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Energy Management of a Photovoltaic–Wind–Battery Energy Storage Microgrid Using Linear Programming and Grey Wolf Optimization Techniques

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Abstract – *This study presents a comprehensive optimization analysis of a renewable energy–based hybrid microgrid integrating photovoltaic (PV), wind generation, and battery energy storage systems (BESS). The microgrid energy dispatch problem is formulated through detailed cost models for PV generation, wind power production, and battery charging–discharging operations. Two optimization techniques—Linear Programming (LP) and Grey Wolf Optimization (GWO) are applied to minimize operational and maintenance costs while improving overall system efficiency. The performance of LP and GWO is systematically evaluated through six operational case studies involving different combinations of PV, wind, battery storage, and grid interaction. For the LP-based optimization, the total operating costs are $14,090.91 for Case Study 1 (Wind–PV–Battery–Grid), $9,761.02 for Case Study 2 (Wind–Grid), and $16,074.56 for Case Study 3 (PV–Battery–Grid). In contrast, the GWO-based optimization yields operating costs of $5,802.44 for Case Study 4 (Wind–PV–Battery–Grid), $6,605.37 for Case Study 5 (Wind–Grid), and $15,668.82 for Case Study 6 (PV–Battery–Grid). A comparative analysis of the results demonstrates that the GWO technique consistently achieves lower operating costs than the LP approach, particularly for the Wind–PV–Battery–Grid configuration, where the minimum cost is $5,802.44. These findings highlight the superior capability of metaheuristic optimization in handling the nonlinear and complex nature of hybrid microgrid energy management problems. Overall, the results provide valuable insights into cost-effective microgrid operation and underscore the potential of advanced optimization techniques for enhancing the economic viability and sustainable integration of renewable energy resources. Results not only reveal the implications for optimizing microgrid operations but also provide indispensable insights for developing cost-effective strategies that emphasize the sustainable integration of renewable energy resources. This study is a valuable resource for researchers and stakeholders seeking to expand the operational efficiency and economic viability of hybrid microgrid systems.*

Keywords: *Battery energy storage, Energy Management, Grey Wolf Optimization, Linear Programming, Microgrids, Photovoltaic system, Renewable Energy, and Wind Energy.*

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I. Introduction

In the planning and operation of contemporary energy systems, particularly those integrating hybrid renewable energy sources, cost minimization is a fundamental goal. The effectiveness of Linear Programming (LP) and Grey Wolf Optimization (GWO) in complex systems necessitates advanced optimization techniques to address intricate decision-making challenges. Linear Programming is considered a deterministic, mathematically rigorous method that precisely identifies an optimal solution while satisfying predefined linear constraints and an objective function. Decision-makers can efficiently navigate large datasets and quantitative variables owing to LP's clarity and structure.

In microgrid energy management, LP has been widely applied [1], achieving a 19% reduction in electricity cost savings. Moreover, up to 38% savings were obtained in mixed-integer LP demand-response frameworks [2].

Compared to Grey Wolf Optimization, a population-based metaheuristic algorithm that mimics grey wolves' social hierarchy and hunting tactics. Unlike the LP algorithm, GWO is an innovative approach that offers remarkable flexibility, enabling it to tackle non-linear and multi-modal problems that traditional methods might struggle with. GWO has been applied to economic load dispatch with battery storage, yielding quantifiable reductions in operational cost [3]. In microgrid contexts, optimal hybrid microgrid sizing reduces the total net present cost by 1.06% while minimizing energy losses and emissions [4]. Further improvements in cost efficiency and robustness in component sizing were achieved in hybrid variants such as GWO-Cuckoo search [5].

By comparing the two optimization methodologies, LP and GWO, the research provides valuable insights into their performance metrics with respect to cost minimization, computational efficiency, and solution robustness. The results highlight the strengths and limitations of each technique and support practitioners in selecting the most appropriate method for specific energy management scenarios, ultimately fostering more sustainable and economically viable energy systems. As countries continue shifting toward cleaner energy, hybrid microgrids (HMGs) are increasingly powered by renewable sources such as solar and wind, with battery storage. This has become an essential part of modern power systems. Microgrids offer a practical means of providing reliable, sustainable electricity to both remote communities and urban areas. However, managing a system built around variable and unpredictable renewable energy sources is not straightforward. Operators must balance generation, storage, and load while dealing with uncertainties, nonlinearities, and cost considerations. This has made optimization a central tool in microgrid planning and operation. [6] presented the size determination and location of an optimal electrical energy storage. Their proposed study employed a cost-benefit analysis to identify the optimal solution. Not only are these considered, but uncertainties in renewable energy sources, load responses, and contributions are also accounted for. These microgrid problems are solved using GWO.

LP and GWO were employed to optimize the configuration of the energy storage system. The primary focus is on developing a coordinated future configuration scheme for wind and solar storage. Both algorithms produce optimal energy scheduling and an energy storage utilization strategy. Optimal operation of microgrids in distribution systems for wind power generation, PV energy systems, battery energy storage systems, EVs, and demand response is increasingly important [7-10]. Island energy management and optimal dispatch were conducted using GWO. Findings emphasize that optimal Island microgrid energy scheduling, as well as reduced overall economic cost, are key elements in the literature [11]. Most researchers are interested in wind-solar-ESS (also known as BESS), an electric-hydrogen storage system [12,13], and in optimal microgrid scheduling [14,15], particularly the fast convergence, accuracy, and robustness achieved in hybrid mode with other algorithms [16,17]. Additionally, a supercapacitor-based energy storage system was used in [18], while [19] optimized both grid-tied and off-grid microgrid systems.

The primary objective of this research is to integrate the strengths of two distinct optimization approaches to manage a modern, renewable-based microgrid more effectively. LP handles straightforward, cost-related decisions, such as when to use PV, charge or discharge the battery, and/or import from the grid. Nevertheless, GWO addresses more complex, nonlinear, and uncertain aspects of the system. The study aims to determine the most cost-effective and reliable operating schedule for the microgrid, ensuring efficient use of renewable resources and storage while minimizing overall costs.

At present, Renewable Energy generation technologies play a very pivotal part in the power system. Microgrid solutions recover the mismatch between generation and load demand. Thus, gained traction due to their ease of operation and ability to operate remotely, using both renewable and fossil-fuel-based power sources. Moreover, renewable energy technologies can provide relatively large and stable power supplies even in remote villages located in dense forests or mountainous regions [20,21]. Greenhouse gas emissions, network overloading, and bloated energy consumption costs are the major problems faced by both developing and developed countries [22]. A microgrid is a localized electricity distribution system that integrates multiple distributed generation units to supply nearby loads. It can operate independently from the central grid, enhancing resilience and energy autonomy. However, integrating inverter-based distributed generators into microgrids presents challenges that must be addressed during planning and operation [23]. In [20], it was reported that India has achieved 100% village electrification; however, many rural areas still face reliability and quality-of-supply issues. West Bengal supplied only 42% of rural regions, indicating that a Renewable Energy-based microgrid is crucial for meeting rural demand. An energy management system in commercial spaces involves measures to reduce electricity consumption costs without compromising work quality.

Our world is already fraught with rising energy demands. According to available data, the world's total energy consumption is expected to increase by 48% before 2040, according to a report published by the US Energy Information Administration (EIA). The integration of distributed micro-generation resources, such as solar, wind, and fuel cells, along with storage units, forms a microgrid that can operate both connected to the primary grid and autonomously. Distributed generation improves overall system performance. Proper planning for effective power system operation involves three phases: long-term, medium-term, and short-term.

Long-term planning, while medium-term planning, and Short-term planning involve forecasting generator procurement based on load demand growth, repairs, maintenance, and fuel costs, and optimizing output power for intervals of one week, one day, and one hour, respectively [24].

Studies conducted by [25] developed solutions for optimal economic scheduling and cost optimization issues in microgrid systems. Thus, also highlighted the most valuable and crucial aspect of microgrid systems for sustainability. Recent technological advancements for modern PV systems, such as Energy Payback Time (EPBT), have considerably improved, reducing the overall carbon footprint. Additionally, integrating PV systems with energy storage solutions and recycling strategies can diminish the environmental impacts. The significant benefits of Renewable Energy technologies have assisted numerous focused researchers.

Research highlighted methodologies for sizing, configuring, and controlling hybrid energy systems, as well as the implementation challenges they pose. In [26], a detailed sizing method for standalone photovoltaic-wind systems was emphasized. Microgrid optimization is crucial in India's rural areas, given infrastructure limitations and the lack of cost-effective grid connectivity, thereby promoting the decentralized deployment of Renewable energy systems for local electrification. Microgrids can function independently, enabling local control of distributed generation [20]. A study on optimal energy management of BSS and Renewable Energies in DC microgrids conducted by [27] discovered strategies to manage demand uncertainty and the variability of solar and wind energy, ultimately reducing total energy costs. A discussion of challenges in maintaining voltage limits and operational constraints in microgrid distribution systems was presented in [28], along with strategies that leverage distributed generators and energy storage with advanced control technologies. Further research on mechanical energy storage using Artificial Intelligence (AI) techniques has shown that microgrids can effectively integrate various renewable energy resources to enhance sustainability and supply quality [29].

A review of the current literature shows that studies focus on traditional optimization algorithms, such as LP, or modern metaheuristic techniques, such as GWO. Still, the literature lacks comparative studies of classical and heuristics-based optimization methods for the microgrid dispatch problem with respect to operating and maintenance cost under the same operating conditions. This makes it difficult to clearly understand how each method performs in real microgrid settings. The literature also reveals noticeable gaps in reporting detailed operational costs and in providing consistent comparisons of grid-tied wind-PV-battery dispatch strategies. To bridge these gaps, this study applies both LP and GWO to the considered microgrid system, which includes a Wind-PV-Battery model along with its equality and inequality constraints, cost models, and renewable profiles for a 24-hour schedule. The simulation results in this study compare the hourly behavior of renewable energy sources with changes in power demand and economic performance. The simulation results for the GWO heuristics indicate that the Wind-PV-Battery model combination is more cost-effective and suitable for practical microgrid applications.

