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Energy management system on multi-Microgrid system using Metaheuristic Algorithms

Dr.M. Sri Suresh[1], A. Sai Pranav Reddy[2], B. Prem Kumar[3], P. Ganesh[4]
[1,2,3,4]Department of Electrical and Electronics Engineering Chaitanya Bharathi institute of technology Hyderabad, Telangana, India

Abstract: The escalating environmental pollution have become major issues that require novel and eco-friendly methods. Integration of renewable energy is one of the possible solutions. resources (RERs) and effective energy. management strategies. Energy management aims at minimizing. and as well as operating, maintenance and generation costs. enhancing system performance by means of methods like minimization of power losses, stability improvement, and emission. reduction. In this respect, the energy management of microgrids has played out to be a major concern in the modern. power systems. An optimization is presented in this paper. model of a multi-objective problem of a renewable. Multi-microgrid (MMG) system is based on energy. The system consisting of three interconnected microgrids, all equipped. and wind turbines (WT) and photovoltaic (PV) panels, became part of the IEEE 33-bus distribution system. The model takes into consideration the variation in PV and WT output, load Sporadic demand, and real-time prices of electricity. Three objective functions are designed in a way that they reduce the overall. cost/year, deviation of voltage, and voltage stability index- developing a cost-performance multi-objective collectively. optimization problem. With the assistance of the, the issue is considered. Particle Swarm Optimization (PSO) algorithm, both with and and without RERs.. Additionally, a comparative analysis is conducted using two other optimization techniques: Mountain Gazelle Optimization (MGO) and Gorilla Troop Optimization (GTO). Simulation results demonstrate that the proposed approach significantly reduces system costs and enhances overall performance.

Keywords: Fake news detection, machine learning, deep learning, ensemble learning, social media analytics, TF-IDF.

I. Introduction

A microgrid shows a local power network that combines energy resources like photovoltaic cells, micro turbines and battery energy storage systems with given loads within the specifically defined limits. The microgrid can operate in both grid connected and islanded mode during interruptions in the main grid supply. Microgrids enhance reliability, renewable energy integration and overall system efficiency in today’s power management systems. A microgrids contain following components like solar PV modules, wind turbines, diesel generators and battery systems, these are classified as Distributed energy resources which means a small-scale generation or storage unit. DERs generally work with distribution network which reduce transmission line losses, improve reliability, renewable energy integration and give improved flexibility to meet local demands.

This flexibility allows microgrids to transfer efficient energy supply locally even during grid outages. Anyway, the unstable nature of renewable resources such as solar irradiation and wind speed creates disturbances in power generation creating instability and safe grid operation. Therefore, assuring reliable, efficient and economically feasible operation. As microgrids mainly depends on wind and solar which are uncertain proper control and management methods are important to ensure system stability, resource utilization , minimal costs and emissions.

It also allows smooth conversion from grid connected mode to islanded mode, ensuring continuous power supply. Multi objective optimisation becomes essential in multi microgrid (MMG) systems since these systems contain conflicting goals which need to be solved together. For example, reducing operating cost may conflict with reducing emissions and increasing renewable utilization may impact reliability and power quality. A multi objective mechanism which help decision makers to examine the trade offs and determine efficient solutions that consider environmental, economic and technical goals simultaneously. In MMG systems this approach improves cooperation between sustainability and operational performance.

Managing energy in multi-microgrid (MMG) systems is tricky because each microgrid has its own unique setup—different power demands, generation capacities, and operating methods. Coordinating them all together creates challenges. On top of that, renewable sources like solar and wind are unpredictable, and electricity demand changes constantly. The system also has to stay stable, figure out fair pricing and power sharing among the grids, and handle the complexity of communication between them.

1. To enhance the MMG system reliability, thereby considering uncertainties in wind speed, solar irradiation, load demand, energy prices, and BESS management, the ANFIS-based soft computing approach is implemented, which reduces the impact of scheduling discrepancies between generation and demand.
2. A 24 hour Day-ahead scheduling was implemented to reduce operational costs, enhance generation reliability, and maximize resource utilization by considering factors like energy prices, load demand, and uncertainties in renewable energy sources (RES).
3. A load management strategy was implemented, which is based on load-shifting techniques is applied to lower the operational costs of a multi-interconnected microgrid system during both grid-connected and islanded operating conditions.
4. Incorporating load growth and uncertainties in both DGs and loads into the planning and operational strategies to ensure effective DG deployment.

