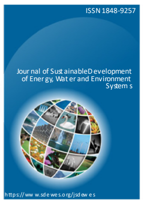
Journal of Sustainable Development of Energy, Water and Environment Systems

http://www.sdewes.org/jsdewes



Year 2025, Volume 13, Issue 3, 1130586

Original Research Article

An Improved Energy Management Strategy for Hybrid Power Systems Using Dual Predator Optimization

Md. Nimul Hasan[1], Md. Akhlaqur Rahman[2], Md. Fatin Ishraque[1], Kamil Ahmad[1], Sk. A. Shezan*[3], Md. Shatez Ahmed[1]

[1]Department of Electrical, Electronic and Communication Engineering, Pabna University of Science and Technology, Pabna-6600, Bangladesh
e-mail: nimul34.din.h@gmail.com, fatineeeruet@gmail.com
kmlahmad237@gmail.com, shatez.eece@gmail.com

[2]Department of Electrical Engineering and Industrial Automation, Engineering Institute and Technology, Melbourne Campus, Australia.
e-mail: akhlaqur.rahman@eit.edu.au

[3]Department of Electrical Engineering, Prince Faisal Centre for Renewable Energy Research, Northern Border University, Arar, Saudi Arabia
e-mail: shezan.ict@gmail.com

Cite as: Hasan, N., Rahman, A., Ishraque, F., Ahmad, K., Shezan, A., Ahmed, S., An Improved Energy Management Strategy for Hybrid Power Systems Using Dual Predator Optimization, J.sustain. dev. energy water environ. syst., 13(3), 1130586, 2025, DOI: https://doi.org/10.13044/j.sdewes.d13.0586

ABSTRACT

In this research work, the proposed Dual Predator Optimization algorithm is inspired by the hybridization of the very well-known Whale Optimization Algorithm and Grey Wolf Optimization. This algorithm integrates with a hybrid micro-grid to optimize the use of renewable resources, reduce reliance on fossil fuel, and increase the cost-effectiveness of using excess energy by adjusting these parameters over time. The Dual Predator Optimization is flexible and more suitable for hybrid energy management. The findings indicate that Dual Predator Optimization effectively manages hybrid systems by substantially lowering electricity expenses and diminishing the likelihood of supply interruptions. It was determined that in comparison to the hybridization algorithms, the Cost of Energy of the proposed Dual Predator Optimization technique is reduced to an average of 20%, however, the Loss of Power Supply Probability rises to an average of 7.5%. it offers zero load shedding within the hybrid system with 100% renewable-satisfied energy production for the microgrid. Moreover, the proposed Dual Predator Optimization outperformed others in terms of producing hydrogen by 21.10% and 17.60% respectively. The findings indicate that Dual Predator Optimization is a superior method for addressing energy reliability and environmental sustainability issues.

KEYWORDS

Optimization, Renewable energy, Hybrid microgrid, Meta-heuristic algorithms, Cost of electricity, Dual predator optimization.

INTRODUCTION

In this era of fast globalization, industrial growth, population expansion, and technological advancements, the global energy demand has reached an all-time high. An internalizing cycle

* Corresponding author

of global economics emerges when countries become mutually dependent on one another for energy supplies, driven by an ever-increasing demand for governments to satisfy their populations' lifestyle expectations. The global instability in particularly fossil fuel markets among nations, leads to an energy crisis concerning developing countries of the world like Bangladesh [1].

At the same time, one of the most vulnerable countries to global warming, Bangladesh has rapidly widening problems [2] like rising sea levels, floods, and cyclones exacerbating energy crisis & thereby economic peril. Using renewable energy is seen to be explored by utilizing the possible source of renewable energy generation domestically. The optimization algorithms will become more crucial to control renewable energy systems efficiently due to high dimension problems even existing methods cannot attend those. Although exact optimization methods are highly effective in some cases, they turn out to be intractable for large non-linear problems due to the search space increasing exponentially. Such cases cannot just be solved in any traditional way like the greedy algorithms [3]. Metaheuristic algorithms [4, 5] are more flexible and better at working with large-dimensional tasks like global searches.

Solar and wind microgrid systems, as part of renewable energy help to tackle the growth in power demand attributed to rapid industrialization and urbanization [6]. The decrease in the use of fossil fuels and their damaging greenhouse gas emissions provides support to this view. Switch to sustainable energy sources for accommodation. The serious scenario regarding the depletion of fossil reserves and challenges related to s emissions underline the need for a transition away from the use of carbon compounds. This is especially true for microgrids, where hybrid systems might be more cost-effective than expanding traditional power networks to rural area [7].

The Whale Optimization Algorithm (WOA), a meta-heuristic optimization algorithm based on humpback whale social behavior and their favorite hunting strategy—bubble-net hunting—is presented in this work in [8, 9]. To replicate the steps involved in hunting ring creation, bubble-net feeding, and prey search, WOA uses three different types of operators. Conversely, WOA is used for six optimization issues in structural engineering (tension/compression spring design and pressure vessel design), demonstrating its superiority and effectiveness over conventional optimization methods. The method's utility for solving various optimization problems is further expanded by current research on binary and multi-objective (MO) WOAs [9].

In the Particle Swarm Optimization (PSO) [10] method, Every particle in the search space represents a possible solution and updates its position in accordance with both its own and the swarm's best-known roles. PSO has evolved into various variants that focus on specific enhancements such as parameter adjustment, multi-objective optimization, and hybrid techniques. Because of its adaptability and ease of coding, PSO has several practical uses (customized), ranging from engineering to artificial intelligence, as well as simple/complex searches [11].

Mirjalili *et al.* introduced a Grey Wolf Optimizer(GWO) [12]. This is similar to their leadership structure, which includes alpha, beta, delta, and omega wolves with distinct positions represented in the algorithm. This implementation has been compared with a few well-established optimization techniques such as PSO and Differential Evolution (DE), demonstrating competitive outcomes on both standard test functions as well as real-world engineering problems [12]. T. Agajie *et al.* explored optimal sizing of Renewable energy sources that are hybrid for dependable, hygienic, and cost-effective power production systems, highlighting essential elements, variables, procedures, and information [13].

In [14] researchers reviewed Microgrid power-quality problems, optimization methods, and management schemes for hybrid microgrids, emphasizing their increased system reliability. According to [15], An electrical energy control technique reduces the proposed energy expenditures and greenhouse gas emissions significantly for hybrid solar-powered electric vehicle charging stations and biogas by 74.67%. A. Karmaker *et al.* proposed a hybrid PV-Wind-FC system with battery energy storage which reduces costs and improves energy management by eliminating converters and minimizing intermittency [16]. In [17] the proposed HFAPSO algorithm effectively optimizes an islanded green energy system, achieving 100% renewable energy and minimizing annual energy costs while meeting energy demands. For electric car hybrid energy storage systems, N.-D. Nguyen *et al.* suggested a predictive control-based energy management approach that boosts performance and efficiency without needing to know the speed of the vehicle or anticipated demands [18]. Another study examined a gradient-based energy management system with deep determinism method that outperforms a twice the width Q-learning-based strategy in hybrid electric tracked cars and increases fuel economy by 13.1% [19]. The proposed predictive control strategy in [20] effectively manages a wind and solar microgrid that is linked to the grid and has hybrid storage for energy, reducing costs and increasing battery life. The proposed energy management strategy by M. Behera and L. Saikia for plug-in hybrid electric buses improves fuel economy and avoids the curse of dimensionality, with a fuel consumption increase of 3.23% compared to the dynamic programming algorithm [21]. The proposed For dual-DC-port dc-port dc-ac converter-connected PV-battery hybrid systems, a zero-vector-regulation-based closed-loop power distribution approach provides flexible power distribution and grid-side current quality without complex Synthesis for the voltage vectors [22].