This paper consists of Section I, the introduction, Section II, Linear Programming, Section III, Grey Wolf Optimization, and Section IV. Description of the

Simulation case studies provides simulation results of the microgrid dispatch problem using LP optimization methods, Sections V-VII provide case studies 4 to 6 simulation results of the microgrid dispatch problem using GWO optimization methods, Section XI provides a discussion of the LP and GWO simulation results, and lastly, Section XII, Conclusion of the study.

II. Linear Programming Optimization

This research explored the potential of a hybrid microgrid system integrated with BSS, focusing on performance enhancement and optimization. The effort involved comprehensive modeling of photovoltaic (PV) systems, wind energy generators, and load demands, with methodologies drawn from established references [23][30]. The basic Linear Programming (LP) optimization and Grey Wolf Optimization model in MATLAB for minimizing the cost of supplying the load using wind power, PV solar, grid import, and load demand. The main objective of the study depicted by Equations (1) and (2) is to minimize the total energy cost.

$$P_{load(t)} = \left(P_{wind(t)} + P_{pv(t)} + P_{BSS(t)} + P_{grid(t)}\right) \tag{1}$$

$$Minimize: \sum_t \left(C_{grid} \cdot P_{grid(t)}\right) \tag{2}$$

Power limits for Wind, PV, and the grid are specified in Equations (3).

$$\begin{aligned} 0 \le P_{wind(t)} &\le P_{wind(t)}^{\max} \\ 0 \le P_{pv(t)} &\le P_{pv(t)}^{\max} \\ 0 \le P_{grid(t)} &\le P_{grid}^{\max} \end{aligned} \tag{3}$$

Battery SOC Constraints are composed of SOC limits denoted by Equation (4), Charge/discharge power, which is computed by utilizing Equation (5). Simultaneous charge/discharge is not considered in this study.

$$SOC_{\min} \le SOC_{(t)} \le SOC_{\max} \tag{4}$$

$$0 \le P_{charge}, P_{discharge} \le P_{bat,\max} \tag{5}$$

Equation (7) outlines the grid limits for consideration.

$$0 \le E_{grid(t)} \le E_{grid}^{\max} \tag{7}$$

To effectively calculate the daily cost of wind power generation in dollars, it's essential to consider several key factors. These include capital costs, ongoing operations and maintenance costs, and the total cost incurred each day. In microgrid planning and dispatch models, the costs associated with wind and photovoltaic (PV) systems are categorized into three main components: (a) annualized capital (investment) costs, (b) fixed operation and maintenance (O&M) costs, and (c) variable O&M costs, alongside occasional replacement or degradation expenses. These components are incorporated directly into a planning objective as an annualized cost term. In operational (hourly) models, variable O&M costs, as well as curtailment and incentive terms, are added to the hourly objective. This methodology is standard in both academic research and technical practice [31]

The annual operation and maintenance costs associated with photovoltaic (PV) generation are calculated based on the system's capacity. In LP models, it is common to transform irradiance data into a time series that represents available PV power output. This conversion enables a more accurate representation of the PV system's energy production over time, accounting for variations in sunlight exposure [32]; [33].

A battery is viewed as an energy storage system; thus, it plays a crucial role in holding and allocating energy rather than generating it directly [34]. The battery components are as follows:

a) Operation & Maintenance (O&M)
- Often small or included in CAPEX
- Can be added as **$/kWh-year** or **$/kWh** throughput

b) Cycle Life
- Number of full charge-discharge cycles before replacement

c) Optional: Cost per kWh Delivered
- Based on daily throughput (how much energy is cycled daily)

BSS, particularly batteries, plays a critical role in ensuring supply-demand balance, stabilizing renewable intermittency, and providing ancillary services in microgrids. In a comparative perspective, wind and PV generation exhibit low marginal costs once installed, with wind costs more dependent on site-specific conditions and PV offering more predictable yields. BSS, however, entails recurring costs due to limited lifetimes and efficiency losses, yet it is indispensable for enabling high penetration of renewables in microgrids. Expressing all resource costs in $/kWh or $/day enables integration into optimization models, such as LP.

This unified cost modeling framework provides a robust basis for selecting the optimal resource mix, which balances economic efficiency with system reliability [34] [35].

The standard form of an LP problem is indicated by

Equation (8):

$$Mimimize: C^T x \tag{8}$$

Subject to:

$$A_{eq^x} = b_{eq} \left(Equality\ constra\,\mathrm{int}\,s\right)$$
$$A_{ineq^x} \leq b_{bineq} \ (Inequality\ constra\,\mathrm{int}\,s$$
$$x \geq 0 \ \ (Variable\ bounds,\ optional)$$

The Microgrid dispatch problem can be formulated as a Linear Programming (LP) optimization problem, as described by Equations (9) and (10), to minimize the system's total operational cost while satisfying demand and adhering to technical constraints. In the context of a microgrid, the decision variable vector typically includes power dispatch quantities from different energy sources and storage devices, such as:

$$x = \left\{P_{pv(t)}, P_{wind(t),} P_{grid(t)} P_{BSS(t)}^{ch}, P_{BSS}^{dish}\right\} \tag{9}$$

$$\min \sum_{t=1}^{T} \left[C_{grid}\, P_{grid(t)} + C_{pv}\, P_{pv(t)} + C_{wind}\, P_{wind(t)} + C_{BSS}^{lifetime}\left(P_{BSS(t)}^{ch} + P_{BSS(t)}^{dis}\right)\right] \tag{10}$$

The cost function coefficients for grid, PV, Wind, and battery prices are given in $/kWh at the bottom of Table 2. The equality constraints require that the power balance be maintained at each time step. These constraints, as expressed in Equation (10), ensure that the total power generated matches the total power consumed, thereby stabilizing the system and preventing imbalances that could disrupt operations.

The inequality constraints embody the innovative spirit and operational boundaries of the microgrid components, pushing us to explore new possibilities as presented by Equation (11).

$$\begin{aligned} &0 \leq P_{pv(t)} \leq P_{pv(t)}^{\max}, \quad 0 \leq P_{wind(t)} P_{wind(t)}^{\max}, \\ &0 \leq P_{grid(t)} \leq P_{grid(t)}^{\max} \\ &0 \leq P_{BSS(t)}^{ch} \leq P_{BSS}^{ch,\max}, \quad 0 \leq P_{BSS(t)}^{dis} \leq P_{BSS(t)}^{dis,\max} \end{aligned} \tag{11}$$

Furthermore, the dynamics of the battery state of charge (SOC) as specified in Equation (12) are incorporated to ensure efficient and practical operation of the storage system. This consideration is vital for optimizing performance and ensuring the battery remains within safe operational limits, thereby maximizing its lifespan and energy management effectiveness.

$$\begin{aligned} &SOC_{(t+1)} = SOC_{(t)} + \eta_{ch} P_{BSS(t)}^{ch} \Delta_t - \frac{1}{\eta_{dis}} P_{BSS(t)}^{dis} \Delta_t \\ &SOC^{\min} \leq SOC_{(t)} \leq SOC^{\max} \end{aligned} \tag{12}$$

Thus, the LP formulation ensures that the microgrid operates at minimum cost, maintains supply-demand balance, and respects the technical limitations of its components. This framework has been widely applied in microgrid scheduling and dispatch studies due to its computational efficiency and ability to handle large-scale optimization problems [36][37]. Table 1 presents the parameter descriptions used in the LP-based optimization method.

Table 1. Description of parameters used in the LP method of optimization

Symbol	Description
$x \in R^n$	Vector of decision variables
$c \in R^n$	Coefficient vector of the objective function
$A_{eq} \in R^{m \times n}$	Matrix of equality constraint coefficients
$b_{eq} \in R^m$	Right-hand side of equality constraints
$A_{ineq},\ b_{ineq}$	Same as above, but for inequality constraints

.

Linear Programming algorithm for the microgrids problem steps are considered:

Step 1: Start

The optimization process commences with a thorough definition of the microgrid dispatch problem. This involves clearly outlining the objectives, constraints, and variables that will guide the effective operation and management of the microgrid system. Key considerations include energy demand forecasts, distributed energy resource generation capacities, and operational constraints, all of which must be integrated to develop a robust framework for optimizing energy distribution and use within the microgrid.

Step 2: Input Data

All required data are collected, including load demand forecasts, renewable generation forecasts (PV and wind), grid electricity tariffs, and battery operational parameters such as efficiency, capacity, and state-of-charge limits. These inputs form the basis for optimization [38]. The flowchart of the LP optimization method applied to the microgrid system is given in Figure 1.

Step 3: Define Decision Variables

The control variables of the LP problem are specified. These include the dispatched power from PV, wind, and the grid, as well as battery charging and discharging decisions over the scheduling horizon [23].

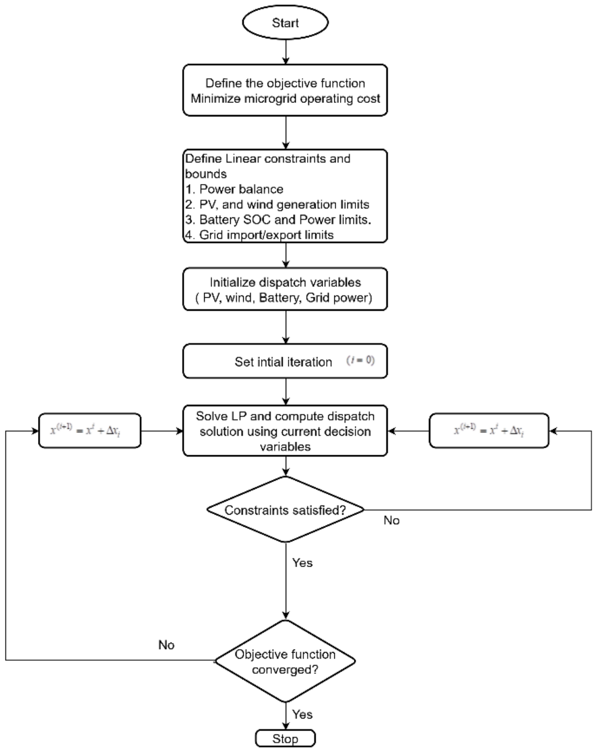

Figure 1. Flow chart for Linear Programming Optimization

Step 4: Formulate Objective Function

The optimization objective is to minimize the microgrid's total operational cost. This typically includes costs of electricity purchased from the grid, battery cycling costs, and penalties for renewable curtailment or unmet demand [24].