II. Multi- Microgrid System Modelling and Problem Formulation

In this section, the mathematical formulation is first introduced. Fig. 1 shows the interaction that occurs between the multi-microgrid structure and the distribution network. The DSO forms a link with the microgrids through which it shares its electricity selling prices, and in return the microgrids supply the required amount of power. The goal of coordinated microgrid energy management is to reduce the MMG's hourly power sharing profile using suitable trade-setting mechanisms.

Photovoltaic System Modelling:

The modelling of photovoltaic (PV) systems is essential for proper design, optimization, and performance evaluation of solar power installations. Accurate modelling helps ensure that PV systems satisfy the energy demand while lowering costs and improving efficiency. The power produced from these PV arrays is influenced by solar irradiation and can be determined using the following equation [21]:

$$P_{Solar} = K * P_{mSolar} * S_t / 1000 \qquad (1)$$

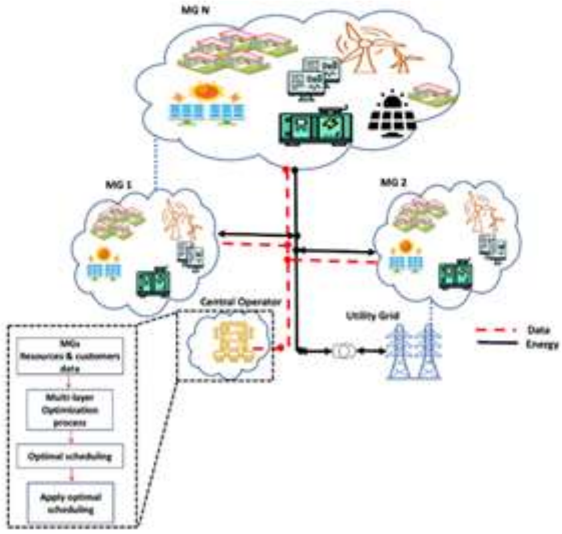

Fig.1 DSO price control for interconnected MG energy management

Where PSolar denotes the electrical power generated from photovoltaic panels, PmSolar specifies the output from each PV array when St=1000, St represents the solar irradiance incident on the panel surface, and K refers to the total number of photovoltaic modules

Modeling of Fuel Cell:

Fuel cell modeling involves analyzing and predicting the characteristics, performance, and efficiency of fuel cells under different operating conditions. Accurate modeling is essential to enhance their design, control strategies, and operational reliability, ensuring efficient integration within sustainable energy systems [22].

$$P_{Fuel-cell} = input\ power * \eta_{FC} \qquad (2)$$

Wind Turbine modeling:

Wind Turbine Modeling:

Wind turbine modelling helps in improving the structure of turbine and feasibility and enabling the effective combining wind energy into modern electric distribution grids. The entire efficiency of wind turbine depends on air density, rotor structure and wind speed conditions. Wind power is considered as an important renewable option due its robust availability around the world and low emissions. The wind turbine model equations are presented below.

$$P_{Wind} = \begin{cases} 0 & V \le V_{c-in},\ V \ge V_{c-off} \\ P_{Wmax} \times ((V\text{-}V_{c\text{-}in}) / (V_{rtd}\text{-}V_{c\text{-}in}))^3 & V_{c-in} \le V \le V_{rtd} \\ P_{rtd} & V_{rtd} \le V \le V_{c-off} \end{cases} \quad (3)$$

Where Vc-in is the cut-in speed, Vc-off the cut-off speed, V denotes wind speed, Vrtd the rated turbine speed, and Pwmax represents the maximum achievable power output.

