P_G}{\eta_G} + C_{inv} \tag{15}$$

Where, P_G is the DG electrical output power (kW), η_G is the DG electrical efficiency, C_{fuel} is the fuel price (natural gas) to supply the DG (\$/kWh), and C_{inv} is the hourly amount of reimbursement of the investment cost of DG in (\$/h) given as

$$C_{inv} = AC \frac{P_{G,nom}}{AP} \tag{16}$$

$$AC = \frac{i(1+i)^n}{(1+i)^n - 1} IC \tag{17}$$

Where, *i* is the interest rate, n is the amortization period in years, and IC is the installation DG cost. The MT electrical efficiency can be estimated as a quadratic function of its output power [72]. These coefficients can be obtained by fitting the electrical efficiency curve of the MT based on the manufacturers' data. The FC efficiency is a non-linear function of the power level and can be expressed as follows (for a Proton exchange membrane fuel cell: PEM-FC) [73]:

$$\eta_{FC} = \frac{1}{2.964}\left[V_0 + \sqrt{V_0^2 - 4\left(V_0 V_{Pnom} - V_{Pnom}^2\right)\xi}\right] \tag{18}$$

Where, V_0 is the theoretical or thermodynamic FC potential (0.9 V), V_{Pnom} is the potential of the selected cell at rated power (0.45–0.75 V), $\xi = P_{FC}/P_{nom}$ is the power level, and P_{nom} is the rated FC power. The coefficients of the quadratic function (14) can be obtained by curve fitting, constructed according to (15) for a power range of PG.

II.3.2 WIND TURBINES AND PHOTOVOLTAIC

The bid functions of WT and PV consider the annual investment cost for depreciation of equipment (AC) (\$/kW) and the annual energy production per kW (AP) (kW h/kW) are given by (15), and (17), respectively.

According to [74] and [75], the power curve of WT can be modeled by means of a function divided into three different:

$$P_{WT} = \begin{cases} 0 & for & v \le v_{ci} \quad and \quad v \ge v_{co} \\ \dfrac{v^2 - V_{ci}^2}{v_{nom}^2 - v_{ci}^2} P_{WT,nom} & for & v_{ci} < v \le v_{nom} \\ P_{nom}, & for & v_{nom} < v \le v_{co} \end{cases} \tag{19}$$

Where, $P_{WT,nom}$, v_{nom}, v_{ci} and v_{co} are, respectively, the rated power, rated wind speed, switch-on wind speed and switch-off wind speed of the WT; P_{WT} is denote the output power of the WT and v is the wind speed [75, 76].

The PV output power P_{PV} depends on the solar irradiation and the ambient temperature of the site as well as the characteristics of the module itself. P_{PV} is calculated as follow [76]:

$$P_{PV} = P_{STC} \frac{I_S}{1000}\left[1+\gamma\left(T_C - 25\right)\right] \tag{20}$$

P_{STC} is the PV maximum power under standard test conditions (STC) (W); I_S is the solar irradiation on the surface of the PV module (W/m^2); γ is the PV module temperature coefficient for power in (°C-1); T_C is the temperature of PV cell (module) in (C). The temperature of PV can be calculated based on the Nominal Operating Cell Temperature (NOCT) as follows, [75]:

$$T_c = T_a + \frac{I_S}{800}\left(T_{NOCT} - 20\right) \tag{21}$$

T_a is the ambient temperature in (°C); T_{NOCT} is the NOCT of the module in (°C).

II.3.3 DIESEL GENERATORS (DEG)

Usually, diesel fuel consumption data in (L/h) is provided by the manufacturer. Based on these data, the fuel consumption characteristic of the DEG can be estimated as a quadratic function of its active power output [68]:

$$Fuel_{DEG} = a_{fuel} P_{DEG}^2 + b_{fuel} P_{DEG} + c_{fuel} \tag{22}$$

Where, $Fuel_{DEG}$ is the fuel consumption in (L/h); P_{DEG} is the DEG power output in (KW); α_{fuel}, b_{fuel} and c_{fuel} are the coefficients of the fuel consumption characteristic. As a result, the DEG bids ($/h) can be calculated as:

$$B_G = C_{fuel} Fuel_{DEG} + C_{inv} \tag{23}$$

C_{fuel} is the price of diesel fuel to supply DEG in ($/L). C_{inv} is the hourly payback amount for the investment cost of the DE ($/h) defined by (17).

II.3.4 ELECTRIC GRID

Market energy costs in ($/h) can be represented by a quadratic function as follows:

$$f_{grd} = a + bP_{grd} + cP_{grd}^2 \tag{24}$$

Where, P_{grd} is the electrical network power in (kW) and *a*, *b* and *c* are the cost coefficients [68].

III. GREY WOLF OPTIMIZATION

Grey wolf optimization (GWO) is a typical swarm-intelligence based meta-heuristic algorithm proposed by Mirjalili et al. in 2014 [77] which is inspired from the leadership hierarchy and hunting mechanism of Grey Wolves (GW) in nature. In nature, GW (Canis lupus) belongs to Candidate family. It is considered as a top level of predators and residing at the top in the food chain.

The population hierarchies of GW are separated by four layers which are named as, alpha (α) is the fittest solution. Beta (β) is the second optimum solution and delta (δ) is the third one. Omega (ω) is the candidate solutions that are left over. Generally, the populations of GW have average crowd size of 5-12 [78] and the cluster organizes compactly through the hierarchy.

The position of the wolves is considered as the variables to be optimized and the distance between prey and GW determine the fitness value of the objective function. The movement of each individual is influenced by four processes, namely

- Searching for prey (exploration);
- Encircling prey;
- Hunting;
- Attacking prey (exploitation).

III.1 SOCIAL HIERARCHY

The GW diverge from each other position for searching a victim. Make use $\vec{A}_M$ with random values to compel search agent to diverge from the victim. $\vec{C}_M$ component provides random weights for searching prey in the search space.

III.2 ENCIRCLING PREY

As mentioned above, GW encircle prey during the hunt. α, β and δ estimate the position of the three best wolves and other wolves updates their positions using the positions of these three best wolves. Encircling behavior can be represented by $\vec{D}_M$. When the wolves do hunting, they tend to encircle their prey [79]. The following equations depicted the encircling behavior [80].

$$\vec{D}_M = \left| \vec{C}_M \, \vec{X}_P(t) - \vec{X}(t) \right| \tag{25}$$

$$\vec{X}_{(t+1)} = \vec{X}_P(t) - \vec{A}_M . \vec{D}_M \tag{26}$$

Where t is the current iteration, $\vec{X}$ is the position vector of GW, $\vec{X}_P$ is the position of the prey, $\vec{A}_M$ and $\vec{C}_M$ are the coefficient vectors calculated using the following expressions [78]:

$$\vec{A}_M = 2\vec{a}.\vec{r}_1 - \vec{a} \qquad and \qquad \vec{C}_M = 2\vec{r}_2 \tag{27}$$

Where $\vec{r}_1$ and $\vec{r}_2$ are random vectors between 0 and 1 and $\vec{a}$ is set to decreased from 2 to 0 over the course of iterations [77, 78]. The three best solutions so far are saved and then the other search agents (omega wolves) update their positions according to the current best position [78, 81].