Step 5: Define Constraints

The LP constraints ensure the microgrid's feasible operation.

a) **Power balance**: total generation plus discharging equals load plus charging.
b) **Technical limits**: maximum and minimum bounds on PV, wind, and grid imports.
c) **Battery SOC dynamics**: the state-of-charge must remain within specified limits [36],[38].

Step 6: Solve LP Optimization

The formulated LP model is solved using standard solvers such as MATLAB, which efficiently compute optimal solutions for linear problems.

Step 7: Obtain Optimal Dispatch

The economic dispatch [39] solution provides the optimal schedule of energy allocation, when to use PV and wind, how much to import from the grid, and when to charge or discharge the battery.

Step 8: End

The process concludes with the optimal dispatch plan, which can then be implemented for real-time microgrid operation or used for planning and analysis. The flowchart for the LP algorithm is depicted in the Figure.1

III. Grey Wolf Optimization

In this section, all cost calculations are meticulously based on the LP equations. Accordingly, the equations initially presented in LP have been carefully adapted to analyze the current financial implications. This ensures a coherent, consistent approach throughout the analysis, enabling a deeper understanding of the cost involved.

The objective function guiding the search is to minimize the total cost of the microgrid, expressed by Equation (13) as:

$$C_{total} = C_{pv} + C_{wind} + C_{BSS} + C_{grid} + C_{O\&M} \quad (13)$$

The dispatch solutions are evaluated subject to the constraints specified in Equations (3) to (7) for power balance, including battery state-of-charge limits.

Five steps are involved in the GWO application process; therefore, a random initialization of a population of grey wolves is performed within the given bounds of PV, wind, battery, and grid.

Step 1: Position vector of a Wolf.

In this context, the grey wolf represents an individual candidate in the search space, characterized by a unique set of parameters or features. This analogy is inspired by the natural behavior of grey wolves, characterized by a distinct social hierarchy and cooperative hunting strategies. Similarly, each candidate solution (or wolf) collaborates and competes with others in an optimization process, striving to adapt and improve, thereby converging toward the optimal solution to a given problem. The dynamics among these wolves reflect the exploration and exploitation strategies used in algorithms to navigate complex solution landscapes efficiently. Each grey wolf, as shown by Equation (14), symbolizes a potential solution vector within a problem-solving framework [40]:

$$Wolf = \left[PV_{size}, Wind_{size}, Battery_{capacity}, Grid_{usage} \right] \quad (14)$$

With the assumption that;

$\vec{X}_{(t)}$ is the position vector of the wolf at iteration t

$\vec{X}_{\alpha(t)}, \vec{X}_{\beta(t)}, \vec{X}_{\delta(t)}$ are the positions of three wolves, which are considered as the best solution, while, $\vec{X}_{\omega(t)}$ The followers are commonly not used in many cases.

Step 2: Encircling the Prey

GWO models encapsulate encircling behavior through a series of strategic movements that mimic wolves' hunting patterns. This involves dynamic adjustments in position and distance, creating a framework in which wolves maintain proximity to prey while optimizing their positions. The models employ complex algorithms that simulate this natural behavior, enabling efficient exploration and exploitation of the search space [29], [40], and [41]. Equations (15) and (16) are utilized in step 2.

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{leader(t)} - \vec{X}_{(t)}\right| \tag{15}$$

$$\vec{X}_{(t+)} = \vec{X}_{leader(t)} - \vec{A} \cdot \vec{D}$$

Where: $\vec{A} = 2a \cdot \vec{r}_1 - a$

$\vec{C} = 2 \cdot \vec{r}_2$

a is linearly decreasing from 2 to 0 over iterations.

$\vec{r}_1, \vec{r}2$ is the random vectors 10 [0,1].

Step 3: Updating Position Using $\alpha, \beta, and\, \delta$

Utilization of the GWO (Gray Wolf Optimization) Equations to effectively update the positions of the search agents, referred to as wolves. Movement of wolves toward the top three leaders within the hierarchy: the Alpha wolf, which represents the best solution found so far; the Beta wolf, embodying the second-best solution; and the Delta wolf, representing the third-best. Each search agent will strategically adjust its position, taking into account the positions and influences of the three superior wolves α, β, and δ, to optimize the search for the best solution in the solution space, as depicted by Equation (16) [42]; [43]; [44].

$$\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \;\Rightarrow\; \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{D}_\beta &= \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \;\Rightarrow\; \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{D}_\delta &= \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \;\Rightarrow\; \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{aligned} \tag{16}$$

In this context, the wolf's updated position is determined by averaging the influences of three key factors: **α, β**, and **δ**. The relationship is elegantly represented in Equation (17), which encapsulates how the variables interact to shape the wolf's new location [42], [43], [45].

$$\vec{X}_{(t+1)} = \frac{1}{3}\left(\vec{X}_1 + \vec{X}_2 + \vec{X}_3\right) \tag{17}$$

Step 4: Decreasing Parameter a

In this step, the focus is on striking a harmonious balance between exploration and exploitation. Thus, embracing the pursuit of new ideas and opportunities while also leveraging and optimizing existing resources and knowledge. This dual approach ensures not only that innovative solutions are identified but also that existing solutions are effectively utilized to identify the optimal solution [45].

Step 5: Termination

This step involves iteratively applying steps 3 and 4 until the predetermined maximum number of iterations is reached or convergence is achieved. Moreso, closely monitoring progress during each cycle to evaluate whether results are stabilizing or if further iterations are necessary is considered [44,45].

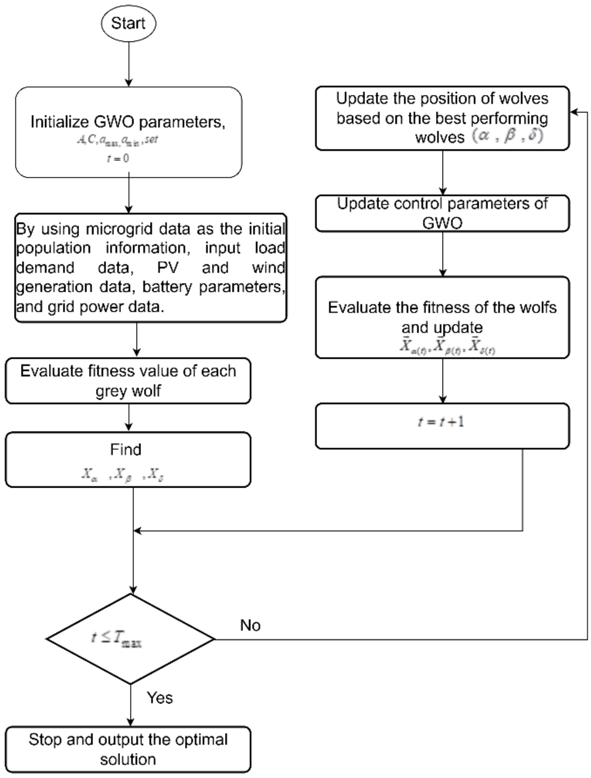

Figure 2. Flowchart of the Grey Wolf Optimization Algorithm for Grid-connected Microgrid dispatch using Wind, PV, and Battery

The process begins with the initialization of the wolf population, where each wolf represents a candidate dispatch schedule for renewable sources (PV and Wind) and the battery storage system (BSS) units. Figure 2 illustrates the modified Grey Wolf Optimization algorithm flowchart tailored for solving the microgrid dispatch problem. The GWO flowchart for Microgrid dispatch is shown in Figure 2.

The fitness function is then evaluated based on the total operational cost, while incorporating technical constraints such as renewable generation limits, storage state-of-charge (SoC) boundaries, and demand-supply balance. The top three solutions are identified as alpha(α), beta (β), and delta (δ), which guide the remaining wolves during the search process. The parameter *a* is updated iteratively to balance exploration and exploitation. For each wolf, new dispatch positions are generated relative to α, β, and δ, and the feasibility of the positions is ensured by checking SoC and power balance constraints. The process is repeated for all wolves until the stopping condition is met. Finally, the α is selected as the optimal dispatch solution, providing the best trade-off between cost minimization and operational feasibility for the microgrid system.

IV. Description of the Case Studies

The main contribution of this study is to minimize the microgrid's operational and maintenance costs by accounting for power exchange between the grid and its renewable energy sources, as well as battery energy storage. Three case studies are conducted, and they are:

- **Case Study 1:** Performing simulations on the Grid-connected Microgrid dispatch with Wind, PV, and Battery using Linear programming (LP) method
- **Case Study 2:** Considering Grid-connected Microgrid dispatch with Wind renewable energy resources using Linear programming (LP) method
- **Case Study 3:** Conceptualize Grid-connected Microgrid dispatch with PV and Battery using Linear programming (LP) method
- **Case Study 4:** Performing simulations on the Grid-connected Microgrid dispatch with Wind, PV, and Battery using Grey Wolf Optimization (GWO) Algorithm.
- **Case Study 5:** Considering Grid-connected Microgrid dispatch with Wind renewable energy resources using Grey Wolf Optimization (GWO) Algorithm.
- **Case Study 6:** Conceptualize Grid-connected Microgrid dispatch with PV and Battery using Grey Wolf Optimization (GWO) Algorithm.