Machine learning as well as artificial intelligence can effectively manage energy in hydrogen fuel cell vehicles, reducing greenhouse gas emissions and improving vehicle-to-everything connectivity [23]. The Artificial Gorilla Troops Optimization (GTO) algorithm effectively solves The optimal power flow problem for hybrid renewable energy systems using probabilistic methods, reducing total system cost [24]. Reinforcement learning (RL) can optimize energy use in smart buildings, hybrid vehicles, and cybersecurity, contributing to a sustainable environment and reducing carbon emissions [25]. DeepEE, a deep reinforcement learning framework, can optimize data center energy consumption by up to 15% and 10%, achieving more stable performance gains [26]. Hybrid policy-based learning through reinforcement (HPRL) energy management effectively optimizes island group energy systems in scenarios where energy transmission is constrained, ensuring energy supply and satisfying particular demands [27]. Learning through reinforcement can effectively manage energy in fuel cell hybrid systems, but requires careful training environments and reward function settings [28].

The hybrid energy storage system (HESS) with hydrogen/bromine redox flow battery and supercapacitor effectively smoothens power and accommodates pulse power loads in grid-integrated solar PV systems, improving overall system dynamics [29]. Compared to alternative approaches, the AMPC-based on an energy handling plan for electric vehicles with fuel cell hybrids reduces system deterioration and increases fuel efficiency [30]. The proposed energy-consumption management system effectively lowers peak-to-average ratios and power bills. by 28% and 49.32%, while maintaining user comfort [31]. The proposed predictive control strategy in [32] effectively allocates load current in Energy storage using a battery-supercapacitor hybrid systems, reducing energy losses and battery degradation in electric vehicle applications.

This paper focuses on the application, modification, and hybridization of WOA in various fields of engineering [8]; and also identifies its pros and areas that still need investigation. WOA techniques are applied in five different sectors with 61% focusing on modifications, 27% on hybridizations, and the remaining 12% involving multi-objective variants. It points to the growing relevance of WOA approaches in engineering [8].

This study's primary goal is to develop an effective optimization algorithm for the energy management of hybrid energy systems while taking into account renewable sources' maximum potential to lower operating costs. The DPO algorithm has been proposed that combines the GWO and WOA and addresses the exploration versus exploitation trade-off in dynamic and highly constrained energy management problems. The benefits of DPO are that it helps keep the cost of electricity (*COE*) down while maintaining reliable service via a reduction in the loss of power supply probability (*LPSP*). Additionally, this optimization can significantly enhance the renewable factor, reduce load shedding, and maximize the production of hydrogen which in turn can be utilized for powering hydrogen vehicles. On top of that, the flexibility of the algorithm allows it to make more cost-effective use of renewable energy sources and hence cuts carbon emissions while boosting environmental sustainability. By intelligently distributing and storing resources, DPO provides a way to transition to cleaner energy infrastructures with significant resilience which will be critical for deploying sustainable future supplies.

Additionally, this paper is structured as follows: The approach is described in Section 2. Techniques for microgrid energy planning and control are covered in Section 3. The findings and discussion are briefly presented in Section 4. The conclusion and future work direction are the main topics of Section 5.

MATERIALS AND METHODS

This section with suitable subsections discusses the methodological approach of this research work. In this section, the methodology is well discussed with appropriate illustrations.

Environmental investigation through renewable energy

The developed mathematical representations for the microgrid's solar, wind, battery, and diesel generator components are discussed in this subsection. These models are required for further evaluations aimed at enhancing the microgrid's performance. Additionally provided is a simple electrolyzer model that might be used to produce hydrogen and oxygen from excess microgrid electricity for use in businesses located inside the designated economic zone. Finally, the subject of simulating the burden on the economic zone is covered.

System configuration for the hybrid system

This section, with suitable subsections illustrates the hybrid system configuration on which the proposed optimization algorithm has been applied. The hybrid system has been shown in **Figure 1**.

Wind Turbine. For electrical power, wind energy is a popular renewable energy source, especially in the country's southeast and south, which have a lot of potential for using this plentiful energy [33]. The velocity of the wind at the height of the anemometer needs to be translated to the appropriate hub heights because wind speed changes with altitude. For this conversion, the power law equation is applied, as this correlation illustrates [1]:

$$\frac{V_{21}}{V_{11}} = (\frac{h_{21}}{h_{11}})^{\alpha} \tag{1}$$

Hither, V_{11} and V_{21} stand for the speed (m/s) at the corresponding height (h_{11}) and hub height (h_{21}) in meters, respectively. The friction coefficient is α, which is also referred to as the power law exponent or Hellmann exponent. The friction coefficient (α) can be impacted by changes in height above the ground, temperature, season, wind speed, and the roughness of the terrain.

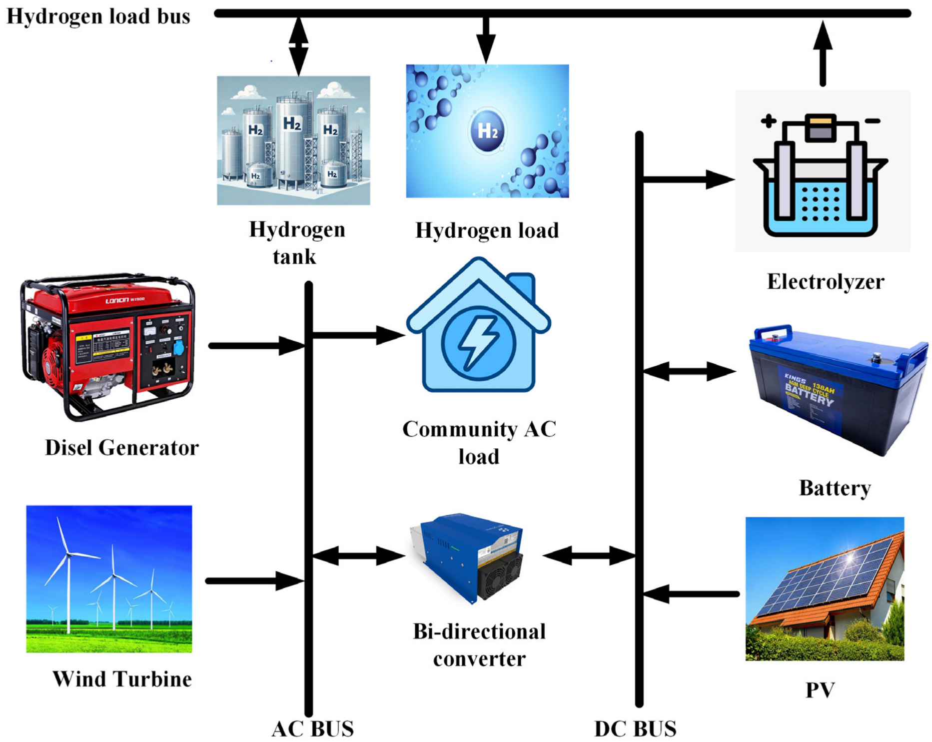


Figure 1. Proposed hybrid microgrid system's schematic diagram

The following formula is used to approximate a wind turbine's power production [34]:

$$P_{\text{wi-output}} = \begin{cases} 0, & V < V_{\text{c-in}}, V > V_{\text{cut-off}} \\ \dfrac{P_{\text{rat}}(V^3 - V^3{}_{\text{c-in}})}{(V^3 - V^3{}_{\text{c-in}})}, & V_{\text{c-in}} \leq V < V_{\text{cut-out}} \\ P_{\text{r}}, & V_{\text{rat}} \leq V < V_{\text{cut-off}} \end{cases} \tag{2}$$

Hither, $P_{\text{wi-output}}$ refers to the wind turbine's kilowatt-output power, P_{rat} refers to the rated power in kW, moreover, $V_{\text{cut-off}}$, V_{rat}, and $V_{\text{c-in}}$ refer to cut-in wind speed, nominal wind speed, and cut-out wind speed similarly. Small-scale wind turbines can operate well even in low wind conditions because of their limited $V_{\text{cut-in}}$.

Eqs. (1) and (2), combined with the wind speed information from the NASA POWER API with a granularity for the specific geographic coordinates of the study area [35] were used to calculate per-unit power generation. Figure 2 shows the outcomes.