III.3 HANTING

Conservation of regional habitat connectivity has the potential to facilitate recovery of the GW. After encircling, α wolf guides for hunting. Later, β and δ wolves join in hunting [78]. It is tough to predict about the optimum location of prey. These situations are expressed in the following expressions [80]:

$$\begin{cases} \vec{D}_{M\alpha} = \left| \vec{C}_{M\alpha} . \vec{X}_\alpha(t) - \vec{X}(t) \right| \\ \vec{D}_{M\beta} = \left| \vec{C}_{M\beta} .. \vec{X}_\beta(t) - \vec{X}(t) \right| \\ \vec{D}_{M\delta} = \left| \vec{C}_{M\delta} .. \vec{X}_\delta(t) - \vec{X}(t) \right| \end{cases} \tag{28}$$

$$\vec{X}_{1\alpha} = \vec{X}_\alpha - \vec{A}_{M1} \vec{D}_{M\alpha}, \; \vec{X}_{1\beta} = \vec{X}_\beta - \vec{A}_{M2} \vec{D}_{M\beta} \; and \; \vec{X}_{1\delta} = \vec{X}_\delta - \vec{A}_{M3} \vec{D}_{M\delta} \tag{29}$$

The best position of wolf is calculated taking average sum of positions and given as

$$\vec{X}_{(t+1)} = (\vec{X}_{1\alpha} + \vec{X}_{1\beta} + \vec{X}_{1\delta}) / 3 \tag{30}$$

III.4 ATTACKING PREY

The GW stop the hunting by attacking the prey when it stops moving. It depends on the value of a. $\vec{A}_M$ is a random value in the interval $[-2a, 2a]$. In GWO, search agents update their positions based on the location of α, β and δ and attack towards the prey [79, 81]. However, GWO algorithm is prone to stagnation in local solutions with these operators. It is true that the encircling mechanism proposed shows exploration to some extent, but GWO needs more operators to emphasize exploration.

IV. SIMULATION AND DISCUSSIONS

The MG (Fig. 1) is used in this work. The MG is considered in order to show how to determine the offers of the different DG units. The system is a MG composed of five different DG units (WT connected to bus 4, a MT is connected to bus 7, a PV connected to bus 11, a DEG connected to bus 19 and an FC connected to bus 23) with ESS and electrical loads. Table 1 presents the data was used to calculate the DG bids coefficients and power limits. It is assumed that all DGs sources produce active power at a single power factor. Based on the decisions of the MG Central Controller (MGCC), there is a power exchange link for one day between the utility and MG.

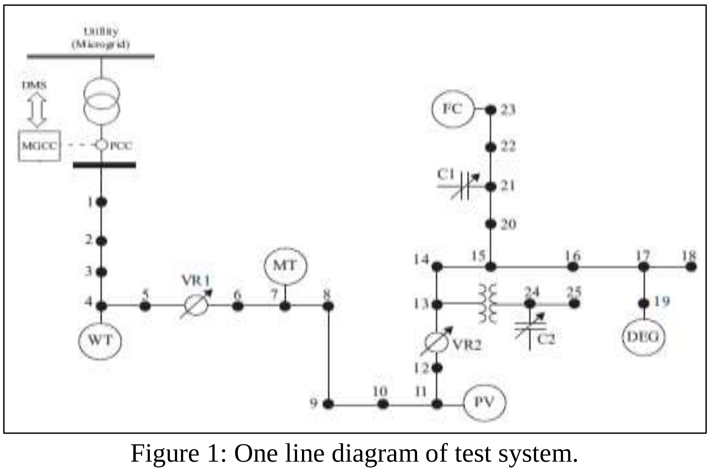

Figure 1: One line diagram of test system.
Source: [68].

Table 1: Power limits and bid coefficients of DG units.

Bus N°	Type	P_{DG}^{min} (KW)	P_{DG}^{max} (KW)	Costs coefficient		
				a	*b*	*C*
23	*FC*	30	300	0.0062	1.62	2.204
19	DEG	0	369	0.0065	12.41	1.177
11	PV	0	250	0	43.57	0
7	MT	90	300	0.0018	2.63	811
4	WT	0	600	0	6.5	0
0	Utility	0	300	0	1e-4	5e-5

Source: [68].

The proposed algorithm implemented and the computations were performed using MATLAB software, and all cases were run on a desktop computer Windows-10, 64-bit, Intel(R) Core(TM) i5-6500 CPU, 3.20 GHz processing frequency and 8.0 GB RAM.

IV.1 ENERGY MANAGEMENT OPTIMIZATION

The GWO method is implemented to find optimal solutions of the EMO problem of the MG in an operating scenario as follows: It is assumed that the PV and WT sources act at their maximum power available during each hour of the day, and the other DGs, including MT, FC and DEG, can operate within their power limits while satisfying the necessary constraints. All DGs with relevant characteristics generate electricity in the MG, and the additional demand or surplus energy inside the grid is exchanged with the utility from the point of common coupling PCC (Fig.1). The utility behaves as an unconstrained unit and exchanges power with the MG without any limitations. In this scenario, the influence of exchanges of energy market price with the utilities on the total operating cost of MG is examined in the following 3 cases:

Case 1: Energy market price is low;
Case 2: Energy market price is average;
Case 3: Energy market price reaches its real value.

The wind speed and ambient temperature are shown, respectively, in Figure 2. It was assumed that the active and reactive power of load on each bus varies according to the daily load diagram shown in Figure 3. Solar irradiance is also shown in Figure 3. Figure 4 depict the forecast energy market prices. It is assumed that, both Figure are scaled for 24h.

Given the low market price in 1st case, especially during periods when the load levels are low and medium, the utility takes the lead in supplying the load inside the MG. In the 2nd case, when the market price is middle range (higher compared to case 1), most of the load portion is provided by MT and FC units. During periods of average load, corresponding to the average market price (5.6 $/kWh), excess energy is exported from the MG to the utility. When the market price is brought to its real value in 3rd case, the MT and FC units are used with their maximum power in periods with medium and high loads levels.

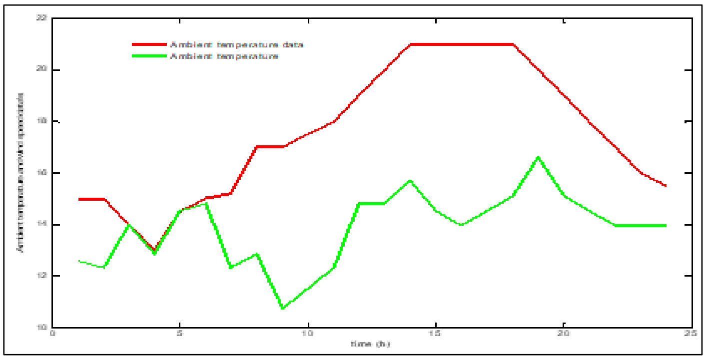

Figure 2: Ambient temperature and wind speed data's.
Source: Authors, (2025).

In addition, surplus energy is exported from the MG to the utility in most period of the day. The simulation results associated with cases 1, 2 and 3 are shown in Figures 5-11, respectively.

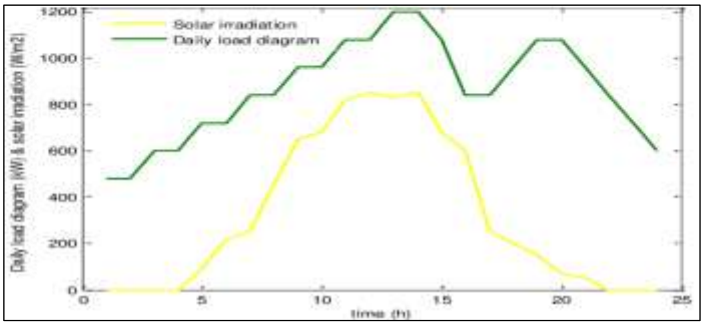

Figure 3: Solar irradiation and daily load diagram data's.
Source: Authors, (2025).