V. Case study 1: Grid-connected Microgrid dispatch with Wind, PV, and Battery using LP algorithm

The power generated from photovoltaic (PV) systems, wind energy, and battery storage is organized in an hourly table spanning 24 hours, along with the grid purchase prices. The arrangement shown in Figure 3 enables effective optimization of energy use.

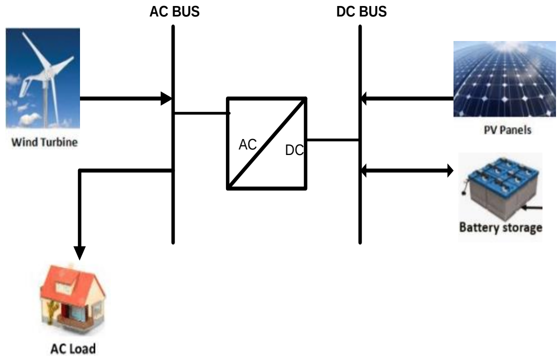

Figure 3. Single-line diagram of the proposed Microgrid network

Table 2 provides a detailed overview of hourly demand, along with various environmental and energy parameters, including wind speed, wind energy generation, solar irradiance, and associated photovoltaic (PV) power output. This comprehensive representation enables deeper analysis of the relationship between energy demand and renewable energy sources throughout the day. The operating and maintenance cost in $/kWh for PV, wind, Battery, and grid energy, as well as the selling and purchasing prices, are given at the bottom of Table 2. The optimization problem formulated in this study was implemented in MATLAB and solved using the linear programming algorithm.

Table 2. Power produced and cost functions of the PV, wind, and load demand for 24 hours

Hour	Power Demand (kW)	Wind speed (m/s)	Wind Power (kW)	Solar irradiance (W/m2)	PV Power (kW)
1	2200	5.7	570	0	0
2	2400	6.5	846	0	0
3	2800	7.5	1299	0	0
4	3200	6.9	1011	0	0
5	3400	8.6	1958	93.5	108.722
6	3800	10.5	3564	212.5	247.095
7	4000	13.6	7744	255	296.514
8	4200	10.4	3463	467.5	543.609
9	4600	9.1	2320	637.5	741.285
10	5000	9.3	2476	680	790.704
11	5200	7.7	1406	816	948.845
12	5400	7	1056	850	988.38
13	5300	5.9	632	833	968.612
14	5200	4.9	362	850	988.38
15	5000	3.5	132	680	790.704
16	4600	3.4	121	595	691.866
17	4000	2.8	68	255	296.514

18	3700	3.1	92	212.5	247.095
19	3400	2.3	37	153	177.908
20	3200	2.9	75	68	79.07
21	3000	3.5	132	42.5	49.419
22	2800	3.8	169	0	0
23	2600	3.8	169	0	0
24	2400	4.8	340	0	0
Energy Operating and Maintenance Costs					
Grid Import cost	Grid Export cost	Battery degradation cost	PV O&M cost	Wind Turbine O&M cost	
0.18 $/kWh	0.04 $/kWh	0.05 $/kWh	0.005 $/kWh	0.01 $/kWh	

Wind power generation is fluctuating, reaching peak at the hours (9,10,17, and 222), PV power is not available during morning periods (from 1 to 7 hours) and night periods (18 -24). Battery charging occurs when excess power is available during the hours (4, 6, 9, 10, 16, 17, 22, 23), whereas battery discharge occurs during the hours (7, 8, 11, 12, 13, 18, 20, 24). Battery SOC power is always active, ranging from 200kW to 950kW, while grid power is either exported or imported, depending on the system's power exchange, as shown in Table 3. The high operating cost occurs at the maximum grid import power and at high battery SOC.

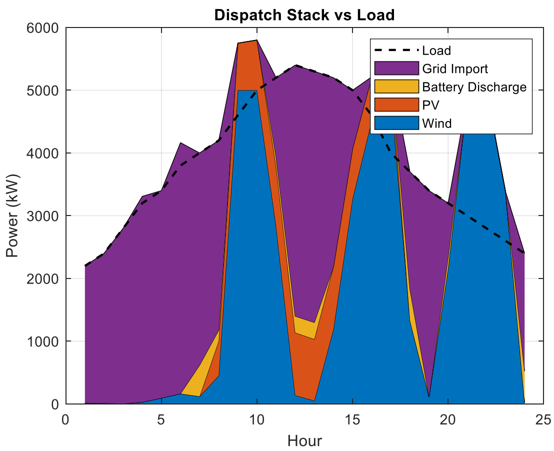

Figure 4. Grid-connected Microgrid dispatch with Wind, PV, and Battery using LP algorithm for 24 hours

Microgrid operating and maintenance cost using LP algorithm simulation results depicted in Table 4 present the cost of PV power, Wind power, grid power import and export, as well as the battery power cost, all in $. Total operating cost is the sum of all costs incurred during a given hour. The highest cost occurs at hour 7, when the system relies on battery power and imports grid power. Figure 4 illustrates the power dispatch characteristics over 24 hours. In this regard, wind power supports imported grid power, whereas PV and battery systems are only active during certain hours. Table 3 presents the microgrid's power dispatch using an LP model.

VI. Case study 2: Grid-connected Microgrid dispatch with Wind Energy using LP algorithm

In this case study, the objective is to optimize wind-grid hybrid power to minimize operating cost while meeting load demand

The results presented in Table 5 show that demand varies widely, ranging from approximately 2200kW to a peak of 5400kW at hour 12, placing pressure on the system during high-load periods. Wind generation starts low but reaches up to 5000kW around 9 and 10, demonstrating moments when it can meaningfully support the grid. During peak demand, especially from 12 to 14, the system relies heavily on grid imports, whereas no imports are needed at hours 9 and 10 due to strong wind output. A brief export of 1000kW at hour 17 indicates a rare period during which supply exceeds demand. However, significant shortfalls remain, such as the 1262.53kW gap at hour 12, indicating that demand sometimes outpaces available generation. These shortages, combined with costs exceeding $700, are depicted in Table 6. The peak periods underscore solutions to enhance reliability and manage costs more effectively.

Table 3. Microgrid Power Dispatch using LP algorithm

Hour	Load Power kW	Wind Power kW	PV Power kW	Battery Charging Power kW (-ve)	Battery Discharging Power kW (+Ve)	Battery SOC kW	Power Import kW	Power Export kW	Total Operating cost $
1	2200	16.17	0.00	0.00	0.00	500.00	2183.83	0.00	393.25
2	2400	13.75	0.00	0.00	0.00	500.00	2386.25	0.00	429.66
3	2800	6.73	0.00	0.00	0.00	500.00	2793.27	0.00	502.86
4	3200	30.61	0.00	108.89	0.00	603.45	3278.28	0.00	699.29
5	3400	95.63	0.00	0.00	0.00	603.45	3304.37	0.00	595.74
6	3800	164.79	0.00	364.79	0.00	950.00	4000.00	0.00	1086.44
7	4000	120.76	0.00	0.00	500.00	394.44	3379.24	0.00	1109.47

8	4200	452.25	550.00	0.00	175.00	200.00	3022.75	0.00	726.37
9	4600	5000.00	750.00	289.47	0.00	475.00	0.00	860.53	377.64
10	5000	5000.00	800.00	500.00	0.00	950.00	0.00	300.00	566.00
11	5200	2828.74	960.00	0.00	145.10	788.78	1266.16	0.00	406.10
12	5400	137.47	1000.00	0.00	262.53	497.08	4000.00	0.00	988.90
13	5300	52.63	980.00	0.00	267.37	200.00	4000.00	0.00	992.80
14	5200	1190.39	1000.00	0.00	0.00	200.00	3009.61	0.00	558.63
15	5000	3269.60	800.00	0.00	0.00	200.00	930.40	0.00	204.17
16	4600	4512.47	700.00	289.47	0.00	475.00	0.00	323.00	351.02
17	4000	5000.00	300.00	500.00	0.00	950.00	0.00	800.00	583.50
18	3700	1333.10	0.00	0.00	500.00	394.44	1866.90	0.00	849.37
19	3400	115.88	0	0.00	0.00	394.44	3284.12	0.00	592.30
20	3200	2167.70	0	0.00	175.00	200.00	857.30	0.00	350.99
21	3000	4870.89	0	0.00	0.00	200.00	0.00	1870.89	123.54
22	2800	5000.00	0	84.80	0.00	280.56	2183.83	2115.20	219.40
23	2600	3385.52	0	500.00	0.00	755.56	2386.25	285.52	545.28
24	2400	22.40	0	0.00	500.00	200.00	2793.27	0.00	838.19

Table 4. Microgrid Operating and Maintenance cost using the LP algorithm

Hour	PV Power cost in $	Wind Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Battery Power cost in $	Total Operating cost in $
1	0.00	0.16	393.09	0.00	0.00	393.25
2	0.00	0.14	429.53	0.00	0.00	429.66
3	0.00	0.07	502.79	0.00	0.00	502.86
4	0.00	0.31	590.09	0.00	108.89	699.29
5	0.00	0.96	594.79	0.00	0.00	595.74
6	0.00	1.65	720.00	0.00	364.79	1086.44
7	0.00	1.21	608.26	0.00	500.00	1109.47
8	2.75	4.52	544.09	0.00	175.00	726.37
9	3.75	50.00	0.00	34.42	289.47	377.64
10	4.00	50.00	0.00	12.00	500.00	566.00
11	4.80	28.29	227.91	0.00	145.10	406.10
12	5.00	1.37	720.00	0.00	262.53	988.90
13	4.90	0.53	720.00	0.00	267.37	992.80
14	5.00	11.90	541.73	0.00	0.00	558.63
15	4.00	32.70	167.47	0.00	0.00	204.17
16	3.50	45.12	0.00	12.92	289.47	351.02
17	1.50	50.00	0.00	32.00	500.00	583.50
18	0.00	13.33	336.04	0.00	500.00	849.37
19	0.00	1.16	591.14	0.00	0.00	592.30
20	0.00	21.68	154.31	0.00	175.00	350.99
21	0.00	48.71	0.00	74.84	0.00	123.54
22	0.00	50.00	0.00	84.61	84.80	219.40
23	0.00	33.86	0.00	11.42	500.00	545.28
24	0.00	0.22	337.97	0.00	500.00	838.19