Consideration of Load Growth:

This describes the prediction of increase in electrical consumption over a entire day within the defined power system or area, precise improvement of dynamic load models plays a crucial role in the planning and expansion of electrical networks so that future energy demands are full filled. Various factors like rising population and development of new industrial facilities. The “load growth coefficient” is just a number that shows how much electricity demand is expected to grow for each type of user (like homes, businesses, or industries) in a given year. Researchers use it to compare different categories and track changes over time, as explained in reference [24]. The duration of the respective load cycle in different years is evaluated based on this coefficient to determine progressive demand variations.

Where is the duration of load cycle at mth year, Cm is the growth in load coefficient, is the duration of load cycle at the initial year.

$$P_l^m = C_m * P_l^{initial} \quad (4)$$

Uncertainty modeling:

Uncertainty in distributed generation investigates the unpredictable variations and possible deviations associated with the behavior, output, and system integration of distributed energy resources. This includes evaluating uncertainties in generation output, fluctuations in load demand, and the effects of environmental factors. Understanding these variations is essential for effective planning, scheduling, and successful integration of DG into modern power systems. The output power prediction of PV and wind sources includes uncertainties arising from the variable characteristics of solar radiation and wind speed. Therefore, considering these uncertainties becomes necessary to enhance planning reliability and ensure optimum utilization of renewable resources. First, the radiation, wind characteristics, and load demand are predicted, and subsequently the generated power values are determined. However, deviations will always exist between predicted and actual values due to uncertain operational conditions as discussed in [25].

$$dP_w = 0.8 * \sqrt{P_{wind}} \quad (5)$$

$$dP_{PV} = 0.7 * \sqrt{P_{Solar}} \quad (6)$$

$$dP_L = 0.6 * \sqrt{P_L} \quad (7)$$

Battery Energy Storage System:

To determine the state of charge (SoC) of the battery in both charging and discharging modes, Eqs. (6) and (7) are applied as follows:

$$SoC(t+1) = SoC(t) + \eta_{charging}\left(\frac{P_b}{W_b}\right)\Delta t \qquad (8)$$

$$SoC(t-1) = SoC(t) + \frac{P_b}{\eta_{discharge} \times w_b}\Delta t \qquad (9)$$

$$P_{BESS} = P_{Solar} + P_{Wind} + P_{FC} - \frac{P_L}{\eta_{inv}} \qquad (10)$$

Loads

The load, which results from consumers' stochastic behavior, is one of the reasons of uncertainty in power networks. Typically, normal PDF is used to model load uncertainty in terms of Equation (22):

$$f_{P_{load}}\left(P_{load}\right) = \frac{1}{\sqrt{2\pi\sigma_{load}^2}}\exp\left[\frac{-\left(P_{load} - \eta_{load}\right)^2}{2\sigma_{load}^2}\right], P_{load} \geq 0 \qquad (11)$$

$f_{P_{load}}\left(P_{load}\right)$ denotes the Weibull probability density function –modeling of the load uncertainity, η_{load} gives the Converter efficiency, σ_{load} named as Standard deviation value, P_{load} represents the Load.