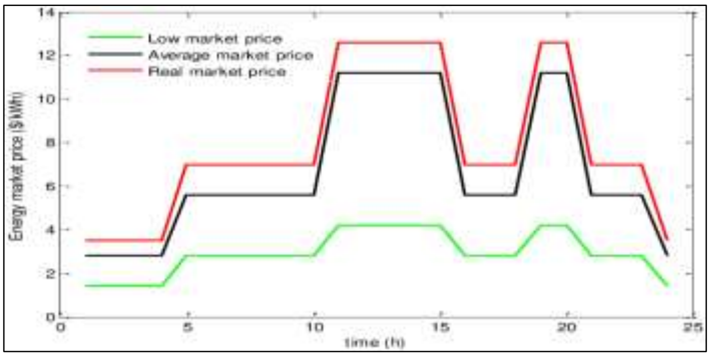

Figure 4: Energy market price dada's.
Source: Authors, (2025).

Due to the low market price for case 1, especially during times of low and medium load levels, the utility supplies the load inside the MG on its own. In this case, 257200 ($/h) is the best operation cost that was found. In the second case, the majority of power supplied to the loads through MT and FC. During periods of average load, corresponding to average market price, excess energy is solded from the MG to the utility. In this case, the best operation cost is 263900 ($/h).

When the market price reaches its genuine value, the MT and FC operate at maximum power during periods of medium and high loads. In addition, for majority of the day, excess energy are exported from the MG to the utility. In this case, the optimal operation cost was achieved at 263500 ($/h).

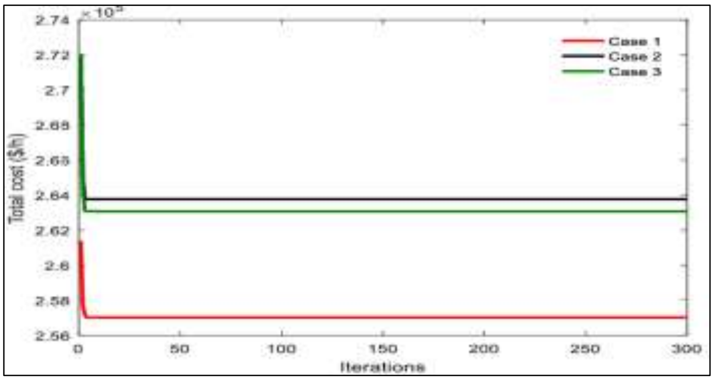

Figure 5: Costs results of 3 cases.
Source: Authors, (2025).

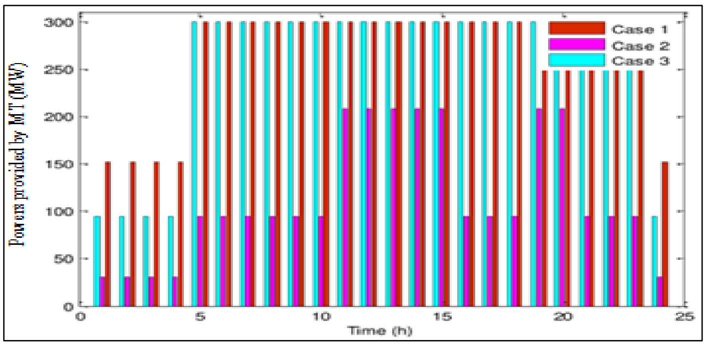

Figure 6: Powers provided by MT.
Source: Authors, (2025).

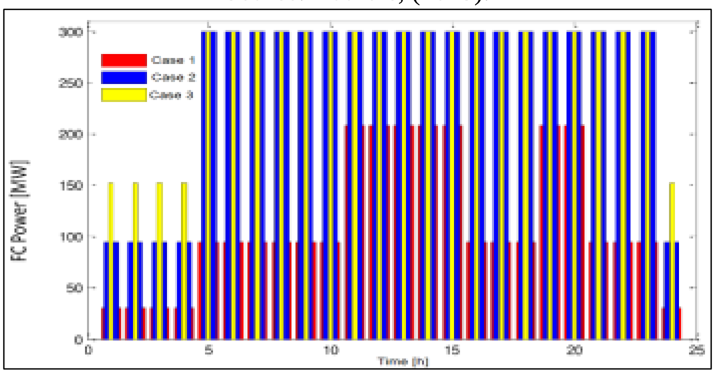

Figure 7: Powers provided by FC.
Source: Authors, (2025).

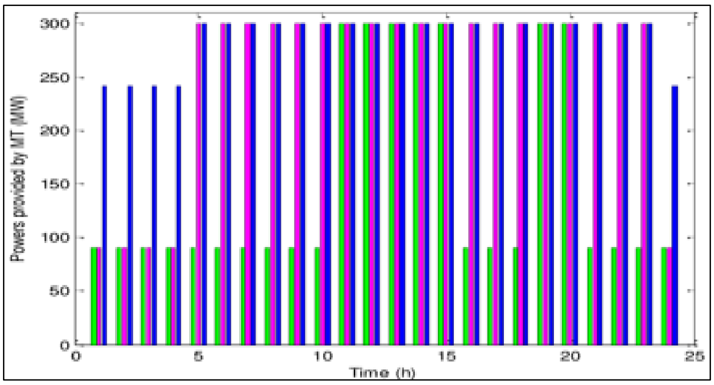

Figure 8: Powers provided by MT.
Source: Authors, (2025).

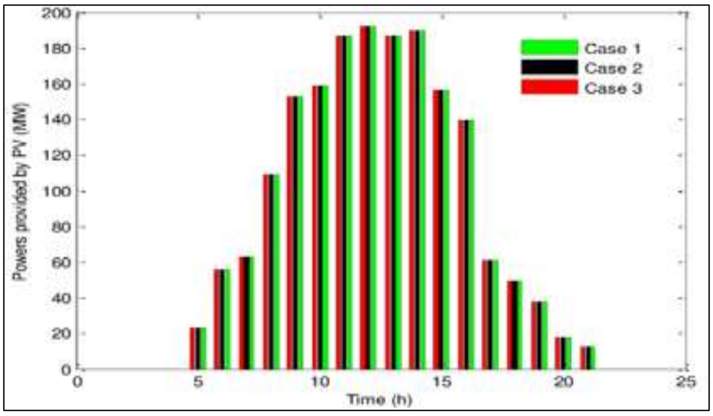

Figure 9: Powers provided by PV module.
Source: Authors, (2025).

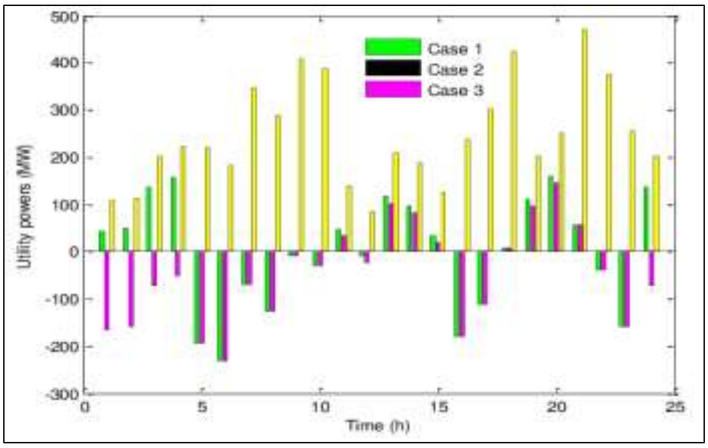

Figure 10: Utility powers.
Source: Authors, (2025).

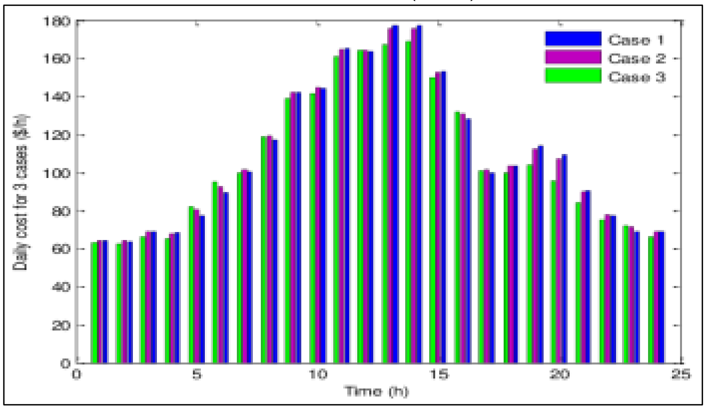

Figure 11: Daily costs of 3 cases.
Source: Authors, (2025).