Solar. Bangladesh's geographic location offers a plethora of opportunities for solar power harvesting [36]. Because Bangladesh is situated in an area with high levels of solar irradiation, it has year-round access to plenty of sunlight. The following formula can be used to determine the power generated by the panels as a function of solar radiation [6]:

$$P_{\text{solarout}} = P_{\text{N-solar}} \times \frac{G}{G_{\text{reference}}} \times [1 + K_{\text{tem}} \left(T_{\text{am}} + (0.0256 \times G)\right) - T_{\text{reference}} \tag{3}$$

Hither, P_{solarout} refers to the output power (kW) of solar, $P_{\text{N-solar}}$ refers to rated power under reference conditions, G refers to solar radiation in Wm^{-2}, $G_{\text{reference}}$ equal to 1000 Wm^{-2}, $T_{\text{reference}}$ equal to 25 °C, K_{tem} equal to -3.7×10^{-3} (1/°C), T_{am} refers to the ambient temperature. Eq. (3) and data were extracted from the NASA POWER API with a granularity for the specific geographic coordinates of the study area [35] can be used to compute the production of solar energy, as illustrated in Figure 3.

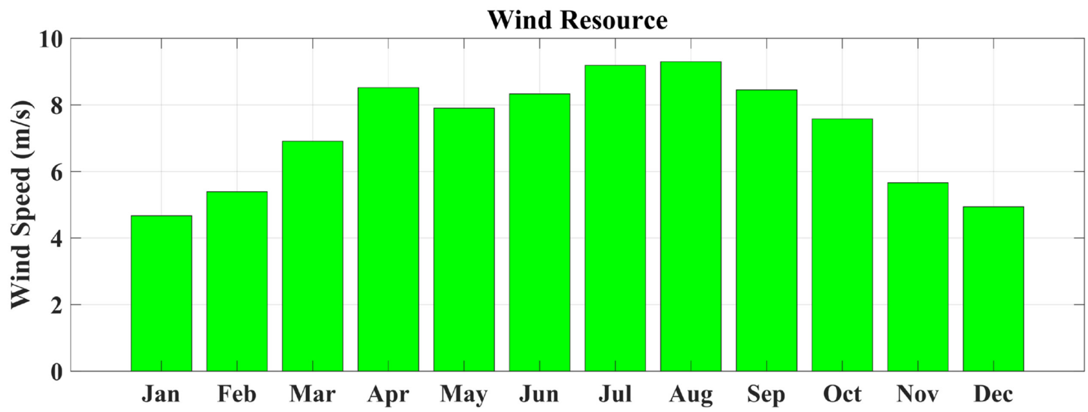


Figure 2. Average monthly wind speed for a specific year

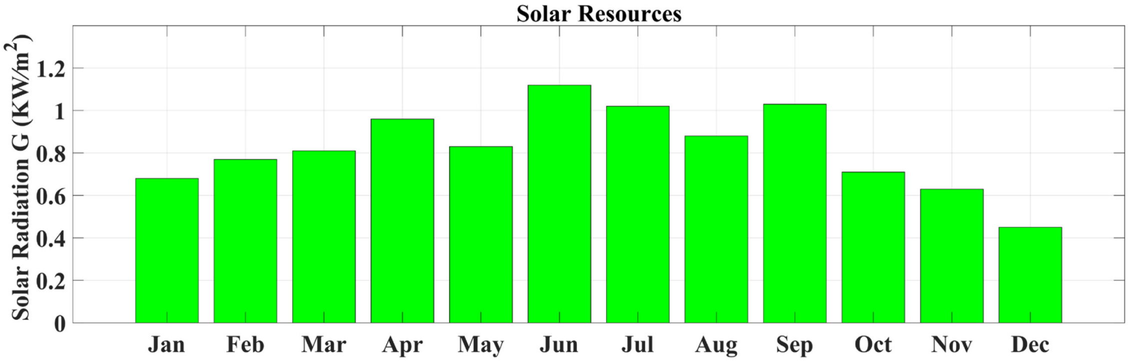


Figure 3. Average monthly Solar radiation for a specific year

Diesel Generator. The diesel generator lessens load shedding and enhances power quality by acting as a backup source when the battery runs low during periods of high demand. When designing a hybrid system, the efficiency and hourly fuel consumption of a diesel generator can be expressed using the following formula [37]:

$$Q(t) = a \times Pi(t) + b \times P_{\text{rated}} \tag{4}$$

Hither, P_{rated} is the rated power (kW), $Q(t)$ is the fuel consumption (L/h), $Pi(t)$ is the generated power (kW), and percentage of fuel consumption is denoted by the parameters (L/kW), a and b are the constant parameters (L/kW). The efficiency of a diesel generator is established by [38]:

$$n_{\text{overall}} = n_{\text{b}} \times n_{\text{g}} \tag{5}$$

Hither, n_{overall} refers to the overall efficiency and n_{b} refers to the brake thermal efficiency of the diesel generator. n_{g} refers to the generator's efficiency.

Electrolyzer. Electrolyzing water to create hydrogen is an intriguing method for producing hydrogen for a Proton Exchange Membrane (PEM) fuel cell. With the help of an electrolyzer made up of numerous cells, each cell having a cathode and anode submerged in electrically conductive water molecules are decomposed into their elements hydrogen and oxygen. The electric power used by the electrolyzer can be defined as the following [39]:

$$H_{2_{\mathrm{f}}} = \begin{cases} Ki_{\mathrm{H_2}} P_{\mathrm{input}} & \text{if} \quad P_{\mathrm{in}} \leq P_{\mathrm{rated}} \\ Ki_{\mathrm{H_2}} P_{\mathrm{r}} & \text{otherwise} \end{cases} \tag{6}$$

$$O_{2_{\mathrm{f}}} = \frac{H_{2_{\mathrm{f}}}}{2} \tag{7}$$

Hither, $O_{2_{\mathrm{f}}}$(Nm^{3}h^{-1}) refers to the per-hour oxygen production and $H_{2_{\mathrm{f}}}$(Nm^{3}h^{-1}) refers to the per-hour Hydrogen production. $Ki_{\mathrm{H_2}}$ (Nm^3/h/KW) refers to the flow rate of hydrogen per kW. P_{input} (kW) refers to the electrolyzer power used.

Battery. The battery compensates for the discontinuous nature of renewable energy and for future applications renewable power is stored in a battery. Hither, the amount of energy retained (kWh) in the batteries during the time slot, t is denoted by $E_{\mathrm{battery}}^{\mathrm{time}}$; $E_{\mathrm{b}}^{\mathrm{minimum}}$ and $E_{\mathrm{b}}^{\mathrm{maximum}}$ refers to the lowest and highest battery capacity for storage (kWh), accordingly. Let $P_{\mathrm{charging}}^{\mathrm{tb}}$ and $P_{\mathrm{discharging}}^{\mathrm{tb}}$ refer to peak battery charge and discharge power (in kW), similarly. $P_{\mathrm{c}}^{\mathrm{m}}$and $P_{\mathrm{d}}^{\mathrm{m}}$ refers to the maximum power of charging and discharging. The system's battery capacity (kW) is calculated based on demand and autonomous days, using the calculation below [40]:

$$\begin{cases} E_{\mathrm{battery}}^{\mathrm{time}} = E_{\mathrm{battery}}^{\mathrm{time-1}} + \\ \left(P_{\mathrm{charging}}^{\mathrm{tb}}, e_{\mathrm{charge}} - \dfrac{P_{\mathrm{discharging}}^{\mathrm{tb}}}{e_{\mathrm{discharge}}} \right) \Delta t \\ \text{when } 0 \leq P_{\mathrm{charging}}^{\mathrm{tb}} \leq u_{\mathrm{b}}^{\mathrm{time}}, P_{\mathrm{charging}}^{\mathrm{tb}} = P_{\mathrm{c}}^{\mathrm{m}} \\ \text{when } 0 \leq P_{\mathrm{d}}^{\mathrm{m}} \leq \left(1 - u_{\mathrm{battery}}^{\mathrm{t}}\right), \\ P_{\mathrm{discharging}}^{\mathrm{tb}} = P_{\mathrm{discharging}}^{\mathrm{max}} \\ E_{\mathrm{b}}^{\mathrm{minimum}} \leq E_{\mathrm{battery}}^{\mathrm{time}} \leq E_{\mathrm{b}}^{\mathrm{maximum}} \\ E_{\mathrm{battery}}^{\mathrm{time}} \leq E_{\mathrm{battery}}^{1} \end{cases} \tag{8}$$

The change in stored energy throughout the time period Δt prior to and there after charging/discharging is shown in the first section of eq. (8). The charging and discharging power should not be greater than their maximum values, as indicated by the second and third claims. The binary parameter $u_{\mathrm{b}}^{\mathrm{time}}$ makes sure the charging and discharge processes do not happen sequentially. The fourth element of eq. (8) constrains the energy stored, ensuring that it remains between its smallest and highest capacity. The last condition states that the energy that remains at the close of the transmit term is the same as its initial state.