Table 5. Wind energy-based Microgrid Power Dispatch using LP algorithm

Hour	Load Power (kW)	Wind Power (kW)	Power Import (kW)	Power Export (kW)	Power unserved (kW)
1	2200	16.17	2183.83	0.00	0.00
2	2400	13.75	2386.25	0.00	0.00
3	2800	6.73	2793.27	0.00	0.00
4	3200	30.61	3169.39	0.00	0.00
5	3400	95.63	3304.37	0.00	0.00
6	3800	164.79	3635.21	0.00	0.00
7	4000	120.76	3879.24	0.00	0.00
8	4200	452.25	3747.75	0.00	0.00
9	4600	5000	0.00	400.00	0.00
10	5000	5000	0.00	0.00	0.00
11	5200	2828.7	2371.26	0.00	0.00
12	5400	137.47	4000.00	0.00	1262.53
13	5300	52.63	4000.00	0.00	1247.37
14	5200	1190.4	4000.00	0.00	9.61
15	5000	3269.6	1730.40	0.00	0.00
16	4600	4512.5	87.53	0.00	0.00
17	4000	5000.0	0.00	1000.00	0.00
18	3700	1333.1	2366.90	0.00	0.00
19	3400	115.88	3284.12	0.00	0.00
20	3200	2167.7	1032.30	0.00	0.00
21	3000	4870.9	0.00	1870.89	0.00
22	2800	5000	0.00	2200.00	0.00
23	2600	3385.5	0.00	785.52	0.00
24	2400	22.40	2377.60	0.00	0.00

Table 6. Wind Energy-based Microgrid Operating and Maintenance cost Using LP Algorithm

Hour	Wind Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Total Operating cost in $
1	0.16	393.09	0.00	393.25
2	0.14	429.53	0.00	429.66
3	0.07	502.79	0.00	502.86
4	0.31	570.49	0.00	570.80
5	0.96	594.79	0.00	595.74
6	1.65	654.34	0.00	655.99
7	1.21	698.26	0.00	699.47
8	4.52	674.59	0.00	679.12
9	50.00	0.00	16.00	66.00
10	50.00	0.00	0.00	50.00
11	28.29	426.83	0.00	455.11
12	1.37	720.00	0.00	721.37
13	0.53	720.00	0.00	720.53
14	11.90	720.00	0.00	731.90
15	32.70	311.47	0.00	344.17
16	45.12	15.75	0.00	60.88
17	50.00	0.00	40.00	90.00
18	13.33	426.04	0.00	439.37
19	1.16	591.14	0.00	592.30
20	21.68	185.81	0.00	207.49
21	48.71	0.00	74.84	123.54
22	50.00	0.00	88.00	138.00
23	33.86	0.00	31.42	65.28
24	0.22	427.97	0.00	428.19

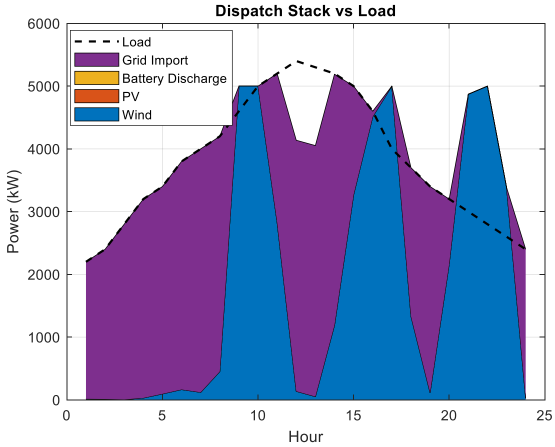

Figure 5. Grid-connected Microgrid dispatch with Wind Energy for 24 hours using LP

The hourly cost analysis of the wind-based microgrid reveals how strongly system costs are shaped by wind availability and the resulting dependence on grid imports. Wind power remains relatively inexpensive throughout the day. Costs range from just a few cents up to a noticeable spike of $50.00 during hours 9 and 10. These variations reflect changing wind conditions and their direct influence on generation output. In contrast, grid import costs fluctuate more sharply, reaching $720.00 in hours 12 and 13 during periods of insufficient wind generation. Consequently, the total cost peaks at $731.90 in hour 14, a period marked by both high demand and limited renewable generation. The lowest operating cost of $50.00 occurs at hour 10, when wind energy effectively offsets the need for imports.

VII. Case study 3: Grid-connected Microgrid dispatch with PV and Battery using LP algorithm

This case study deals with Grid-PV-BSS dispatch. As noted earlier, the developed LP algorithm is used in MATLAB simulations. During the morning hours, the system relies on battery storage and grid import since the PV is active between 8 and 17. There is a regular import power of 4000kW for several hours in this case study, thereby increasing operating and maintenance costs.

The results are tabulated in Table 7. The results for operating and maintenance costs for PV and Battery using the LP algorithm are presented in Table 8.

Table 8 provides a clear view of how operating and maintenance costs shift throughout the day as the microgrid draws power from PV, the grid, and the battery. During the night, when solar energy is unavailable, the system relies almost entirely on grid imports. This becomes the primary driver of operating costs. As daylight increases, PV generation begins to alleviate the burden, most noticeably between hours 8 and 10. Thus offering a welcome reduction in the overall cost.

From hour 11 onward, however, the system relies heavily on battery power, thereby increasing total operating costs due to associated battery usage charges. The results show that during the late-night and early-morning hours, operating costs are entirely attributable to grid imports. This situation reflects the absence of PV support and emphasizes how the availability of renewable energy directly shapes the microgrid's cost profile.

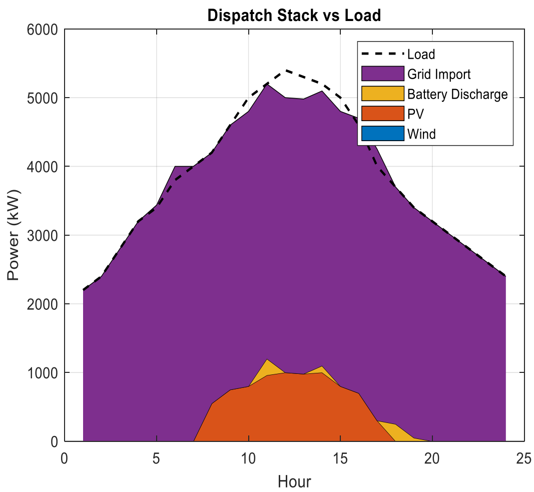

Figure 6. Grid-connected Microgrid dispatch with PV and Battery results for 24 hours using LP

Table 7. Microgrid Power Dispatch with PV and Battery using LP algorithm

Hour	Power Demand (kW)	PV power (kW)	Battery Charging Power kW (-ve)	Battery Discharging Power kW (+Ve)	Battery SOC kW	Power Import kW	Power Export (kW)	Power Unserved in kW	Total Operating cost $)
1	2200	0.00	0.00	0.00	250.00	2200.00	0.00	0.00	396.00
2	2400	0.00	0.00	0.00	250.00	2400.00	0.00	0.00	432.00
3	2800	0.00	0.00	0.00	250.00	2800.00	0.00	0.00	504.00
4	3200	0.00	0.00	0.00	250.00	3200.00	0.00	0.00	576.00
5	3400	0.00	36.84	0.00	285.00	3436.84	0.00	0.00	655.47
6	3800	0.00	200	0.00	475.00	4000.00	0.00	0.00	920.00
7	4000	0.00	0.00	0.00	475.00	4000.00	0.00	0.00	720.00
8	4200	550	0.00	0.00	475.00	3650.00	0.00	0.00	659.75
9	4600	750	0.00	0.00	475.00	3850.00	0.00	0.00	696.75
10	5000	800	0.00	0.00	475.00	4000.00	0.00	200.00	724.00
11	5200	960	0.00	240	208.33	4000.00	0.00	0.00	964.80
12	5400	1000	0.00	0.00	208.33	4000.00	0.00	400.00	725.00
13	5300	980	0.00	0.00	208.33	4000.00	0.00	320.00	724.90
14	5200	1000	0.00	97.5	100.00	4000.00	0.00	102.50	822.50
15	5000	800	0.00	0.00	100.00	4000.00	0.00	200.00	724.00
16	4600	700	100	0.00	195.00	4000.00	0.00	0.00	823.50
17	4000	300	250	0.00	432.50	3950.00	0.00	0.00	962.50
18	3700	0.00	0.00	250.00	154.72	3450.00	0.00	0.00	871.00
19	3400	0.00	0.00	49.25	100.00	3350.75	0.00	0.00	652.39
20	3200	0.00	0.00	0.00	100.00	3200.00	0.00	0.00	576.00
21	3000	0.00	0.00	0.00	100.00	3000.00	0.00	0.00	540.00
22	2800	0.00	0.00	0.00	100.00	2800.00	0.00	0.00	504.00
23	2600	0.00	0.00	0.00	100.00	2600.00	0.00	0.00	468.00
24	2400	0.00	0.00	0.00	100.00	2400.00	0.00	0.00	432.00

Table 8. Microgrid Operating and Maintenance cost with PV and Battery using LP algorithm

Hour	PV Power cost ($)	Grid Power Import cost ($)	Grid Power Export cost ($)	Battery Power cost ($)	Total Operating cost ($)
1	0.00	396.00	0.00	0.00	396.00
2	0.00	432.00	0.00	0.00	432.00
3	0.00	504.00	0.00	0.00	504.00
4	0.00	576.00	0.00	0.00	576.00
5	0.00	618.63	0.00	36.84	655.47
6	0.00	720.00	0.00	200.00	920.00
7	0.00	720.00	0.00	0.00	720.00
8	2.75	657.00	0.00	0.00	659.75
9	3.75	693.00	0.00	0.00	696.75
10	4.00	720.00	0.00	0.00	724.00
11	4.80	720.00	0.00	240.00	964.80
12	5.00	720.00	0.00	0.00	725.00
13	4.90	720.00	0.00	0.00	724.90
14	5.00	720.00	0.00	97.50	822.50
15	4.00	720.00	0.00	0.00	724.00
16	3.50	720.00	0.00	100.00	823.50
17	1.50	711.00	0.00	250.00	962.50
18	0.00	621.00	0.00	250.00	871.00
19	0.00	603.14	0.00	49.25	652.39
20	0.00	576.00	0.00	0.00	576.00
21	0.00	540.00	0.00	0.00	540.00
22	0.00	504.00	0.00	0.00	504.00
23	0.00	468.00	0.00	0.00	468.00
24	0.00	432.00	0.00	0.00	432.00

Compared with the optimal cost obtained in the three case studies, case study 1 has a total operating cost of $9250.82, case study 2 of $9761.03, and case study 3 of $14912.15. Therefore, the best solution is case stduty1.