II.2 OPTIMAL DG CONTROL

The proposed approach has been implemented on modified IEEE 24-bus test system shown in Figure 1. In this study, the OC is solved for the following 3 different purposes:

Case A: Voltage deviation (VD) optimization.

$$\min F(x,u) = \min VD(x,u) = \min \sum_{i=1}^{NL} \left| V_i - V_i^{ref} \right| \quad (31)$$

Case B: Total power loss (Plosses) optimization.

$$\min F(x,u) = \min P_{loss}(x,u) = \min \sum_{i=1}^{NB} R_i I_i^2 \quad (32)$$

Case C: simultaneous optimization (VD+Ploss).

$$\min F(x,u) = \min \{ w_V . VD(x,u) + w_p . P_{loss}(x,u) \} \quad (33)$$

w_i are the weighting factors. The objective functions results for the three cases are presented in Figures 12-14 The optimal control variable for all cases are shown in table 2. The bus voltages, the optimal DGs voltage, the active and reactive powers of DGs are shown in Figures 15-18, respectively.

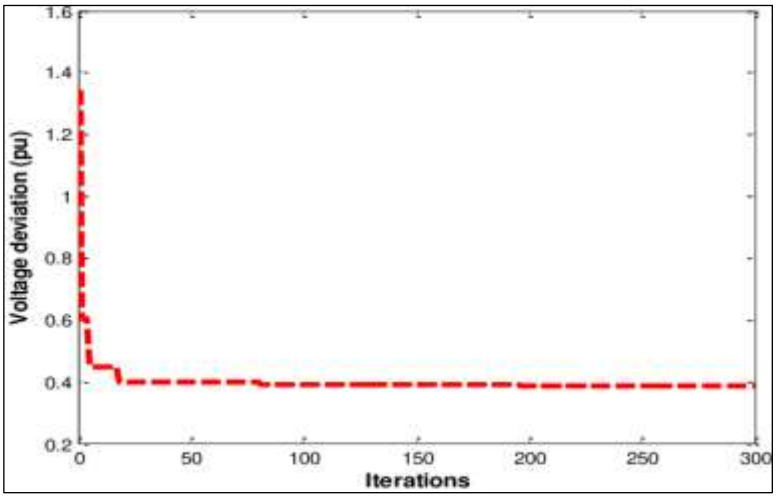

Figure 12: Results of case 1.
Source: Authors, (2025).

As a results of the voltages at bus 4, 7, 11, 19, and 23 being maintained at predetermined levels to reduce VD throughout the rest of the network, there are high reactive power compensation (QC) values and a wide range of reactive power variations of the DG, QDG, in the first scenario. Reactive power compensation is intimately related to voltage control. The active and reactive powers losses in the lines acquired for the prior situations are displayed in Figure 16.

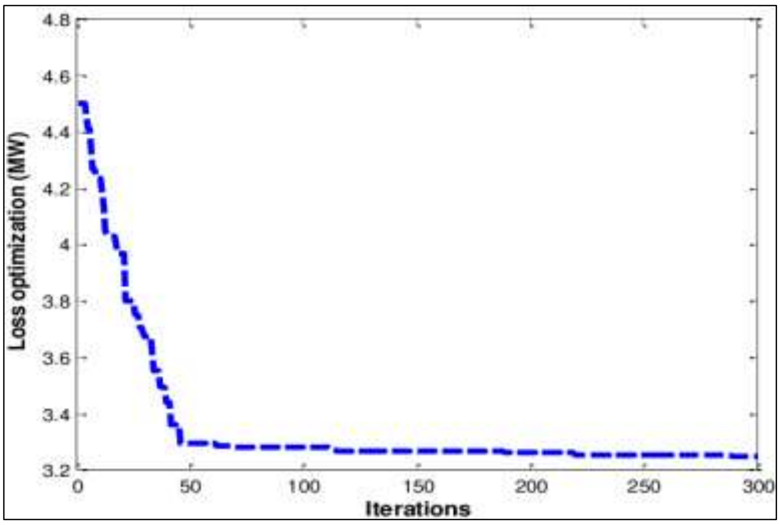

Figure 13: Results of case 2.
Source: Authors, (2025).

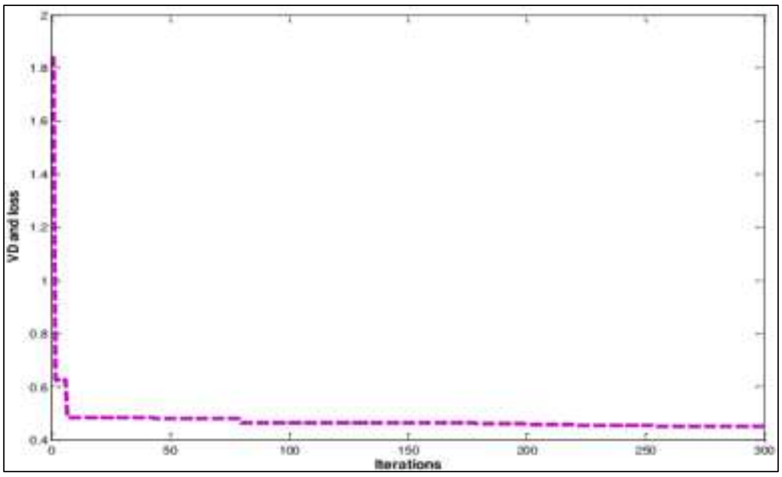

Figure 14: Results of case 3.
Source: Authors, (2025).

High values for V0 and V_{DG}, obtained throughout the whole load range in the second scenario. In fact, a constant active and reactive power model (PQ model) has been used to represent the loads. Considering that power losses are inversely correlated with branch current squared. By enhancing the voltage bus using DG, power losses for a constant power load can be reduced. As illustrated in Figure 11, case C can be viewed as a middle-ground option because it simultaneously lowers power losses and VDs.

Table 2: Control variables for all cases using GWO.

Control variables	Case 1	Case 2	Case 3
PG_4	0.2304	0.2304	0.2300
PG_7	0.1468	0.2539	0.2031
PG_{11}	0.1588	0.1588	0.1580
PG_{19}	0.1501	0.3690	0.2482
PG_{23}	0.2458	0.3000	0.0793
$P_{Utility}$	0.5401	0.3433	0.3810
$V_{Utility}$	1.0061	1.0491	1.0060
V_{23}	1.0437	1.0314	1.0274
Q_{com21}	0.1774	0.1611	0.1389
Q_{com24}	0.1140	0.0947	0.1050
T_{5-6}	0.9815	0.9971	0.9810
T_{12-13}	0.9532	1.0084	0.9510
Cost ($/h)	141.25	143.77	144.10
Losses (MW)	5.5820	3.2480	6.0460
VD (pu)	0.3858	0.8871	0.3894
CPU time (s)	136.00	154.09	144.30

Source: Authors, (2025).