Load. The seasonal pattern of energy demand for a typical day in Rangpur has been illustrated by the monthly average load curve as shown in **Figure 4** which reveals that peak loads occur during the summer months (higher cooling loads) and minimum during the winter months (higher heating loads).

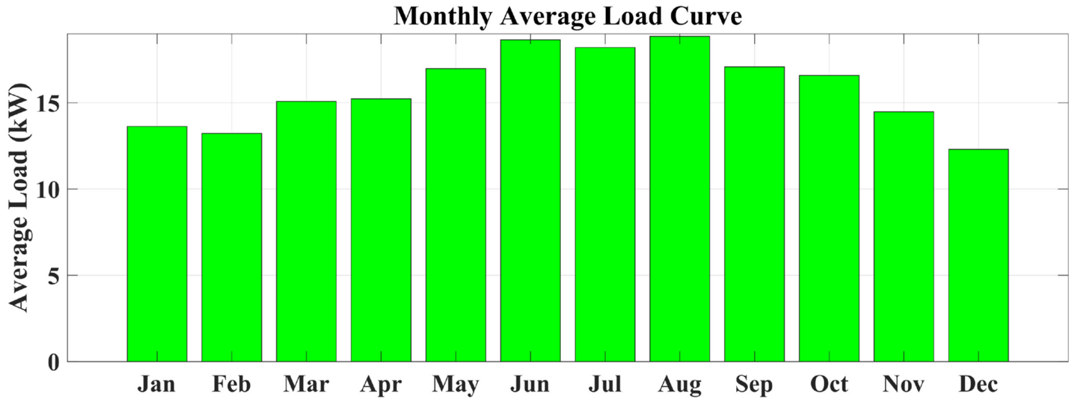


Figure 4. Average monthly load Curve for a specific year

Strategies for microgrid energy planning and control

When it comes to microgrid energy management, there are two possible outcomes: one where the load can be met by renewable energy sources, and another where they can't. In the first case, the system operates efficiently with clean energy. Excess power can be stored or used for other applications. In the second case, backup sources must be utilized to maintain a stable supply, such as batteries and diesel generators.

Case 1: Renewables Cover Total Load: In this case, the surplus energy is directed toward charging the battery and operating the electrolyzer. Any amount of power left over after the electrolyzer operates at its full capacity is deemed waste. In this scenario, load shedding remains zero.

Case 2: Inadequate Renewable Energy: When renewable resources are not enough to meet the load in the second scenario:

- Finding out if the battery can close the energy deficit is the first step in the procedure. In this case, there is no waste, load shedding, or hydrogen produced by the electrolyzer. The battery drains to its lowest level if it can bridge the energy gap.
- If the battery is completely discharged, to compensate for the shortfall and ensure uninterrupted power supply, the diesel generator comes into consideration. By preventing load shedding when both renewables and battery storage are insufficient, this backup mechanism ensures system reliability. The diesel generator is the last possible alternative here meaning the emission is avoided for the whole time other than emergency.

Formulation of problems

Cost of Electricity. One popular and frequently used indicator for evaluating the economic feasibility of hybrid renewable energy systems is the cost of electricity (*COE*). It is the set cost or price per unit of electricity or energy. With the help of eq. (9), the calculation is completed:

$$COE = \frac{TC}{TL} \tag{9}$$

Hither, *TC* prefers total cost and *TL* prefers total load. Every component utilized in the microgrid has its installation, running, and maintenance expenses included in the overall cost. Additionally included is the whole expense of gasoline for the diesel generator unit.

Loss of Power Supply Probability. A statistical assessment of the probability of a power supply failure due to a lack of renewable resources or technical problems meeting demand is known as the loss of power supply probability, or *LPSP*. Two distinct ways are used to calculate *LPSP*: probabilistic methods, which base the calculation on the total energy impact of an energy storage system, and chronological simulation, which employs time-series data over a predetermined period [34], shown by eq. (10):

$$LPSP = \frac{\sum(P_{\mathrm{L}} - P_{\mathrm{solar}} - P_{\mathrm{wind}} - P_{\mathrm{SOC}_{\mathrm{minimum}}} + P_{\mathrm{D}})}{\sum P_L} \quad (10)$$

Hither, P_{L} refers to the load (kW), P_{solar} refers to the electricity produced by solar energy sources (kW), P_{wind} refers to the electricity produced by wind turbines (kW), $P_{\mathrm{SOCminimum}}$ refers to the least amount of charge, and P_{D} refers to the power generated by diesel engines (kW).

Renewable Factor. The renewable factor (*RFact*) controls how energy is distributed between the diesel generator and the renewable side. A situation where the energy system is entirely dependent on renewable sources is indicated by a 100% contribution from renewables. Conversely, if the renewable factor is zero percent, then all of the energy produced by diesel generators is equivalent to all of the energy produced by renewable sources. This statistic accurately captures the system's level of balance between renewable and non-renewable resources. The renewable factor is computed using the study's eq. (11) [41]:

$$RFact(\%) = (1 - \frac{\sum_{n=1}^{T} P_{\mathrm{die}}\,(t)}{\sum_{n=1}^{T} P_{\mathrm{sol}}(t) + \sum_{n=1}^{T} P_{\mathrm{win}}(t)}) \quad (11)$$

Heither, P_{die} refers to energy can produced by diesel generator, P_{sol} refers to energy can produced by solar, P_{win} refers to energy can produced by wind turbine. The aim of optimization is to increase the *RFact* value.

Load Shedding. Direct power outages occur when the total amount of power available falls short of the demand. Different load suppliers in the system are separated by a central control unit during load shedding (*LSD*). The fraction of the overall load that is subject to load shedding is calculated. In this investigation, load shedding was computed using the following eq. (12):

$$LSD(\%) = \frac{\sum_{n=1}^{T} PC1(t)}{\sum_{n=1}^{T} P_{\mathrm{L}}1(t)} \quad (12)$$

Here, "*PC*1" means "power outage." Minimal power outages is the core aim through optimization. The load shedding in the final MCF is given a heuristically high weight in order to achieve this, and it will be reduced to the lowest feasible level.

Hydrogen Production. In the current work, the electrolyzer is the only load that is connected to use excess energy in order to minimize energy waste. In an electrolyzer, H_2 and O_2 can provide conflicting results. This enables the system to become more cost-effective at the electrolyzer's maximum. Therefore, using an electrolyzer is one of the goals of this very research work, which is explain as follows [1]:

$$Utilization\ of electrolyzer(\%) = \frac{\sum_{n=1}^{T} f_{\mathrm{H_2}}(t)}{f_{\max \mathrm{H_2}} \times T} \quad (13)$$

Heither, $\sum_{n=1}^{T} f_{H_2}(t)$ refers to summation of hydrogen production over time, f_{maxH2} refers to the maximum flow rate of hydrogen that the electrolyzer can handle.