III. Implementation of Metaheuristic Algorithm Of Multi-Microgrid System

A. Metaheuristic Algorithm:

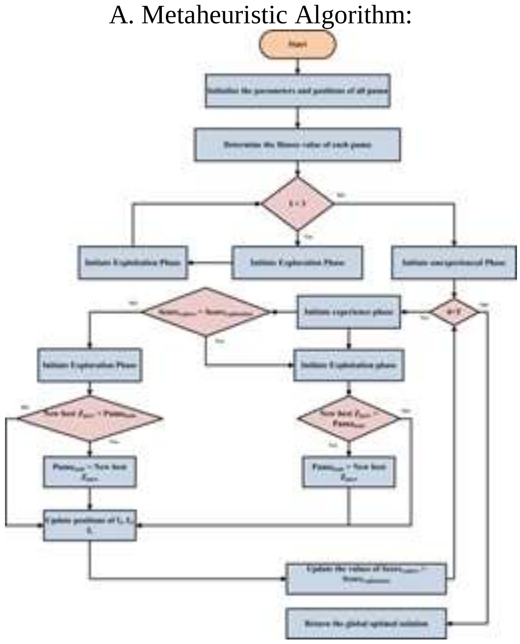

Fig.2 Flow Chart of Metaheuristic algorithm for MMG structure

Fig.2 demonstrates the operational process of the metaheuristic algorithm, which initially starts by assigning the control parameters and the initial positions of all pumas inside the entire search region, followed by computing their fitness values under the defined objective function. According to the iteration index variation, the algorithm shifts through four behavioral states—exploration, exploitation, unexperienced, and experienced—to maintain balance between global diversification and local refinement. In the initial stage (I<3), pumas mostly perform exploration to scan a wider region of the search area and simultaneously conduct exploitation to enhance and refine beneficial promising zones.

As the iteration number increases, the algorithm alternates between experienced and unexperienced phases, where experienced pumas utilize earlier derived knowledge for movement guidance, while unexperienced pumas explore unseen locations to preserve search diversity. The fitness of exploration and exploitation outcomes are compared, and the highest performing puma (male puma) is regularly updated whenever a superior enhanced solution (Zjnew) appears. During all iterations, the positions and fitness values of pumas are continuously updated to improve convergence toward the optimal global result. After satisfying the termination condition, the algorithm finally delivers the global best solution representing the most optimal output.

B. Proposed bi-layer energy management Framework:

In the proposed bi-layer energy management architecture, the local energy management layer is responsible for optimizing the operational performance of individual microgrids (MGs) using the Metaheuristic Algorithm. At this stage, each MG functions independently, aiming to minimize operational cost and maintain local energy balance by optimally scheduling distributed energy resources (DERs) such as photovoltaic generation, wind turbines, battery energy storage systems (ESS), and diesel generator units. The POA evaluates the fitness of each candidate solution by considering parameters such as fuel consumption, emission reduction, and reliability indices, while also ensuring that local operational constraints including power balance, capacity limitations, and state-of-charge (SoC) boundaries are satisfied.

After determining the optimal setpoints at the MG level, these optimal values are transferred to the global energy management layer, which is responsible for coordinating power exchange among interconnected MGs within the multi-microgrid (MMG) system. At this global supervisory layer, the algorithm is executed again to achieve system-level optimization by determining optimal energy trading schedules, tie-line power flows, and network reconfiguration policies that reduce overall MMG operational cost while enhancing resilience and system stability. The algorithm continuously updates the global best solution through iterative exploration and exploitation phases, ensuring effective cooperation among MGs even under varying renewable generation and dynamic load scenarios.

Exploitation phases, ensuring optimal coordination between MGs under varying load and renewable generation conditions. This hierarchical approach allows algorithm to efficiently balance local self-sufficiency with global cooperation, resulting in improved economic performance, reliability, and energy utilization across the entire MMG system.

C. Objective Function:

The proposed multi-objective EMS framework, integrated with a day-ahead scheduling strategy, aims to achieve these objectives. It efficiently addresses uncertainties stemming from the intermittent output of Renewable Energy Resources (RERs), dynamic load differences, and fluctuating electricity prices, thereby improving the scheduling performance of grid-connected microgrid operations. The core focus lies in assessing the trade-off between Energy Generation Cost (EGC) and Loss of Power Supply Probability (LPSP), while complying with DER operational constraints and maintaining overall system power balance.

The Total Present Worth (TPW) of the Multi-Microgrid was calculated using the following equation:

$$TPW = Solar_{Cost} + WT_{Cost} + FC_{Cost} + BESS_{Cost} + Power_{Cost}^{Purchase} - Power_{Cost}^{Sell} \quad (17)$$

Where NSolar, NWT, NFC are the number of solar modules, wind turbines, fuel cells respectively. SolarCost, WTCost, FCCost, BESSCost are the investment cost of Solar, Wind turbine, fuel cell, battery energy storage system respectively.