VIII. Case study 4: Microgrid Operating and Maintenance cost of the Wind-PV-Battery dispatch Using the GWO algorithm

The simulation results indicate a flexible, responsive energy system that uses renewables as much as possible while relying on storage and the grid as needed, particularly during high-demand periods. The cost patterns reinforce the value of thoughtful energy management: it can reduce expenses and capitalize on opportunities to generate revenue when conditions permit.

Table 9 gives a clear picture of how power is generated, consumed, and managed in 24 hours. The cast implications of the operation are also provided. Total load demand starts at 2200kW, increases steadily, peaks at 5400kW, and then declines. Wind generation contributes heavily during several hours, particularly at hour 9, where the value is 5132.67kW, although it dips at other times. Subsequently, solar PV power remains inactive during the early hours but begins contributing from hour 4 onward, reaching a maximum output of 1263.72 at hour 12. Occasional negative values indicate that the battery is offsetting demand by discharging. The battery plays a crucial balancing role, alternating between charging and discharging to stabilize the system, with outputs sometimes reaching 100kW but also falling below zero during energy release. Grid fills the gaps when renewable generation is insufficient and even exports excess energy when available. Thus, the presence of both positive and negative values is explained. These dynamics directly influence operational costs, which shift between positive and negative depending on whether the system is purchasing power or selling surplus back to the grid. Notably, several hours, such as 1, 2, 4, 5, and 9, indicate income from excess generation. Nevertheless, hour 5 records the highest cost at 622.52kW, due to a heavier reliance on grid power.

Table 9. Power dispatch solution using the GWO method

Hour	Power demand (kW)	PV Power (kW)	Wind Power (kW)	Grid Power (kW)	Battery Power (kW)
1	2200	0	3444.74	-1344.74	100.00
2	2400	0	3216.03	-916.03	100.00
3	2800	0	2648.94	51.06	100.00
4	3200	0	2559.36	1309.86	-669.22
5	3400	0	843.55	3225.67	-669.22
6	3800	0	3308.77	1160.45	-669.22
7	4000	0	1468.85	1661.93	869.22
8	4200	673.0	4213.15	-1555.37	869.22
9	4600	1019.1	5132.67	-2420.96	869.22
10	5000	700.2	2869.78	2099.26	-669.22
11	5200	474.5	3962.56	1432.20	-669.22
12	5400	1264	4354.19	451.30	-669.22
13	5300	1115	5399.63	-545.23	-669.22
14	5200	828	960.86	4080.16	-669.22
15	5000	833	1604.19	2461.87	100.00
16	4600	665	3422.45	412.93	100.00
17	4000	506	1489.19	1905.83	100.00
18	3700	0	1092.97	1737.81	869.22
19	3400	0	3437.84	-907.07	869.22
20	3200	0	889.54	1441.24	869.22
21	3000	0	2260.01	-129.23	869.22
22	2800	0	1485.54	1983.68	-669.22
23	2600	0	4733.99	-1464.77	-669.22
24	2400	0	1042.36	1257.64	100.00

The 24-hour period depicted in Table 10 provides a clear view of how operational costs change across different energy sources, namely PV, wind, battery storage, and grid power, as they are used to meet demand. Solar PV power remains consistently inexpensive, often costing nothing, reflecting either low operating expenses or periods when solar power is not actively contributing. For wind power, many more variations are observed, with costs that fluctuate with wind availability, ranging from \$8.44 to \$54.00. A major contributor to overall expenses is grid power imports, which are especially costly between hours 4 and 14, peaking at \$734.43 in hour 14.

Thus, indicating heavy reliance on external energy during those times. In contrast, grid export results in credits during some hours, such as a notable -\$62.21 in hour 8, showing moments when surplus energy is sold back to the grid. Battery usage incurs a steady degradation cost of \$5.00 per hour, though it spikes to \$43.46 at specific points, adding extra pressure to the total cost. As a result, total operating costs vary widely, ranging from \$40.52 in hour 2 to \$781.64 in hour 14. The period of high grid import aligns closely with the total operating costs. Early hours tend to be more affordable because they rely more on renewable energy, whereas later hours depend more on the grid, driving costs higher. There is a delicate balance between renewable generation, battery usage, and grid dependence. This highlights a clear opportunity to optimize energy management, primarily by reducing grid reliance during peak cost periods.

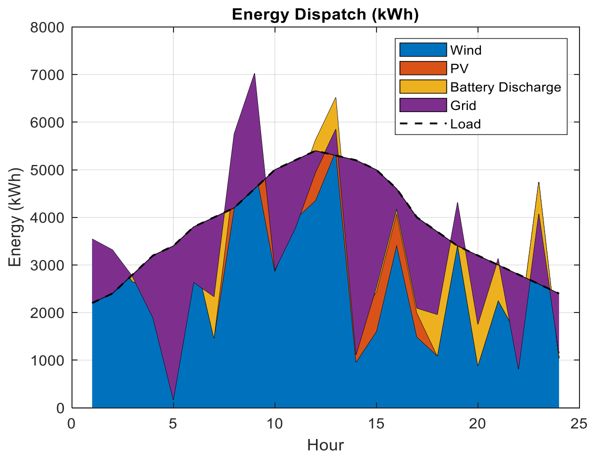

Figure 7. Energy Dispatch simulation results for 24 hours using GWO

Figure 7 presents the energy dispatch analysis for the hybrid renewable energy system, indicating that the system relies on wind, grid, battery, and PV, with each source contributing the majority of the supply. Moreover, Figure 8 conceptualizes the operating and maintenance cost results for 24 hours using GWO. Grid import has the highest cost, followed by grid export, battery degradation cost, wind cost, and PV cost; battery degradation cost has the lowest cost.

Table 10. Power dispatch solution using the GWO method

Hour	PV Power cost ($)	Wind Power cost ($)	Grid Power Import cost ($)	Grid Power Export cost ($)	Battery Power Degradation ($)
1	0.00	34.45	0.00	-53.79	5.00
2	0.00	32.16	0.00	-36.64	5.00
3	0.00	26.49	9.19	0.00	5.00
4	0.00	25.59	235.77	0.00	33.46
5	0.00	8.44	580.62	0.00	33.46
6	0.00	33.09	208.88	0.00	33.46
7	0.00	14.69	299.15	0.00	43.46
8	3.37	42.13	0.00	-62.21	43.46
9	5.10	51.33	0.00	-96.84	43.46
10	3.50	28.70	377.87	0.00	33.46
11	2.37	39.63	257.80	0.00	33.46
12	6.32	43.54	81.23	0.00	33.46
13	5.57	54.00	0.00	-21.81	33.46
14	4.14	9.61	734.43	0.00	33.46
15	4.17	16.04	443.14	0.00	5.00
16	3.32	34.22	74.33	0.00	5.00
17	2.52	14.89	343.05	0.00	5.00
18	0.00	10.93	312.81	0.00	43.46
19	0.00	34.38	0.00	-36.28	43.46
20	0.00	8.90	259.42	0.00	43.46
21	0.00	22.60	0.00	-5.17	43.46
22	0.00	14.86	357.06	0.00	33.46
23	0.00	47.34	0.00	-58.59	33.46
24	0.00	10.42	226.38	0.00	5.00

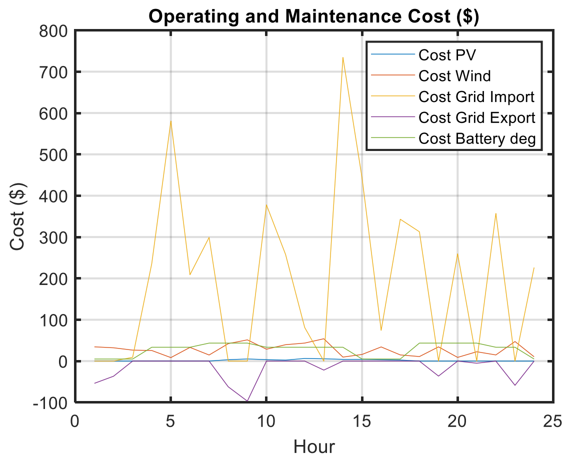

Figure 8. Operating and Maintenance cost results for 24 hours using GWO

IX. Case-study 5: Grid-connected Microgrid dispatch with Wind renewable energy resources using the GWO algorithm

In this case study, the objective is to dispatch a grid-connected microgrid with renewable energy resources. The GWO algorithm is applied to solve the wind-grid energy-based supply. The obtained results are reported in Table 11. Load demand is still the same as in case study 1. Also, the total operating costs are included in Table 12, whereas PV power and battery storage are excluded in this case study. Load demand varies between the values of 2200kW and 5400kW, while the wind output varies from 843.55kW to 5399.63kW as presented in Table 11. Surpluses are always exported to the grid. Moreover, the total operating cost is the sum of grid and operating costs, as depicted in Table 12. Grid exporting occurs during hours 2, 3, 4, 8, 16, 20, 22, and 24; the remainder of the time. Power is being supplied from the grid.