DUAL PREDATOR OPTIMIZATION ALGORITHM

The Dual Predator Optimization Algorithm (DPO) is a meta-heuristic algorithm that is proposed in the course of this research. The proposed DPO algorithm combines the WOA and the GWO characteristics to efficiently tune the trade-off between exploration and exploitation for hybrid energy systems optimization. This flexible structure allows DPO to deal with renewable energy resources, multiple contingency plans, batteries, and diesel engines among others as required always having energy available. The DPO comprises the following seven primary steps:

- Initialization
- Evaluation
- Selection
- Exploration
- Adjustment
- Reassessment
- Identification

I. Initialization

Initially, the search agents are dispersed around the search space at random. They all can start by exploring different solution spaces due to the fact that each agent is initialized in a different state. In the first part, since there is a lot of variability, it allows for the algorithm to within a few iterations quickly around where in the search space it is.

II. Evaluation

The fitness of each agent is calculated which helps to find out, how well the agents are capable of solving the problem. This feature identifies the agents who are productive and the ones that are a burden. The foundation for selecting the best agents is fitness assessment, which is also used to monitor an algorithm's development in terms of quality.

III. Selection

In fitness evaluations, the three highest-scoring agents, are chosen as leaders named Alpha, Beta, and Delta. These agents represent the optimal solutions at that iteration and are used as a reference for other agents to learn the way to reach a potentially optimum solution.

IV. Exploration

The loop continues up to a predefined maximum number of iterations. During each iteration, parameters are updated to define the movement strategy. If the parameters suggest insufficient progress, movement is directed toward Alpha (α), Beta (β), or Delta (δ). Otherwise, random exploration of the search space is performed to identify new potential solutions. Additionally, if no improvement is observed over several iterations, repositioning is applied using a chaotic map to escape local optima.

V. Adjustment

In the main loop, all agents are forced to move inside the search space boundary. This is done to ensure all the agents are within valid bounds which allows the search process to work well.

VI. Reassessment

After each iteration, the fitness of every agent is evaluated with their new position. This new fitness value gives you an idea of which agents are the top performers at this point. In case some agent has a better value than the current leaders, i.e. if one of the α, β, or δ values is worse than that shown by an individual of the population then based on this comparison will update their corresponding α, β, and δ to move towards ideal solutions.

VII. Identification

The loop ends after that number of iterations. The best agent is honored as Alpha, a by-product, or output of an optimal solution. This last stage finds the optimal solution and its exploration in the search space is exhaustively scrutinized.

Pseudo code for the proposed DPO algorithm

The DPO algorithm is described in this point step by step,

1. Randomly initialize search agents to be within the specified ranges across all dimensions of a solution in population space.
2. Calculate the Fitness Value of each Candidate Solution.
3. These agents with the most excellent fitness are identified as Alpha (X_α), Beta (X_β), and Delta(X_δ).
4. While (t < Max_iterations):
    4.1 For each search agent i:
        4.1.1 Update control parameters
        4.1.2 If $|A| < 1$:
            4.1.2.1 Update the agent's position towards the leaders X_α, X_β, and X_δ.
        4.1.3 Else if $|A| \geq 1$:
            4.1.3.1 Random search to encourage exploration of the agent's location
        4.1.4 If $p \geq 0.5$:
            4.1.4.1 If the agent has not improved:
                4.1.4.1.1 Reset the position of the agent by the chaotic map and release it from local Optimum.
                4.1.4.2 Update the position.
        4.1.5 Ensure the agent's position is within the search space boundaries.
    4.2 Re-evaluate the fitness value for each search agent.
    4.3 Update Alpha (X_α), Beta (X_β), and Delta (X_δ) if better solutions are found.
    4.4 Increment the iteration counter $t = t + 1$.
5. Return the best solution found, Alpha (X_α).

RESULT AND DISCUSSION

The 'Result and Discussion' consists of two main headings (primary analysis and commercial analysis). The central analysis directs to the results relating to the critical findings extracted from experimental or survey data with an in-depth analysis of the results. In the commercial analysis looks at what the data reveals in the more practical terms of economics or business and in what ways it is reasonable to use these findings commercially.

Primary analysis

This section discusses the findings of the research work by dividing the contribution into several subsections in the following. It is divided into eight individual cases such as Cost of Electricity (*COE*) analysis using DPO, GWO, and WOA, Loss of Power Supply Probability (*LPSP*) evaluation, Renewable Energy Utilization Comparison, Load Shedding Analysis, Hydrogen Production Comparison, Carbon Emissions Reduction, Net Present Cost (*NPC*) Analysis. Each of these individual cases are discussed below.

Case 1: A yearly profit comparison for the average electricity cost (relative to DPO) over the course of a full year is displayed in **Figure 5**. DPO typically produces the lowest *COE*, saving between 13% and 27%, and roughly 10% to 15% when compared to GWO. As an example, in January, DPO's *COE* was 4.02 Taka, which is 14.1% less than WOA's 4.68 Taka and 27.04% less than GWO's 5.51 Taka [1 USD = 117.70 Taka as of 21st December, 2024]. The DPO algorithm efficiently lowers the *COE* by optimizing the combination of backup resources, like diesel generators, and renewable resources, like wind and solar power. This includes everything from how the hybrid system components are designed, constructed, and packaged through to their installation in a vehicle as well as all other factors checked upfront cost, materials for making each component of the hybrid systems, and even maintenance needs throughout ownership. Simulations showed that the best resource allocation method of the DPO algorithm makes it a more reliable cost reduction performance than traditional energy management algorithms.

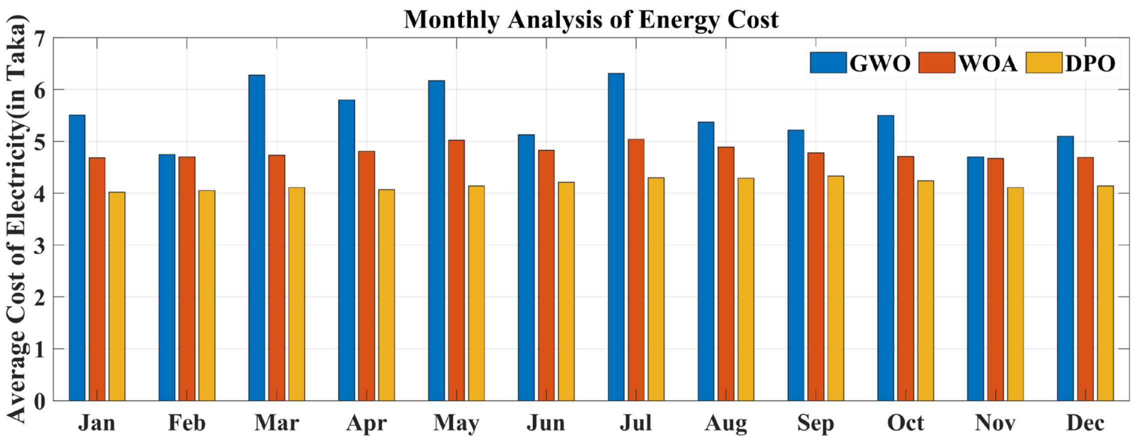


Figure 5. Average energy cost for a specific year

Case 2: This case illustrates the effectiveness of the DPO algorithm in reducing the *LPSP* that is satisfactory with the security and dependability constraints under consideration. In the absence of adequate renewable and functional systems, the power supply indicated by the LPSP score has a higher chance of turning non-dispatchable. The DPO algorithm consistently produces lower *LPSP* values as indicated in **Figure 6**; in this case, it eliminates 7.2% improvements over GWO and can even surpass WOA by 7.7%. These gains resulted in April *LPSPs* for WOA and GWO of 10% and 5.8%, respectively, versus an increasingly high one for DPO of just 1.93%. The DPO algorithm was able to reduce the *LPSP* by approximately 60% due to the ability of a battery storage approach for time-varying response from sustainable resources as well as support these gaps. By giving priority to battery discharge (the first rule of reductions), the algorithm not only provides more reliable performance but also improves fuel efficiency and reduces greenhouse gases in the process. This is done regardless of whether there are batteries to discharge from, or the diesel generator must be started at the earliest sign that intermediate battery states of charge will predict being out-of-usefulness in some future distribution cycle. The above image shows the very low *LPSP* of 0 which shows how the developed DPO algorithm is able to deliver relatively constant power output under such highly variable renewable conditions.