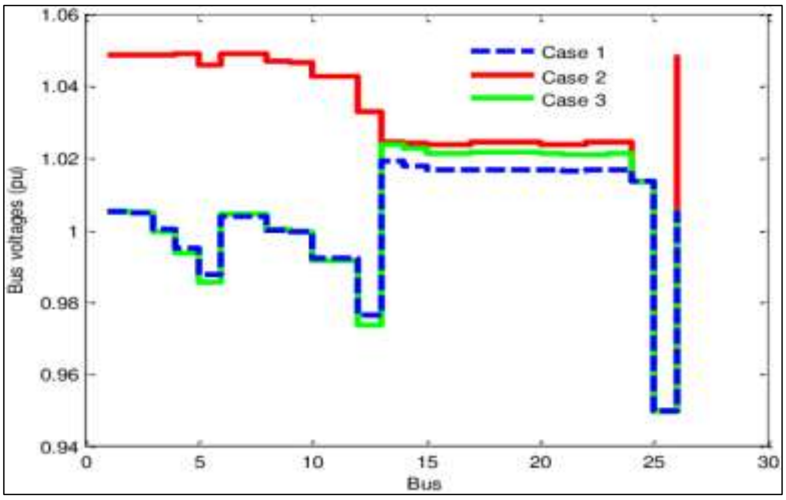

Figure 15: Bus voltages of three cases.
Source: Authors, (2025).

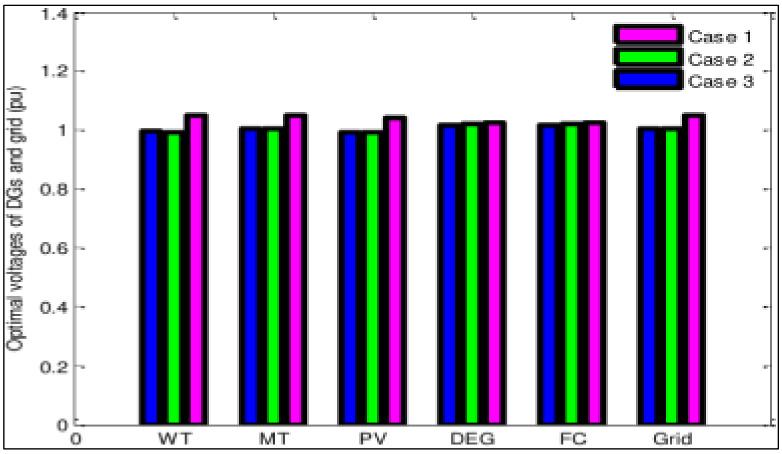

Figure 16: DG and grid optimal voltages.
Source: Authors, (2025).

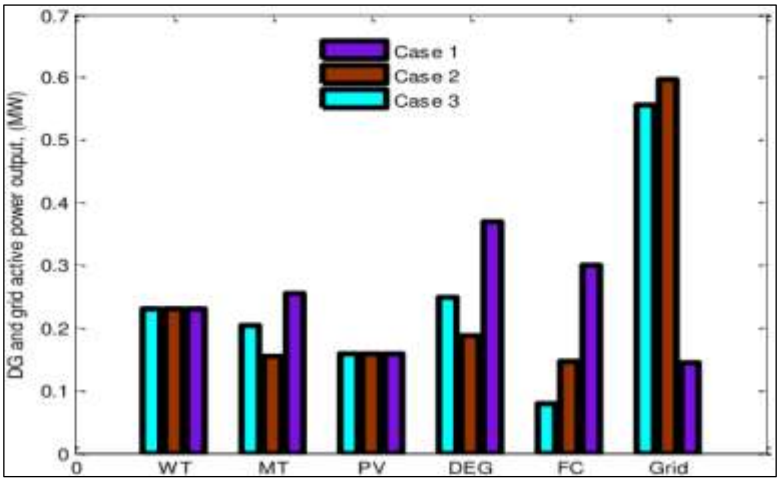

Figure 17: DG and grid active power output.
Source: Authors, (2025).

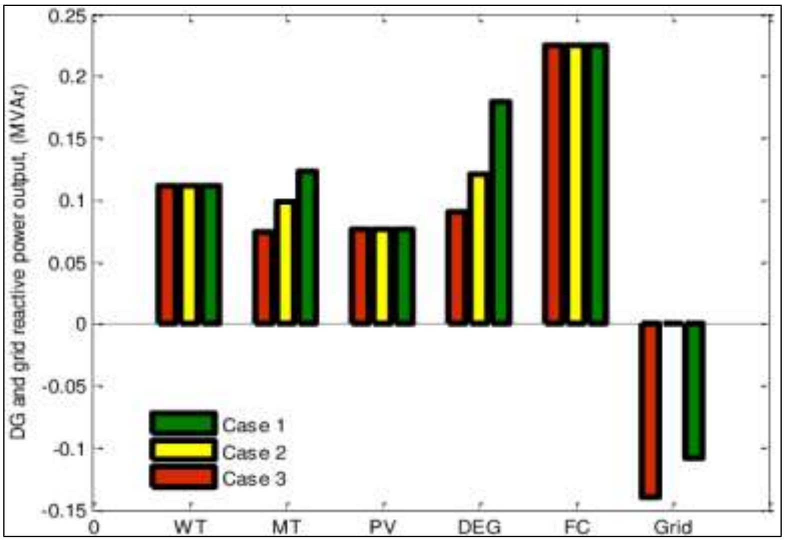

Figure 18: DG and grid reactive power output.
Source: Authors, (2025).

The second section of this study demonstrate how well the GWO approach works to address the OC in MG. Consequently, the aforementioned findings demonstrate the improved capacity of the GWO algorithm to produce solutions of the highest calibre while maintaining computational efficiency and robustness.

The simulation results presented in this paper show that the GWO method is very suitable to solve the EMO and OC problems of MG. Therefore, in a computationally efficient and robust manner, the above results establish the enhanced ability of GWO algorithm to achieve superior quality solutions.

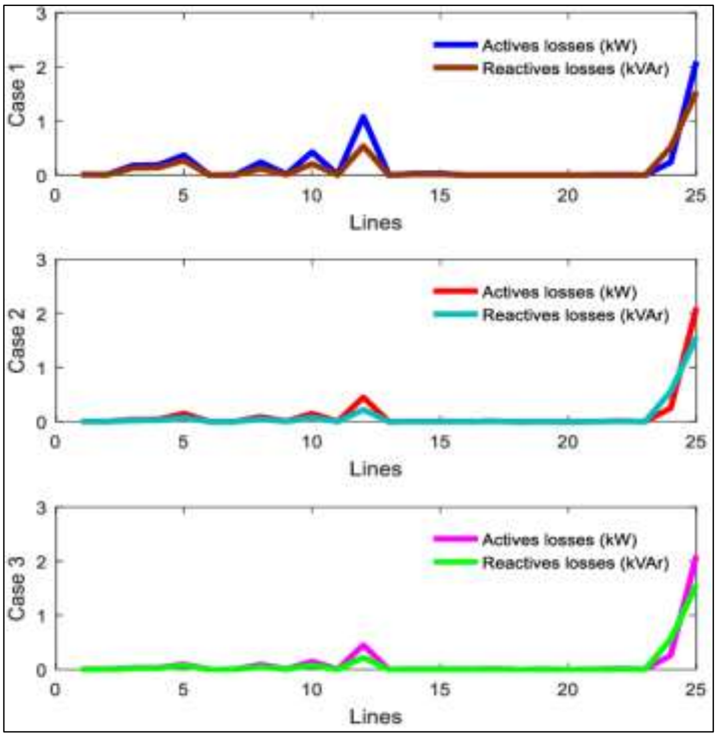

Figure 19: Active and reactive power losses.
Source: Authors, (2025).

V. CONCLUSION

Based on the nature-inspired approaches, this study offers a successful solution to an MG's challenges. The GWO method successfully applied to solve the EMO and OC problems of a MG. The suggested method has been investigated and tested on an MG that is connected various DG units via an ESS. The outcomes of the simulation demonstrate how well the suggested strategy works to address EMO and OC in various operating scenarios. Moreover, the obtained results using GWO are either better or comparable to those obtained by other technique reported in the literature. In terms of the computational effort, convergence speed and performance of the solutions reveal the superiority of GWO algorithm.