Simultaneously, the Energy Generation Cost (EGC) can be determined, representing the actual cost of producing energy from Distributed Energy Resources (DERs) and the utility grid. This calculation can be performed over short timeframes, such as daily, monthly, or annually, for short-term planning purposes, as presented in Eq.

$$Energy\ Generation\ Cost\ (EGC) = \frac{TPW}{\sum_{i=1}^{8760} P_L} * Capital\ Recovery\ Factor \quad (18)$$

This approach focuses on lowering both the Energy Generation Cost and the Probability of Power Supply Deficit (PPSD), as outlined in the related equations.

$$O.F_1 = Minimize\ (EGC) \quad (19)$$

The index of Probability of Power Supply Deficit (PPSD) can be evaluated as follows:

$$PPSD = \frac{P_L - \left\{P_{Solar} + P_{WT} + P_{FC} + P_{BESS} + P_{Buy} - P_{Sell}\right\}}{P_L} \quad (20)$$

$$O.F_2 = Minimize(PPSD) \quad (21)$$

$$Objective\ Function = Minimize\ (O.F_1, O.F_2) \quad (22)$$

Constraints:

$$P_{Solar}^{\min}(t) \le P_{Solar}(t) \le P_{Solar}^{\max}(t) \quad (23)$$

$$P_{WT}^{\min}(t) \le P_{WT}(t) \le P_{WT}^{\max}(t) \quad (24)$$

$$P_{FC}^{\min}(t) \le P_{FC}(t) \le P_{FC}^{\max}(t) \quad (25)$$

$$P_{BESS}^{\min}(t) \le P_{BESS}(t) \le P_{BESS}^{max}(t) \quad (26)$$

IV. Analysis of Simulation

The proposed Metaheuristic algorithm was used in Energy Management of microgrid system. The results are corresponding to the grid-connected mode with load management aiming to minimize the Energy Generation Cost (EGC) and %Probability of power supply deficit (PPSD) which are detailed discussed in below. The simulations are performed in the MATLAB environment on a Windows 10 system. The results are shown for the following case studies:

A scheduling approach for Multi-Microgrid Systems a day in advance that includes load management:
The integration of Distributed Energy Resources (DERs) and Renewable Energy Sources (RESs) within Multi-Microgrid (MMG) systems has introduced significant operational difficulties due to the intermittent and stochastic nature of efficient generation and the variability of demand load. To address these complexities, an effective Energy Management System (EMS) is essential to optimize the generation, storage, and distribution of energy within the interconnected microgrids. Incorporating Load Management (LM) strategies within the EMS framework further enhances system reliability and operational flexibility by enabling powerful control over demands of consunmers. Load management involves shifting, shedding, or rescheduling non-critical loads based on system conditions, price signals, or generation availability, thereby reducing peak demand, alleviating network stress, and improving the overall economic and operational efficiency of the MMG system.

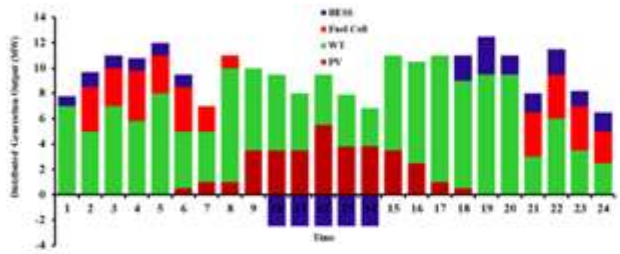

Fig 5.shows the coordinated power contribution of PV, Wind, Fuel Cell and BESS over 24 hours to balance and stabilize microgrid energy supply.

The Fig.5 This figure represents the distributed power generation output of a hybrid microgrid over a 24-hour period, where four different energy sources (PV, Wind Turbine, Fuel Cell, and Battery Energy Storage System) are supplying power according to availability and demand variations. The green color (Wind Turbine) contributes most of the generation throughout the day, indicating wind is the primary source in this system. The red portion (Fuel Cell) supports intermittently during different hours to balance the load whenever wind and solar supply are insufficient. During day time, especially between hours 10 to 14, the PV generation (light red) increases due to strong solar radiation, and since solar power is high during this interval, the BESS output (blue) becomes negative, which indicates charging mode. During early morning and night hours when PV is zero and wind gradually reduces, the battery discharges (positive BESS output) and supports the system to maintain stable power supply.