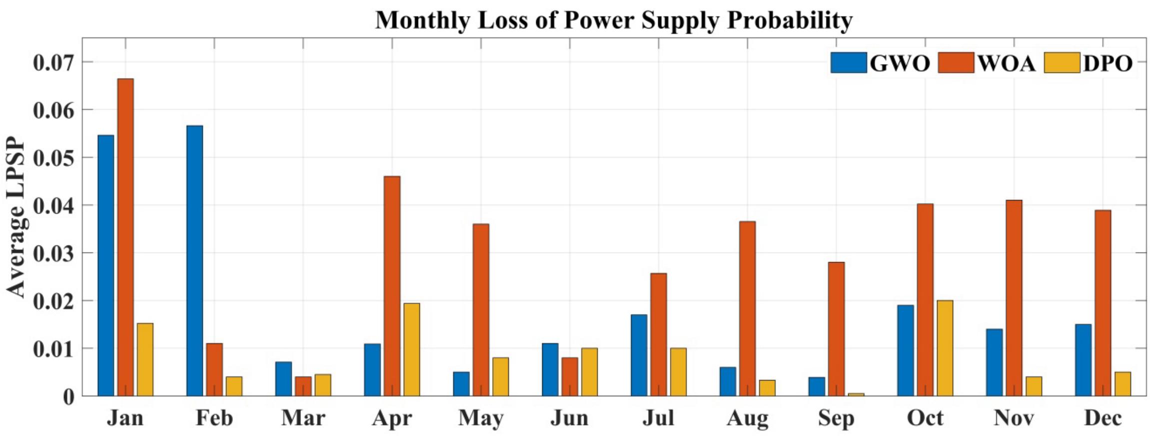


Figure 6. Average loss of power supply probability for a specific year

Case 3: Monthly analysis of renewable energy for a year is shown in **Figure 7**, where the comparison between DPO, WOA and GWO algorithm is discussed. For DPO algorithm the value of renewable energy utilization is almost 100% for the whole year. On the other hand, the values for WOA and GWO are on average 3-5% less than DPO for every months of the year. The utilization of DPO results very practical and reliable results which proves the potential of greater optimization for this algorithm.

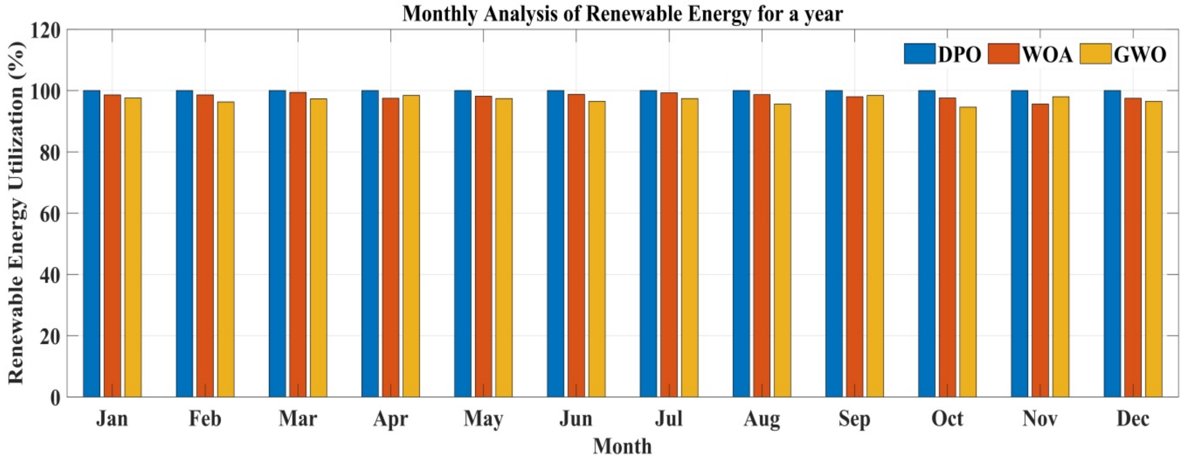


Figure 7. Average renewable energy for a specific year

Case 4: The annual load shedding analysis for a year is illustrated in **Figure 8** where the comparison of DPO, WOA and GWO is shown. In case of WOA and GWO the values of load shedding are on average more than 8 kW/month and 10 kW/month, respectively. Meanwhile the load shedding for DPO algorithm is 0 kW/month which proves the fact that DPO algorithm is the most promising algorithm. It is quite evident from the data that DPO is also superior to WOA, GWO in terms of steadfastness in the energy distribution free from any interruption. It's zero load shedding throughout the months proves that the system has the maximum ability to have an optimal and stable system and is even preferable to be used for critical applications where the supply of power cannot be interrupted. While the relatively lower load shedding is with WOA, GWO these remain open to challenge under high-stress operational conditions, as experienced in the latter half of Enhancing Operational Conditions.

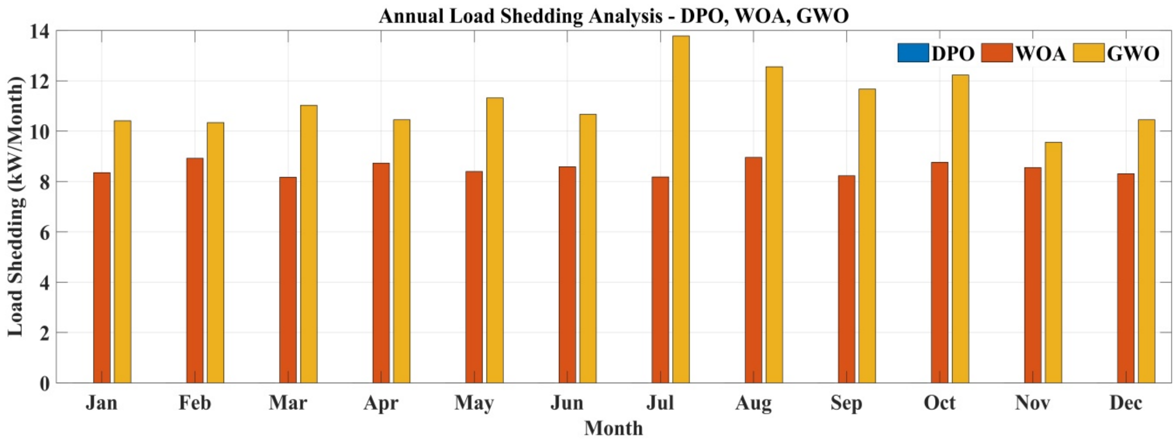


Figure 8. Average load shedding for a specific year

Case 5: In **Figure 9**, the monthly production of hydrogen for a year is compared with DPO, WOA and GWO algorithm. From the figure it is evident that DPO algorithm produces the highest amount of hydrogen over the whole year which is around 1.75×10^4 kg/month on average. The hydrogen production using WOA and GWO algorithm is significantly lower than DPO and the average amounts are around 1.5×10^4 kg/month for both of them. Hence the

DPO algorithm maximizes the hydrogen production and makes the algorithm efficient and reliable. Looking at the average monthly analysis, average DPO performance was outstanding all around; it created 17.60% more hydrogen than WOA, 21.10% better than GWO. This consistent increase demonstrates that DPO is the most effective method of all for getting H_2 month by month.