VI. AUTHOR’S CONTRIBUTION

Conceptualization: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Methodology: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Investigation: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Discussion of results: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Writing – Original Draft: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Writing – Review and Editing: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Resources: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Supervision: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.
Approval of the final text: Nabil Mezhoud, Ahmed Bahri , Bilel Ayachi, Farouk Boukhenoufa and Lakhdar Bouras.

VII. REFERENCES

[1] Farhangi, H. (2010). The path of the smart grid, IEEE power and energy magazine, 8(1), 18–28. doi:10.1109/MPE.2009.934876.

[2] Zia, M. F., Elbouchikhi, E., Benbouzid, M., & Guerrero, J. M. (2019). Energy management system for an islanded microgrid with convex relaxation, *IEEE Transactions on Industry Applications*, 55(6), 7175-7185. doi:10.1109/TIA.2019.2917357.

[3] Wu, H., Li, H., & Gu, X. (2020). Optimal energy management for microgrids considering uncertainties in renewable energy generation and load demand, *Processes*, 8(9), 1086. doi:10.3390/pr8091086.

[4] Jiayi, H., Chuanwen, J., & Rong, X. (2008). A review on distributed energy resources and microgrid, Renewable and Sustainable Energy Reviews, 12(9), 2472–2483. doi.org/10.1016/j.rser.2007.06.004.

[5] Mohamed, F. A., & Koivo, H. N. (2012). Online management genetic algorithms of microgrid for residential application, *Energy Conversion and Management*, 64, 562–568. doi:10.1016/j.enconman.2012.06.010.

[6] Chen, C., Duan, S., Cai, T., Liu, B., & Hu, G. (2011). Smart energy management system for optimal microgrid economic operation, IET renewable power generation, 5(3), 258–267. doi:10.1049/iet-rpg.2010.0052.

[7] Radosavljevic´, J., Jevtic´, M., & Klimenta, D. (2016). Energy and operation management of a microgrid using particle swarm Optimization, Engineering Optimization, 48(5), 811–830. doi:10.1080/0305215X.2015.1057135.

[8] Lopes, J. A. P., Moreira, C. L., & Madureira, A. G. (2006). Defining control strategies for microgrids islanded operation, IEEE Transactions on power systems, 21(2), 916–924. doi: 10.1109/TPWRS.2006.873018.

[9] Hatziargyriou N. D., Anastasiadis A. G., Tsikalakis, A. G., & Vasiljevska, J. (2011). Quantification of economic, environmental and operational benefits due to significant penetration of microgrids in a typical LV and MV Greek network, European Transaction on Electrical Power, 21(2), 1217–1237. doi:10.1002/etep.392.

[10] Tsikalakis A. G., & Hatziargyriou N. D. (2007). Centralized control for optimizing microgrids operation, *IEEE Transactions on Energy Conversion*, 23(1), 241–248. doi:10.1109/TEC.2007.914686.

[11] Ustun, T. S., Ozansoy, C., & Zayegh, A. (2011). Recent developments in microgrids and example cases around the world—a review, *Renewable and Sustainable Energy Reviews*, 15(8), 4030–4041. doi:10.1016/j.rser.2011.07.033.

[12] Radosavljevic´, J., Jevtic´, M., Klimenta, D., & Arsić N. (2015). Optimal power flow for distribution networks with distributed generation, *Serbian Journal of Electrical Engineering*, 12(2), 145–170. doi:10.2298/SJEE1502145R.

[13] Saleh, A. H., & Afta, A. O. (2024). Analytical review study of the Grid connected Micro grid Energy Management system, *Fifth International Scientific Conference of Alkafeel University (ISCKU 2024)*, 97. doi.org/10.1051/bioconf/20249700066.

[14] Sanjari, M. J., & Karami H. N. (2020). Analytical approach to online optimal control strategy of energy storage devices in energy system, *Journal of Energy Storage*, 29, doi.org/10.1016/j.est.2020.101328.

[15] Tenfen, D., & Finardi, E. C. (2014). A mixed integer linear programming model for the energy management problem of microgrids, *Electric Power Systems Research*, 122, 19–28. doi:10.1016/j.epsr.2014.12.019.

[16] Anthony R. (2021). Energy management of microgrids: from a mixed-integer linear programming problem to a rule-based real-time algorithm, 7th Annual Conference of the IEEE Industrial Electronics Society, Oct 2021, Toronto, Canada. 1-6, doi:10.1109/IECON48115.2021.9589438.

[17] Sarda J. S., Lee K., Patel, H., Patel, N., Patel, Dh. (2022). Energy Management System of Microgrid using Optimization Approach, IFAC-PapersOnLine, 55(9), 280-284. doi.org/10.1016/j.ifacol.2022.07.049.

[18] Mohamed, F. A., & Koivo, H. N. (2009). System modelling and online optimal management of microgrid using mesh adaptive direct search, International Journal of Electrical Power & Energy Systems,. 32(5), 398–407. doi:10.1016/j.ijepes.2009.11.003.

[19] Kuznetsova, E., Ruiz, C., Li, Y. F., & Zio, E. (2015). Analysis of robust optimization for decentralized microgrid energy management under uncertainty, International Journal of Electrical Power and Energy Systems, 815–832. doi:10.1016/j.ijepes.2014.07.064.

[20] Arabali, A., Ghofrani, M., Amoli, M., Etezadi, F. M. S., & Baghzouz, Y. (2013). Genetic-algorithm-based optimization approach for energy management, IEEE Transactions on Power Delivery, 28(1), 162–170. doi:10.1109/TPWRD.2012.2219598.

[21] Fong, K. F., Hanby, V. I., & Chow, T. T. (2006). HVAC system optimization for energy management by evolutionary programming, Energy and Buildings, 38(3), 220-231. doi:10.1016/j.enbuild.2005.05.008.

[22] Bentouati, B., Khelifi, A., Shaheen, A. M., & El-Sehiemy, R. A. (2020). An enhanced moth-swarm algorithm for efficient energy management based multi dimensions optimal power flow problem, Journal of Ambient Intelligence and Humanized Computing, 12(1), 9499-9519. doi: 10.1007/s12652-020-02692-7.

[23] Mandal, S., & Mandal, K. (2020). Optimal energy management of microgrids under environmental constraints using chaos enhanced differential evolution, Renewable Energy Focus, 34, 129-141. doi:10.1016/j.ref.2020.05.002.

[24] Li, Y., Mohammed, S. Q., Saman, G., Aljojo, N. (2020). Energy Management of Microgrid considering Renewable Energy Sources and Electric Vehicles using Backtracking Search Optimization Algorithm, *Journal of Energy Resources Technology*, Transactions of the ASME, vil. 142(5), 1-18. doi:10.1115/1.4046098.

[25] Nikmehr, N., & Ravadanegh, S. N. (2014). Optimal operation of distributed generations in micro-grids under uncertainties in load and renewable power generation using heuristic algorithm, *IET Renewable Power Generation*, 9(8), 882–890. doi:10.1049/iet-rpg.2014.0357.

[26] Zhang, Z. Cheng, X., Xing, Z., & Wang, Z. (2024). Energy management strategy optimization for hybrid energy storage system of tram based on competitive particle swarm algorithms, *Journal of Energy Storage*, 75. doi.org/10.1016/j.est.2023.109698.

[27] Marzband, M., Azarinejadian, F., Savaghebi, M., & Guerrero, J. M. (2015). An Optimal Energy Management System for Islanded Microgrids Based on Multiperiod Artificial Bee Colony Combined With Markov Chain, IEEE Systems Journal, 11(3). doı**:**10.1109/JSYST.2015.2422253.

[28] Kamarposhti, M A., Colak I., & Eguchi, K. (2021). Optimal energy management of distributed generation in micro-grids using artificial bee colony algorithm, *National Center for Biotechnology Information advances science and health,* 18(6), 7402-7418. doi:10.3934/mbe.2021366.