Table 11. Wind energy-based Microgrid Power Dispatch using GWO algorithm

Hour	Power demand (kW)	Wind Power (kW)	Grid Power (kW)	Total Operating cost
1	2200	1993.81	206.19	57.05
2	2400	3646.83	-1246.83	-13.41
3	2800	3188.38	-388.38	16.35
4	3200	4442.35	-1242.35	-5.27
5	3400	2534.41	865.59	181.15
6	3800	1489.10	2310.90	430.85
7	4000	3242.72	757.28	168.74
8	4200	4779.35	-579.35	24.62
9	4600	2223.54	2376.46	450.00
10	5000	1592.26	3407.74	629.32
11	5200	945.54	4254.46	775.26
12	5400	817.60	4582.40	833.01
13	5300	4432.56	867.44	200.47
14	5200	3264.86	1935.14	380.97
15	5000	1527.01	3472.99	640.41
16	4600	5074.74	-474.74	31.76
17	4000	5257.64	-1257.64	2.27
18	3700	958.92	2741.08	502.98
19	3400	576.33	2823.67	514.02
20	3200	3801.08	-601.08	13.97
21	3000	586.23	2413.77	440.34
22	2800	3597.72	-797.72	4.07
23	2600	459.97	2140.03	389.80
24	2400	5312.05	-2912.05	-63.36

The optimal cost over 24-hour periods is presented as the total operating cost, which is the power-exchange cost between wind power generation and the grid. The highest cost occurred at hour 12, when demand is at its peak, while wind generation is very low; therefore, the total operating power cost is also at its maximum.

This is considered the objective function in this case study. The optimal wind speed is observed approximately 18 hours into the time series, whereas the minimum occurs in the late hours, such as at 23 hours. Thus, indicating the key role in enhancing energy dispatch strategies. Variations in wind speed underscore the importance of optimizing energy dispatch and grid interactions. As stated earlier, during high-wind hours, excess power is exported to the grid. When wind hours are low, the grid becomes essential. At this juncture, lower speeds during high demand elevate operating costs ($833.01). This emphasizes the need for cost-effective battery storage or hybrid systems to secure reliability and economic efficiency.

Table 12 . Wind Energy-based Microgrid Operating and Maintenance Cost Using the GWO Algorithm

Hour	Wind Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Total Operating cost ($)
1	19.94	19.94	37.11	0.00
2	36.47	36.47	0.00	-49.87
3	31.88	31.88	0.00	-15.54
4	44.42	44.42	0.00	-49.69
5	25.34	25.34	155.81	0.00
6	14.89	14.89	415.96	0.00
7	32.43	32.43	136.31	0.00
8	47.79	47.79	0.00	-23.17
9	22.24	22.24	427.76	0.00
10	15.92	15.92	613.39	0.00
11	9.46	9.46	765.80	0.00
12	8.18	8.18	824.83	0.00
13	44.33	44.33	156.14	0.00
14	32.65	32.65	348.32	0.00
15	15.27	15.27	625.14	0.00
16	50.75	50.75	0.00	-18.99
17	52.58	52.58	0.00	-50.31
18	9.59	9.59	493.39	0.00
19	5.76	5.76	508.26	0.00
20	38.01	38.01	0.00	-24.04
21	5.86	5.86	434.48	0.00
22	35.98	35.98	0.00	-31.91
23	4.60	4.60	385.21	0.00
24	53.12	53.12	0.00	-116.48

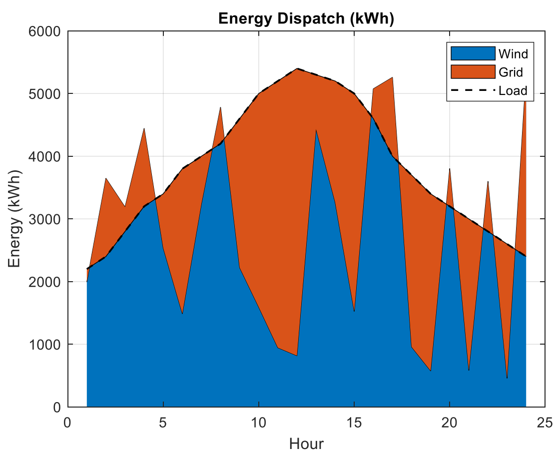

Figure 9. Energy Dispatch simulation results for 24 hours using GWO

The analysis of energy dispatch for the wind-grid hybrid system requires a better understanding of how to effectively manage and utilize the generated wind energy from both the wind energy system and the conventional grid. Figure 9 shows the wind contribution in a wind-grid hybrid system. Wind output is variable and depends on wind speed; therefore, grid integration provides a stable electricity supply that can be dispatched as needed. The grid supports wind energy when output is low and draws surplus power from wind when generation is high. In the operating and maintenance cost analysis of the wing-grid system, the cost of grid import is very high. Compared with the grid export, the low cost of grid export is captured, as shown in Figures 9 and 10. This conceptualization of operating and maintenance costs provides valuable insights into economic viability. The efficiency of utilizing both wind energy and traditional power must be considered.

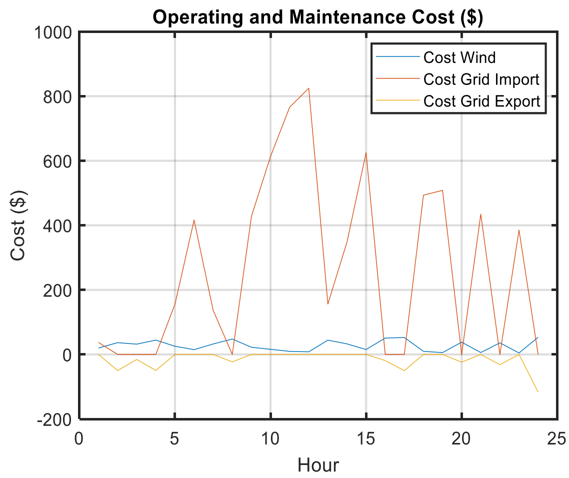

Figure 10. Operating and maintenance cost for 24 hours using GWO

X. Case study 6: Grid-connected Microgrid dispatch with PV and Battery using GWO algorithm

In this case, the energy dispatch of the grid-PV-Battery Storage hybrid is the objective function, and GWO is employed for optimization. The results obtained for Grid power dispatch with PV and Battery storage using GWO are presented in Table 13. The load demand is the same across all case studies and ranges from 2200kW to 5400kW. Table 14 presents the results of the operating and maintenance cost obtained. This is where the grid, PV, Battery, grid import, and grid export costs are captured and tabulated in Table 14.

Table 13. Microgrid Power Dispatch with PV and Battery using GWO algorithm

Hour	Load Power kW	PV Power kW	Battery Power kW	Grid Power kW
1	2200	0.00	100.00	2100.00
2	2400	0.00	100.00	2300.00
3	2800	0.00	100.00	2700.00
4	3200	0.00	-643.22	3843.22
5	3400	0.00	-643.22	4043.22
6	3800	0.00	-643.22	4443.22
7	4000	0.00	843.22	3156.78
8	4200	759.41	843.22	2597.37
9	4600	686.74	843.22	3070.04
10	5000	940.47	-643.22	4702.74
11	5200	1094.10	-643.22	4749.11
12	5400	651.96	-643.22	5391.26
13	5300	1055.98	-643.22	4887.24
14	5200	1089.73	-643.22	4753.49
15	5000	707.68	100.00	4192.32
16	4600	460.09	100.00	4039.91
17	4000	578.14	100.00	3321.86
18	3700	0.00	843.22	2856.78
19	3400	0.00	843.22	2556.78
20	3200	0.00	843.22	2356.78
21	3000	0.00	843.22	2156.78
22	2800	0.00	-643.22	3443.22
23	2600	0.00	-643.22	3243.22
24	2400	0.00	100.00	2300.00

The operation and maintenance cost of a Grid-PV-Battery hybrid system constitutes a pivotal factor in assessing the overall economic feasibility of the energy solution. The systematic treatment of hybrid cost elements is essential for enhancing the efficiency, reliability, and financial sustainability of energy dispatch in grid-connected microgrid frameworks. The optimization process typically involves analyzing PV generation forecasts, battery degradation, Grid exports, and Grid imports, and the sum of these costs is referred to as the system's total operating cost, as shown in Table 14.

Table 14. Microgrid Operating and Maintenance cost with PV and Battery using GWO algorithm

Hour	PV Power cost in $	Grid Power Import cost in $	Grid Power Export cost in $	Battery Power degradation cost in $
1	0.00	378.00	0.00	5.00
2	0.00	414.00	0.00	5.00
3	0.00	486.00	0.00	5.00
4	0.00	691.78	0.00	32.16
5	0.00	727.78	0.00	32.16
6	0.00	799.78	0.00	32.16
7	0.00	568.22	0.00	42.16
8	3.80	467.53	0.00	42.16
9	3.43	552.61	0.00	42.16
10	4.70	846.49	0.00	32.16
11	5.47	854.84	0.00	32.16
12	3.26	970.43	0.00	32.16
13	5.28	879.70	0.00	32.16
14	5.45	855.63	0.00	32.16
15	3.54	754.62	0.00	5.00
16	2.30	727.18	0.00	5.00
17	2.89	597.94	0.00	5.00
18	0.00	514.22	0.00	42.16
19	0.00	460.22	0.00	42.16
20	0.00	424.22	0.00	42.16
21	0.00	388.22	0.00	42.16
22	0.00	619.78	0.00	32.16
23	0.00	583.78	0.00	32.16
24	0.00	414.00	0.00	5.00

Since the hybrid system has no grid export, operating and maintenance costs are substantially higher because PV power is available only from hour 8 to hour 17. Again, the battery charging/discharging pattern is the same as in case study 1; therefore, the system incurs high operating and maintenance costs, especially during periods of high load demand.