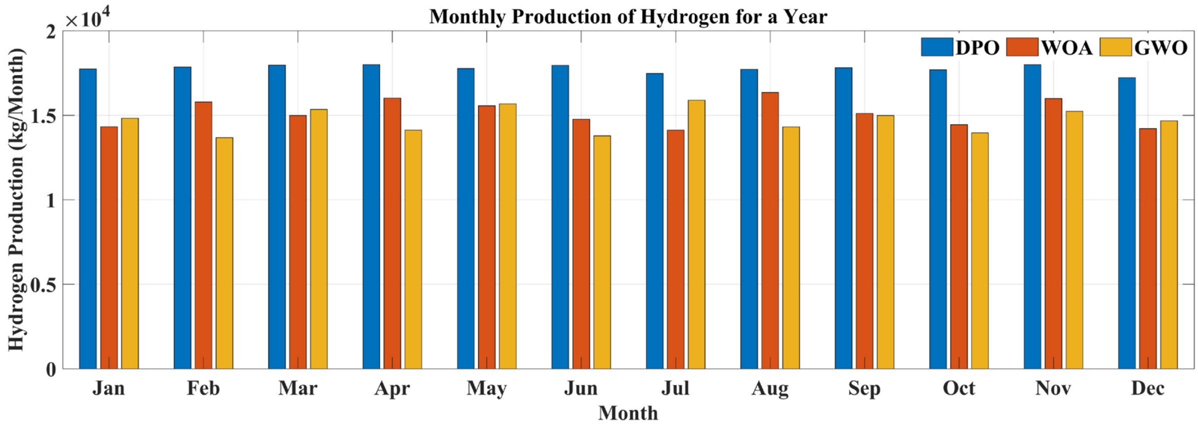


Figure 9. Average hydrogen production for a specific year

Case 6: DPO algorithm can also optimize generation and demand while backing out carbon-intensive fossil fuels from the mix. Power Management Update, the DPO also establishes a carbon-smart approach by continuing to increase the use of solar and wind resources which emit less carbon compared to diesel generators in order for further reduction of emissions in **Table 1**, moving progress towards outcomes envisaged by the New Energy Industrial plan. Furthermore, it maximizes the use of stored energy that is generated from renewable energy sources and helps to store them effectively for periods when high demand occurs and possibly prevents the plant at some times from utilizing non-renewable sources. In addition to improving the efficiency and lifespans of the overall energy system, it conserves resources by using less fuel. Flow batteries that generate safe, zero-carbon energy storage solutions must be integrated with the work of upstream engineers in order to be delivered in a system design.

Table 1. Emission of gases per year

Quantity	Value (kg/yr)
Carbon Dioxide	0
Carbon monoxide	0
Sulfur Dioxide	0
Nitrogen Oxides	0

Case 7: The Dual Predator Optimization algorithm, applied to an analysis of the Net Present Costs (NPC) of the different energy components of Rangpur in **Figure 10**, outlines the economic implications of adopting an integrated generation facility for the defined hybrid energy system, providing excellent detail on financial feasibility. At USD 20,649.88 for all components, this is a rather costly investment to perform this system in this area. The electrolyzer has the highest NPC (USD 7,859.85). The cost is very high, which suggests that the hydrogen production technology, an essential technology for energy storage and release, is very expensive, which may be due to its high technology and material needs. Next in line is the load-flowing element, a crucial component for the energy distribution throughout the system, costing USD 5,378.25, again highlighting the significant infrastructure investment associated with effective energy distribution. The photovoltaic systems that utilize energy from the sun make up another big piece of the investment, accounting for USD 3,936.89. Solar panels, while

declining in price over the years, still take a large capital investment and likely represent the ballpark market rate for such technology. The investment can be lower in terms of dollars per kilowatt for wind turbines (USD 1,840.38) because of regional wind profiles and the technology maturing and driving down costs over time. Items like the System Converter and Hydrogen Tank come in at USD 422.35 and USD 279.28, respectively, so they shouldn't put too much of a dent in your wallet. While these are the basic components of the technology to convert energy produced into energy that can be readily used and that of hydrogen storage, they also suggest that the technology is approaching economic viability. At the low end, the battery and generator cost USD 476.09 and USD 456.79, respectively. This lower cost is indicative of their secondary system roles as energy storage and backup power, roles that are essential to maintaining system reliability but do not carry the same technology investment needs as generation components.

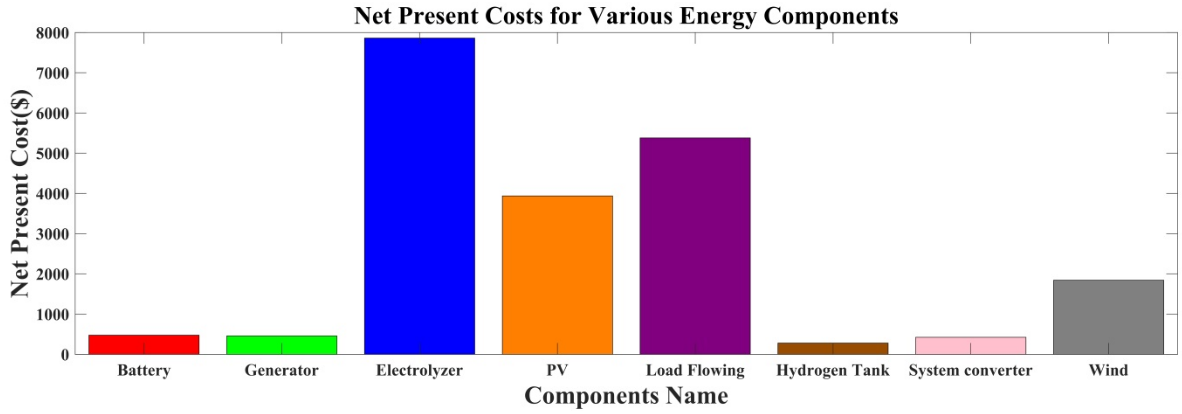


Figure 10. The Total Net Present Cost Analysis of Various Energy Components in Rangpur

Commercial analysis

For a commercial analysis between DPO and HOMER Pro, need to focus on several key aspects. The comparison between the DPO Algorithm and Homer Pro is demonstrated in the **Table 2**. It can be seen that both models achieve a 100% renewable factor with zero emissions and load shedding. However, the DPO Algorithm significantly reduces the cost of electricity as shown in the table that for DPO Algorithm it is 4.08 Taka and 6.12 Taka for Homer Pro, indicating better economic performance. Additionally, DPO Algorithm has lower Net Present Costs (NPC) (USD 20,649.88) than Homer Pro (USD 20,807.10). Both DPO Algorithm has no load shedding and 0 kg/year of harmful gas emission.

Table 2. Comparison between Homer Pro and DPO Algorithm

Description	DPO Algorithm	Homer Pro
Cost of Electricity (in Taka)	4.08	6.12
Renewable factor (% percentage)	100	100
Net Present Costs (in USD)	20,649.88	20,807.10
Load shedding (kW)	0	0
Harmful gas emission (kg/yr)	0	0

The summary of the results is presented in the **Table 3** below:

Table 3. Summary of Case Studies and Results

Case No.	Description	Key Findings
Case 1	Cost of Electricity (*COE*) analysis using DPO, GWO, and WOA	DPO achieved the lowest *COE*, reducing costs by 13-27% compared to other algorithms
Case 2	Loss of Power Supply Probability (*LPSP*) evaluation	DPO showed a 7.2% improvement over GWO and 7.7% over WOA, achieving a nearly 60% *LPSP* reduction
Case 3	Renewable Energy Utilization Comparison	DPO ensured ~100% renewable energy utilization throughout the year, outperforming WOA and GWO by 3-5%
Case 4	Load Shedding Analysis	DPO resulted in zero load shedding, whereas WOA and GWO had 8-10 kW/month on average
Case 5	Hydrogen Production Comparison	DPO produced 17.60% more hydrogen than WOA and 21.10% more than GWO
Case 6	Carbon Emissions Reduction	DPO resulted in zero emissions of CO_2, CO, SO_2, and NO_x, making it a carbon-free energy solution
Case 7	Net Present Cost (*NPC*) Analysis	DPO showed an optimal cost distribution, with the highest cost associated with the electrolyzer, followed by energy storage and PV systems
Commercial analysis	Comparison between Homer Pro and DPO Algorithm	DPO Algorithm showed lower cost of electricity and net present cost than Homer Pro