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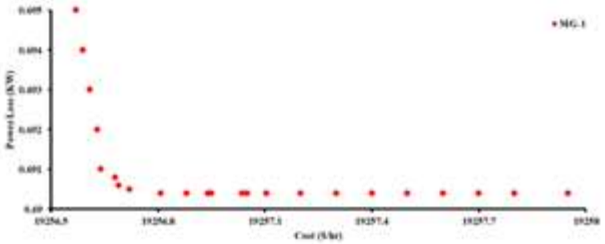

Fig.6 This graph shows that as the total operational cost of MG-1 decreases, the power loss also reduces and then becomes almost constant at an optimal point.

Fig.6.This figure represents the relationship between the total operational cost ($/hr) and the power loss (kW) in Microgrid-1 (MG-1). Each red point shows an evaluation result obtained from different optimization iterations or different scheduling solutions. At the left side of the graph, when the cost is higher, the power loss value is also high. As the optimization progresses and cost is reduced, the power loss rapidly decreases. After a certain point, both cost and power loss values reach a near-flat and stable region. This indicates the optimal operating point where minimum cost and minimum power loss are achieved simultaneously.

In simple terms, this graph proves that for MG-1, better scheduling and optimal resource allocation significantly reduce both power loss and cost, and after reaching optimal conditions, further improvement is not significantly possible. The curve gradually stabilizes showing the convergence of the optimization method.

The Fig.7 This figure illustrates the relationship between the total operating cost (per hour - $/hr) and the power loss (kW) of Microgrid-2 (MG2). The red points of the plot indicate the possible solution that could be obtained in the process of optimization when considering the alternative version of scheduling. In the left side, where the cost is more expensive (approximately 7.09 $/hr), the power loss also is larger (approximately 9.67 kW). With the cost slowly lowering the power loss also begins to reduce meaning that the less the microgrid is run efficiently the less the economic cost and losses of the system.

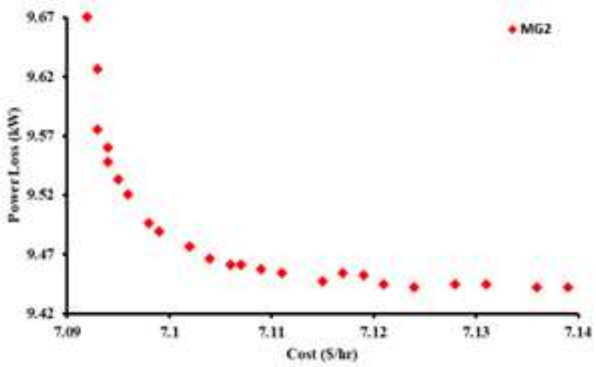

Fig 7 shows that for MG-2, as the operational cost decreases, the power loss also decreases and reaches an optimal minimum region.

Beyond a specific point (approximately 7.11 7.12 $/hr) the cost and power loss value will enter a stable area, where any additional cost reduction will not cause much change in the power loss. This demonstrates the point of convergence of optimization in which MG2 is at the optimal point with minimum power loss at the minimum cost possible. The graph, in general, indicates that an optimized operational strategy of MG2 will lead to a decreased power loss, as well as economic gain, demonstrating the usefulness of the scheduling and optimization method.

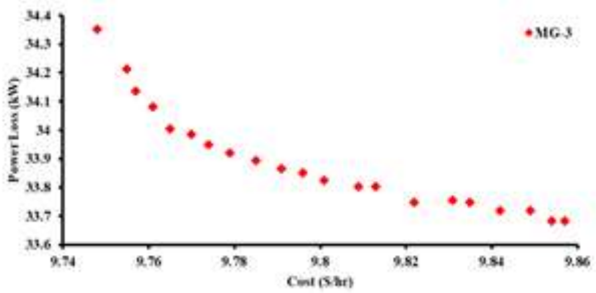

Fig 8 shows that in MG-3, the power loss decreases as the operational cost reduces and it approaches an optimal minimum zone.