Figure 11 shows the system's energy dispatch, with the grid as the primary supplier of load demand. This implies a high operational and maintenance cost for the grid. PV and Battery systems are only available during their respective availability periods. The battery system stores energy only during off-peak hours, charging the battery until it reaches a maximum capacity of 643.33kWh.

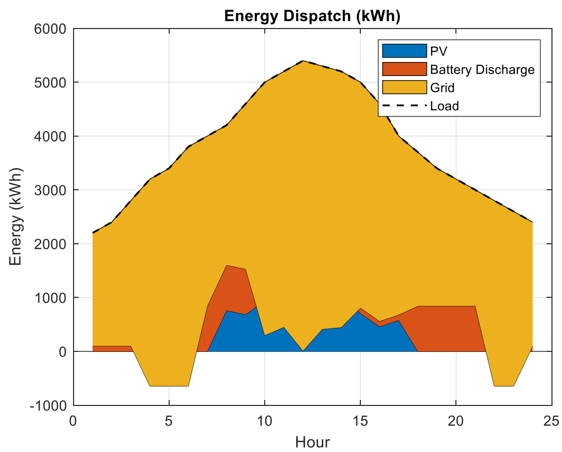

Figure 11. Energy Dispatch for 24 hours using GWO

XI. Discussion of Results of both LP and GWO methods for the Microgrid dispatch problem

The scenario that includes Wind, PV, Battery, and Grid generally has a lower cost than the PV, Battery, and Grid scenario during most hours, suggesting that incorporating wind energy reduces cost, especially during hours of higher demand. The combination of Wind and Grid shows lower costs than other alternatives in some cases, particularly during periods when wind generation is optimal. Overall analysis of the algorithms' cost across the three scenarios is presented in Figure 12 for the LP-based simulation.

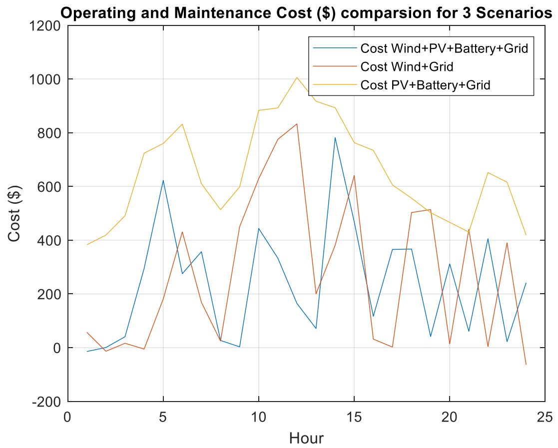

Figure 12. Operating and Maintenance cost Comparison for 3 Scenarios

For the LP algorithm, the lowest total cost is $9,250.82 for the Wind, PV, Battery, and Grid scenario, while the highest is $14,912.15 for the PV, Battery, and Grid scenario. Similarly, with the GWO algorithm, the Wind, PV, Battery, and Grid scenario again yields the lowest cost of $5,802.44. The total costs obtained by the GWO algorithm are lower across all scenarios than those obtained by the LP algorithm. This suggests that optimizing dispatch using GWO may be more effective, based on the data presented. The variability suggests that strategies should focus on enhancing the predictability and utilization of wind and solar resources, in conjunction with battery storage, to minimize grid dependence. The operational strategy could emphasize scheduling battery charging during low-cost periods and efficiently dispatching renewable generation when it is most available.

Figure 13 for GWO-based simulations. GWO identifies the optimal cost solution across all scenarios. The best solution is obtained in case study 1, in which all renewable resources participated.

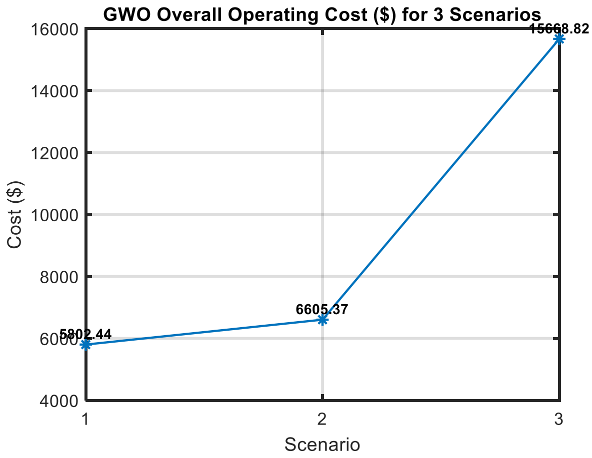

Figure 13. GWO Overall Operating cost for 3 Scenarios.

Figures 14 and 15 provide the simulation results of the hourly operating cost and overall operating cost, respectively, for the six case studies using LP and GWO techniques. A comparative analysis of the results demonstrates that the GWO technique consistently achieves lower operating costs than the LP approach, particularly for the Wind–PV–Battery–Grid configuration, where the minimum cost of $5,802.44 is achieved in case study 4, as shown in Figure 15. These findings highlight the superior capability of metaheuristic optimization in handling the nonlinear and complex nature of hybrid microgrid energy management problems. The computational efficiency of the optimization techniques was evaluated by measuring elapsed execution time. The Linear Programming (LP) algorithm required 4.252047 seconds to converge to an optimal solution, whereas the Grey Wolf Optimization (GWO) technique converged in 2.062354 seconds. This reduction in computational time demonstrates the superior efficiency of the GWO approach for the microgrid optimization problem considered.

The longer execution time of the LP method can be attributed to its reliance on deterministic solvers and constraint-handling mechanisms, which become increasingly complex as multiple distributed energy resources, battery operational constraints, and grid interaction limits are incorporated. In contrast, GWO employs a population-based metaheuristic that effectively explores the solution space and rapidly converges to near-optimal solutions with reduced computational overhead. The observed computational advantage of GWO is particularly beneficial for real-time or large-scale microgrid energy management applications, where fast decision-making is essential. These results indicate that, in addition to achieving lower operating costs, the GWO technique offers improved computational performance relative to LP, making it a more suitable candidate for practical, scalable hybrid microgrid optimization.

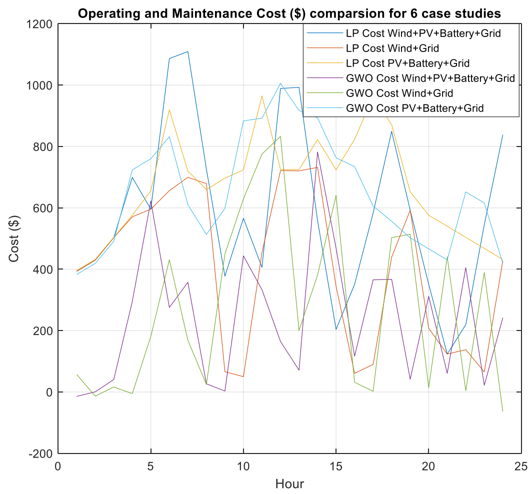

Figure 14. LP and GWO Operating cost for 6 Case Studies

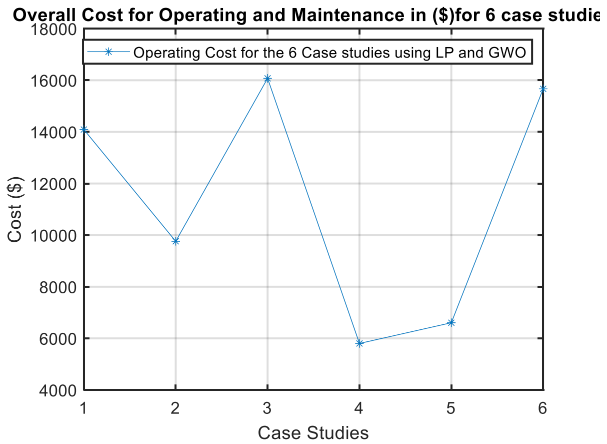

Figure 15. LP and GWO Overall Operating cost for 6 case studies

XII. Conclusion

This study optimized a hybrid system comprising PV, wind, and BSS. LP and the GWO optimization were successfully applied to minimize the operational cost of the hybrid microgrid system. The Wind and PV system supplements demand rather than fully meeting it, with LP and GWO optimization balancing capacity and costs to prevent oversizing while maximizing production during high-demand, sunlit hours. The comparison of LP and GWO optimization results demonstrates that integrating multiple renewable sources, particularly wind and PV, with battery storage significantly enhances the microgrid's operational efficiency.

Across all three scenarios, the hybrid wind-PV-Battery-Grid configuration consistently delivered the lowest operating costs. This highlights the value of diversified energy portfolios in smoothing variability and reducing reliance on grid imports. While both optimization methods improved dispatch decisions, the GWO algorithm outperformed the other method, yielding lower total operating costs across all scenarios. This indicates that GWO is more effective at capturing nonlinearities and variability in renewable generation, leading to more optimal scheduling outcomes. Overall, the findings suggest that combining advanced optimization techniques with hybrid renewable systems can substantially improve cost efficiency and reliability in microgrid operations.

The results show that LP has a total operating cost of $9,250.82, whereas GWO achieved a significantly lower total operating cost. of $5.802.44. This represents a 37.28% reduction in operating costs when using GWO rather than LP, confirming GWO's superior ability to optimize dispatch under fluctuating renewable energy conditions. When comparing scenarios more broadly, the LP algorithm's most expensive configuration (PV-Battery-Grid) at $14,912.15 is 61% higher than its most economical configuration(wind-PV-Batter-Grid) at $9,250.82. It highlights the vital importance of integrating wind energy. Meanwhile, the GWO algorithm not only reduces costs across all scenarios but also consistently outperforms LP, delivering 30%-40% improvements in each scenario. The results support the adoption of intelligent dispatch strategies, particularly those that leverage nature-inspired algorithms, such as GWO, to increase renewable utilization. Moreover, to enhance battery management and minimize operational expenses.

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Declaration

- The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.
- The authors declare that this article has not been published before and is not in the process of being

published in any other journal.

- The authors confirmed that the paper was free of plagiarism

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