[29] Moghaddam, A. A., Seifi, A., Niknam, T., & Pahlavan M. R. A. (2011). Multi-objective operation management of a renewable MG (micro-grid) with back-up micro-turbine/fuel cell/battery hybrid power source, Energy, 36(x), 6490–6507. doi:10.1016/j.energy.2011.09.017.

[30] Esmat, A., Magdy, A., ElKhattam, W., & ElBakly, A. M. (2013). A novel Energy Management System using Ant Colony Optimization for micro-grids, 3rd International Conference on Electric Power and Energy Conversion Systems (EPECS), doi:10.1109/EPECS.2013.6713023.

[31] Kamarposhti, M. A., Shokouhandeh, H., Lee, Y., Kang, S. K., Colak, I., & Barhoumi, E. M. (2024). Optimizing energy management in microgrids with ant colony optimization: enhancing reliability and cost efficiency for sustainable energy systems. *International Journal of Low-Carbon Technologies*, 19(2024), 2848–2856. https://doi.org/10.1093/ijlct/ctae230.

[32] Nimma, K. S., Al-Falahi, M. D. A., Nguyen, H. D., Jayasinghe, S. D. G., Mahmoud, T. S. & Negnevitsky M. (2022). Grey wolf optimization-based optimum energy-management and battery-sizing method for Grid-Connected Microgrids, *Energies*, 11(4), 847-864. doi:10.3390/en11040847.

[33] Alsmadi, Y. M., Abdel-hamed, A. M., Ellissy, A. E., El-Wakeel, A. S., Abdelaziz A. Y., Utkin, V., Uppal, A. A. (2019). Optimal configuration and energy management scheme of an isolated micro-grid using Cuckoo search optimization algorithm, *Journal of the Franklin Institute*, 356, 4191-4214. doi:10.1016/j.jfranklin.2018.12.014.

[34] Roy, K. Mandal, K. K., & Mandal, A. Ch. (2019). Ant-Lion Optimizer algorithm and recurrent neural network for energy management of micro grid connected system, *Energy*, 167, 402-416. doi.org/10.1016/j.energy.2018.10.153.

[35] Ocaña, B. H., Torruco, J. H., Bosquez, O. C., Yáñez, M. B. C., & Flores, O. A. P. (2019). Bacterial foraging-based algorithm for optimizing the power generation of an isolated microgrid, *Applied Sciences*, 9(6), 1261. doi:10.3390/app9061261.

[36] Hasan, W. A., Abed, I. A., & Shary, D. K. (2021). Energy Management Optimization of Generators using Modified Firefly Algorithm, 2nd International Multi-Disciplinary Conference: Integrated Sciences and Technologies, IMDC-IST, 7-9, Sakarya, Turkey, September 2021, doi:10.4108/eai.7-9-2021.2314839.

[37] Mezhoud, N. (2023). Multi-objective Optimal Power Flow and Emission Index Based Firefly Algorithm, Periodica Polytechnica Electrical Engineering and Computer Science, 67(2), 172-180. doi:10.3311/PPee.20922.

[38] Rafi, A. M., Ali, M., Ismail, M. Hossain, Al-Sulaiman, F. A., & Shafiullah, M. (2022). Whale Optimization Algorithm for Community Microgrid Energy Scheduling, Saudi Arabia Smart Grid (SASG), doı:10.1109/SASG57022.2022.10200591.

[39] Lodhi, E., Wang, F. Y., Xiong, Gang, Mallah, G. A., Javed, M. Y., Tamir, T. S., & Gao, D. W. (2021). Dragonfly Optimization Algorithm for Extracting Maximum Power of Grid-Interfaced PV Systems, *Sustainability, 13(*19*)*. doi.org/10.3390/su131910778.

[40] Christopher, S. J. B., & Mabel, M. C. (2020). A bio-inspired approach for probabilistic energy management of micro-grid incorporating uncertainty in statistical cost estimation, Energy, 203. doi.org/10.1016/j.energy.2020.117810.
[41] Christopher, S. J. B. (2010) Optimal energy management in a microgrid incorporating demand response using modified glowworm swarm algorithm

[42] Zhang, Y. Liu, P., & Li, Y. (2024). Implementation of an Enhanced Crayfish Optimization Algorithm. *Biomimetics*, *9*(6), 341. https://doi.org/10.3390/biomimetics9060341.

[43] Kommula, B. N., Song, H., Chen, L., & Xu, Ch. (2021). Efficient energy management of hybrid renewable energy sources-based smart-grid system using a hybrid IDEA-CFA technique, *International Transactions on Electrical Energy Systems*, 31(1), https://doi.org/10.1002/2050-7038.12833.

[44] Sun, Y., Wang, X., Gao, L., Yang, H., Zhang, K., Ji, B., & Zhang, H. (2024) Multi-Objective Optimal Scheduling for Microgrids—Improved Goose Algorithm. *Energies*, 17(24), 6376. https://doi.org/10.3390/en17246376.

[45] Peng, L., Weina, X., Zeyuan, Z., & Rui, Li. (2013). Optimized operation of microgrid based on gravitational search algorithm, *Proceedings of International Conference on Electrical Machines and Systems*, Busan, Korea, 338–342, doi:10.1109/ICEMS.2013.6754475.

[46] Mezhoud, N., & Amarouayache, M. (2023). Multi-objective optimal power flow based combined non-convex economic dispatch with valve-point effects and emission using gravitation search algorithm, *Journal of Applied Research in Electrical Engineering*, 1(2), 26-36. doi:10.22055/jaree.2022.40549.1055.

[47] Mezhoud, N., Bahri, A., & Ayachi, B. (2024). Wind Driven Optimization Based Optimal Energy Management of Microgrid Impregnated With Renewable Energy Sources, Algerian Journal of Renewable Energy and Sustainable Development, 5(2), 202-218. https://asjp.cerist.dz/en/article/238715.

[48] Kamel, F. Al-Gazzar, M. M., & Mehanna, M. A. (2022). Energy management in smart inter-connected micro-grids using archimedes optimization algorithm. *Research Square*. https://doi.org/10.21203/rs.3.rs-2214046/v1.

[49] Debata, S., Samanta, C. K., & Panigrahi, S. P. (2013). Efficient energy management strategies for hybrid electric vehicles using shuffled frog-leaping algorithm, International Journal of Sustainable Engineering, 8(2), 1-7. doi:10.1080/19397038.2014.919363.

[50] Sadeghi, A. R., M. & Agha, J. (2018) Modified imperialist competitive algorithm for environmental constrained energy management of microgrids, *Journal of Cleaner Production*, 20, 273-292. doi:10.1016/j.jclepro.2018.08.129.

[51] Kaveh A., & Mahdavi, V. R. (2014). Colliding bodies optimization: A novel meta-heuristic method, Computers & Structures, 139, 18-27. doi.org/10.1016/j.compstruc.2014.04.005.

[52] Krishna, R., & Hemamalini, S. (2022). Optimal Energy Management of Virtual Power Plants with Storage Devices Using Teaching-and-Learning-Based Optimization Algorithm, International Transactions on Electrical Energy Systems, 1-17. doi:10.1155/2022/1727524.

[53] Lazar, E., Ignat, A., Petreus D., & Etz, R. (2018). Energy management for an islanded microgrid based on harmony search algorithm, 41st International Spring Seminar on Electronics Technology (ISSE), 16-20. doi:10.1109/ISSE.2018.8443673.

[54] Hussain, I, Ullah, I., Ramar, R., & Tanzila T. (2022). Smart energy management system for university campus using sine-cosine optimization algorithm, International Virtual Conference on Power Engineering Computing and Control: Developments in Electric Vehicles and Energy Sector for Sustainable Future (PECCON), 05-06, doi:10.1109/PECCON55017.2022.9851066.