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The plot depicts the relationship between the cost (/hr) and the power loss (kW) of Microgrid-3. All the red markers are solutions to the optimization of MG-3. At the start (on the left side of the graph) the cost is more expensive and the power loss is also more (approximately 34.3-34.4 kW). The power loss also decreases as the cost gradually decreases and this results in a direct improvement in system performance. Once at approximately 9.80-9.84 $/hr region, the cost and power loss values become nearly constant and are in a low range (approximately 33.7-33.8 kW) which represents an optimal solution range.

This value shows that MG-3 has a higher operating efficiency with a minimum of the economic cost, which also minimizes power losses. The shape of the curve is a clear indication that the optimization strategy employed works well to locate a desired region of trade-off in which the cost and the power loss achieve the lowest realistic values. Emphasizing the need to have a good management of energy and tactical planning to ensure that the systems are reliable and that they improve efficiency of operations.

Table-I: Hourly Multi-Microgrid Energy Generation Cost comparison using POA, GWO algorithm

Day hours Puma Optimization (POA) Grey Wolf Optimization (GWO)

Day hours	Puma Optimization (POA)	Grey Wolf Optimization (GWO)
1	534.11	573.62
2	647.2	658.78
3	542.22	586.98
4	621.21	687.98

5	539.24	567.23
6	609.36	636.54
7	708.92	762.35
8	303.57	339.42
9	745.19	768.94
10	608.63	635.68
11	722.21	735.65
12	744.65	770.68
13	801.34	826.97
14	478.67	498.98
15	728.96	787.23
16	764.34	776.63
17	756.75	786.14
18	812.72	824.65
19	908.34	915.94
20	704.36	721.32
21	519.05	535.69
22	517.45	549.89
23	524.98	576.25
24	505.72	544.29

The Table I shows a comparative analysis of the hourly energy generation costs of a system with different microgrids in detail, with two metaheuristic algorithms: Puma Optimization (POA), Grey Wolf Optimization (GWO), The results, in units per hour, show that there are measurable differences in cost minimization performance over the 24-hour operation. Out of the two methods, POA is always less expensive to generate at the majority of time intervals, which implies that it is better than TSA in terms of optimization of the cost of operation in the MMG framework. As an example, POA has a generation cost of 534.11 at hour 1, which is better than GWO (573.62). This trend in performance is continued through the day cycle, with significant variations observed in most demanding hours.

At hour 9, POA has a cost of 745.19 and GWO has higher costs of 768.940 respectively. All algorithms have the highest cost of generation at hour 19 and POA, GWO and recording are 908.34, 915.94 respectively. On the other hand, the lowest cost of generation is at hour 8, POA (303.57) is still performing better than GWO (339.42). Over the complete period of operations GWO typically incurs the greater costs, indicating a relatively lower efficiency in optimization in this usage. These results clearly indicate that Puma Optimization (POA) offers the most cost effective approach to energy generation of the proposed multi-microgrid system, with a consistent lower cost of operation as compared to GWO throughout the 24-hours.

V. Conclusion

This paper successfully used the metaheuristic algorithm in the multi objective optimization of microgrid systems highlighting the potential of the algorithm to enhance the efficiency of operation, lower costs and enhance reliability. The optimization model combines different distributed energy sources such as wind turbines, solar PV panels, diesel generators and battery storage devices on functional constraints. The algorithm was able to strike a balance between conflicting goals such as operating rates, power losses and voltage stability by executing the behavior of collaborative hunting of prairie dogs, which merges quickly and provides better solution accuracy than the traditional ones.. The flexible nature of exploration and utilizing capabilities ensured vibrant adjustments making sure that performance does not varies under different conditions. There was a noticeable difference in the flexibility of the system with the addition of battery energy storage systems (BESS) that is provided as a load balancing and peak shaving. The proposed algorithm gives highest performance and reduces the overall energy generation cost and probability of power supply deficit to to 0.15$/kWh, 0.12%. moreover, the precise modelling of renewable energy resources considering their uncertainness, was highlighted as important for practical optimization. Altogether, the MHA based framework provides the best solution to multi microgrid management and further studies are aimed at the real time demand response implementation and optimization using machine learning models in dynamic grids.

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