[55] Toughzaoui, Y., Obeid, H., Petrone, R., Louahlia, H., & Gualous H. (2022). System Sizing and Energy Management Optimization using a Hybrid Model. 10th International Conference on Systems and Control (ICSC), 23-25/11, 2022. doi:10.1109/ICSC57768.2022.9993857.

[56] Moradi, M. H., & Abedini, M. A. (2012). Combination of genetic Algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems", Electrical Power and Energy Systems, 34(1), 66–74. doi.org/10.1016/j.ijepes.2011.08.023.

[57] Kouba, N. E. Y., Sadoud, S. (2021). Optimal Energy Management of Hybrid MicroGrid Using Storage System and Fuzzy-GA Method, Journal of Renewable Energies ICREATA'21 Adrar (2021),129–141. doi:https://doi.org/10.54966/jreen.v1i1.1049.

[58] Kumar, M. J., Sampradeepraj, T., Sivajothi, E., & Singh, G. (2024). An efficient hybrid technique for energy management system with renewable energy system and energy storage system in smart grid. *Energy,* 306(15), 13245. https://doi.org/10.1016/j.energy.2024.132454

[59] Ullah Z., Qazi H. S., Alferidi A., Alsolami M., Lami B., & Hasanien H. M. (2024). Optimal energy trading in cooperative microgrids considering hybrid renewable energy systems, *Alexandria Engineering Journal, 86(1),* 23-33, https://doi.org/10.1016/j.aej.2023.11.052.

[60] Sireesha R., Coppisetty, S. R., & Kumar, M. V. (2023). Hybrid optimization to enhance power system reliability using GA, GWO, and PSO, *Paladyn, Journal of Behavioral Robotics*, 14, https://doi.org/10.1515/pjbr-2022-0119.

[61] Kamel F., Mehanna, M. A., & Al-Gazzar M. M. (2023). Energy management in smart inter-connected micro-grids using a hybrid sperm swarm optimization and gravitational search algorithm, *Journal of Al-Azhar University Engineering Sector*, 18(66), 98-115. 10.21608/auej.2023.283030.

[62] Haneef Ullah, H., Khan, M. Hussain I., Ullah, I., Uthansakul, P., & Khan, N. (2021). An Optimal Energy Management System for University Campus Using the Hybrid Firefly Lion Algorithm (FLA), *Energy***,** 14(19), 6028. https://doi.org/10.3390/en14196028.

[63] Lakshmi, G. V. N., Jayalaxmi, A., & Veeramsetty, V. (2021). Optimal Placement of Distribution Generation in Radial Distribution System Using Hybrid Genetic Dragonfly Algorithm, Technology and Economics of Smart Grids and Sustainable Energy, 6(9), 1-13. doi.org/10.1007/s40866-021-00107-w.

[64] Javaid, N., Javaid, S., Abdul, W., Ahmed, I., Almogren, A., Alamriand, A., & Niaz I. A. (2017). A hybrid genetic wind driven heuristic optimization algorithm for demand side management in smart grid, Energies, 10(3), 319-346. doi:10.3390/en10030319.

[65] Tan, W. S., Hassan, M. Y., Abdul Rahman, H., Abdullah, M., Pauzi & F. Hussin, (2013). Multi-distributed generation planning using hybrid particle swarm optimization-gravitational search algorithm including voltage rise issue. *IET Generation, Transmission & Distributio*n, 7(9), 929–942. doi.org/10.1049/iet-gtd.2013.0050.

[66] Alyu, A. B., Salau, A. O., Khan, B. & Eneh, J. N. (2023). Hybrid GWO-PSO based optimal placement and sizing of multiple PV-DG units for power loss reduction and voltage profile improvement, *Scientific Reports*, 13(x). doi.org/10.1038/s41598-023-4057-3

[67] Kefayat, M., Ara, A. L., & Niaki, S. A. N. (2015). A hybrid of ant colony optimization and artificial bee colony algorithm for probabilistic optimal placement and sizing of distributed energy resources, Energy Conversion and Management, 92(1), 149–146. doi.org/10.1016/j.enconman.2014.12.037.

[68] Radosavljević, J. (2018). Metaheuristic optimization in power engineering, The Institution of Engineering and Technology, *Michael Faraday House*, Six Hills Way, Stevenage, Herts, SG1 2AY, United Kingdom, doi:10.1049/PBPO131E.

[69] Zhang, Y., Gatsis, N., & Giannakis, G. B. (2013). Robust energy management for microgrids with high-penetration renewable, IEEE Transactions on Sustainable Energy, 4(4), 944-953. doi:10.1109/TSTE.2013.2255135.

[70] Wu H., Liu, X., & Ding, M. (2014). Dynamic economic dispatch of a microgrid: Mathematical Models and Solution Algorithm, *International Journal of Electrical Power and Energy Systems*, 63, 336–346. doi:10.1016/j.ijepes.2014.06.002.

[71] Azmy, A. M., & Erlich, I. (2005). Online optimal management of PEM fuel cells using neural networks", IEEE Transactions on Power Delivery, 20(2), 1051–1058. doi:10.1109/PES.2005.1489132.

[72] Campanari, S., & Macchi, E. (2004). Technical and tariff scenarios effect on microturbine trigenerative applications", Journal of Engineering for Gas Turbines and Power, 126(3), 581–589. doi.org/10.1115/1.1762904.

[73] Barbir, F., & Gómez, T. (1997). Efficiency and economics of proton exchange membrane (PEM) fuel cells. International Journal of Hydrogen Energy, 22(10/11), 1027–1037. doi.org/10.1016/S0360-3199(96)00175-9.

[74] Villanueva, D. Pazos J. L., & Feijo, A., (2011). Probabilistic load flow including wind power generation. *IEEE Transactions on Power Systems*, 26(3), 1659–1667. doı:10.1109/TPWRS.2010.2096436.

[75] Atwa Y. M., El-Saadany, E. F., Salama, M. M. A., Seethapathy, R., Assam, M., & Conti, S. (2011). Adequacy evaluation of distribution system including wind/solar DG during different modes of operation, IEEE Transactions on Power Systems, 26(4), 1945–1952. doi:10.1109/TPWRS.2011.2112783.

[76] Tiwari, G. N., & Dubey, S. (2009). Fundamentals of photovoltaic modules and their applications, *London: RSC Energy Series Cambridge, ebook collection*, ECCC Environmental eBooks 1968-2022, 424. doi.org/10.1039/9781849730952.

[77] Mirjalili S., Mirjalili, S. M., & Lewis, A. (2014). Grey Wolf Optimizer, Advances in Engineering Software, 69, 46-61. doi.org/10.1016/j.advengsoft.2013.12.007.

[78] K. S. Kadali, et al. "Environmentally Sustainable Economic Dispatch using Grey Wolves Optimization", ARPN Journal of Engineering and Applied Sciences, vol. 13, No. 6, pp. 2068-2079, 2018.

[79] Pradhan, M., Roy, P. K., & Pal, T. (2016). Grey Wolf Optimization Applied to Economic Load Dispatch Problems, *Electrical Power and Energy Systems*, 83, 325-334. doi.org/10.1016/j.ijepes.2016.04.034.

[80] Sharma, S., Bhattacharjee, S., & Bhattacharya, A. (2015). Grey wolf optimization for optimal sizing of battery energy storage device to minimize operation cost of microgrid, IET Generation, Transmission and Distribution: Optimal Utilization of Storage Systems in Transmission and Distribution Systems, *The Institution of Engineering and Technology*, 10(3), 625-637. doi.org/10.1049/iet-gtd.2015.0429.

[81] Sultana, U., Khairuddin, A. B., Mokhtar, A. S., Zareen, N., & Sultana B. (2016). Grey wolf optimizer based placement and sizing of multiple distributed generation in the distribution system, *Energy*, 111, 525-536. doi.org/10.1016/j.energy.2016.05.128.