CONCLUSION

In this paper, a new metaheuristic optimization method called Dual Predator Optimization (DPO) has been proposed, which combines the strengths of Grey Wolf Optimization (GWO) and Whale Optimization Algorithm (WOA) and also, further addresses the shortcomings of the mentioned algorithms. The results of the DPO method are promising, showing a significant reduction in both the Cost of Electricity (*COE*) and the Loss of Power Supply Probability (*LPSP*). Specifically, the DPO method achieves a decrement of an average 15-20% in *COE*, making it highly efficient in reducing energy costs. Furthermore, the *LPSP* is reduced by an average of 7.5%, which is an also a significant improvement over the other mentioned established methods such as GAO (7.2%) and WOA (7.7%). With zero load shedding and 100% renewable energy utilization, DPO sets a novel milestone ensuring greater operational efficiency and improved sustainability. It's capabilities to lead in renewable energy technologies and hydrogen production are demonstrated by its 21.10% efficiency advantage over GWO and its 17.60% hydrogen production advantage over WOA, which highlights its superior technology and energy management effectiveness. To conclude, the results are competitive enough to other established algorithms to provide sustainable optimization solutions to the hybrid energy systems. However, as future upgradation to this proposed algorithm, further investigation is needed to analyze the DPO algorithm's scalability and how it may perform in larger and more complex energy systems. While the system can scale up and down to accommodate fluctuating energy needs, integrating machine learning algorithms into real-time prediction and balancing could further optimize it. A possibility would be to further develop the idea with other renewable energy sources such as biomass or hydropower included in a hybrid system, suggests DPO. Embracing flow batteries would bring the goals of a resource-efficient and CO_2 neutral energy system one step nearer to fruition.

ACKNOWLEDGMENT(S)

The authors extend their appreciation to the Deanship of Scientific Research at Northern Border University, Arar, KSA for funding this research work through the project number “NBU-FFR-2025-3623-02”.

AUTHOR CONTRIBUTIONS

M.N.H.: Conceptualization, methodology, formal analysis, writing—original draft, resources, M.F.I.; supervision, resources, project administration, K.A.; writing—review and editing, S.A.A.; writing—review and editing, project administration, validation, M.S.A.; writing—review and editing. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

1. A. I. Abeg, M. R. Islam, M. A. Hossain, M. F. Ishraque, M. R. Islam, and M. Hossain, "Capacity and operation optimization of hybrid microgrid for economic zone using a novel meta-heuristic algorithm," *Journal of Energy Storage,* vol. 94, p. 112314, 2024, https://doi.org/10.1016/j.est.2024.112314.
2. M. M. Q. Mirza, "Global warming and changes in the probability of occurrence of floods in Bangladesh and implications," *Global environmental change,* vol. 12, no. 2, pp. 127-138, 2002, https://doi.org/10.1016/S0959-3780(02)00002-X.
3. A. Vince, "A framework for the greedy algorithm," *Discrete Applied Mathematics,* vol. 121, no. 1-3, pp. 247-260, 2002, https://doi.org/10.1016/S0166-218X(01)00362-6.
4. M. Abdel-Basset, L. Abdel-Fatah, and A. K. Sangaiah, "Metaheuristic algorithms: A comprehensive review," *Computational intelligence for multimedia big data on the cloud with engineering applications,* pp. 185-231, 2018, https://doi.org/10.1016/B978-0-12-813314-9.00010-4.
5. A. H. Gandomi, X.-S. Yang, S. Talatahari, and A. H. Alavi, "Metaheuristic algorithms in modeling and optimization," *Metaheuristic applications in structures and infrastructures,* vol. 1, pp. 1-24, 2013, https://doi.org/10.1016/B978-0-12-398364-0.00001-2.
6. F. Ahmad and M. S. Alam, "Optimal sizing and analysis of solar PV, wind, and energy storage hybrid system for campus microgrid," *Smart Science,* vol. 6, no. 2, pp. 150-157, 2018, https://doi.org/10.1080/23080477.2017.1417005.
7. M. F. Ishraque, S. A. Shezan, M. Ali, and M. Rashid, "Optimization of load dispatch strategies for an islanded microgrid connected with renewable energy sources," *Applied Energy,* vol. 292, p. 116879, 2021, https://doi.org/10.1016/j.apenergy.2021.116879.
8. H. M. Mohammed, S. U. Umar, and T. A. Rashid, "A systematic and meta‐analysis survey of whale optimization algorithm," *Computational intelligence and neuroscience,* vol. 2019, no. 1, p. 8718571, 2019, https://doi.org/10.1155/2019/8718571.
9. S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Advances in engineering software,* vol. 95, pp. 51-67, 2016, https://doi.org/10.1016/j.advengsoft.2016.01.008.
10. D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: an overview," *Soft computing,* vol. 22, no. 2, pp. 387-408, 2018, https://doi.org/10.1007/s00500-016-2474-6.
11. M. Jain, V. Saihjpal, N. Singh, and S. B. Singh, "An overview of variants and advancements of PSO algorithm," *Applied Sciences,* vol. 12, no. 17, p. 8392, 2022, https://doi.org/10.3390/app12178392.

12. S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software,* vol. 69, pp. 46-61, 2014, https://doi.org/10.1016/j.advengsoft.2013.12.007.
13. T. Agajie *et al.*, "A Comprehensive Review on Techno-Economic Analysis and Optimal Sizing of Hybrid Renewable Energy Sources with Energy Storage Systems," *Energies,* 2023-01-05 2023, https://doi.org/10.3390/en16020642.
14. E. Hernández-Mayoral *et al.*, "A Comprehensive Review on Power-Quality Issues, Optimization Techniques, and Control Strategies of Microgrid Based on Renewable Energy Sources," *Sustainability,* 2023-06-20 2023, https://doi.org/10.3390/su15129847.
15. A. Karmaker, M. A. Hossain, H. Pota, A. Onen, and J. Jung, "Energy Management System for Hybrid Renewable Energy-Based Electric Vehicle Charging Station," *IEEE Access,* vol. 11, pp. 27793-27805, 2023, https://doi.org/10.1109/ACCESS.2023.3259232.
16. M. Gulzar, A. Iqbal, D. Sibtain, and M. Khalid, "An Innovative Converterless Solar PV Control Strategy for a Grid Connected Hybrid PV/Wind/Fuel-Cell System Coupled With Battery Energy Storage," *IEEE Access,* vol. 11, pp. 23245-23259, 2023, https://doi.org/10.1109/ACCESS.2023.3252891.
17. A. F. Güven, N. Yörükeren, E. Tag-Eldin, and M. Samy, "Multi-Objective Optimization of an Islanded Green Energy System Utilizing Sophisticated Hybrid Metaheuristic Approach," *IEEE Access,* vol. 11, pp. 103044-103068, 2023, https://doi.org/10.1109/ACCESS.2023.3296589.
18. N.-D. Nguyen, C. Yoon, and Y. Lee, "A Standalone Energy Management System of Battery/Supercapacitor Hybrid Energy Storage System for Electric Vehicles Using Model Predictive Control," *IEEE Transactions on Industrial Electronics,* vol. 70, pp. 5104-5114, 2023, https://doi.org/10.1109/TIE.2022.3186369.
19. R. Han, R. Lian, H. He, and X. Han, "Continuous Reinforcement Learning-Based Energy Management Strategy for Hybrid Electric-Tracked Vehicles," *IEEE Journal of Emerging and Selected Topics in Power Electronics,* vol. 11, pp. 19-31, 2023-02-01 2023, https://doi.org/10.1109/JESTPE.2021.3135059.
20. M. B. Abdelghany, A. Al‐Durra, and F. Gao, "A Coordinated Optimal Operation of a Grid-Connected Wind-Solar Microgrid Incorporating Hybrid Energy Storage Management Systems," *IEEE Transactions on Sustainable Energy,* vol. 15, pp. 39-51, 2024-01-01 2024, https://doi.org/10.1109/TSTE.2023.3263540.
21. X. Sun, Z. Jin, M. Xue, and X. Tian, "Adaptive ECMS With Gear Shift Control by Grey Wolf Optimization Algorithm and Neural Network for Plug-In Hybrid Electric Buses," *IEEE Transactions on Industrial Electronics,* vol. 71, pp. 667-677, 2024-01-01 2024, https://doi.org/10.1109/TIE.2023.3243304.
22. L. Liu, D. Zhou, J. Zou, and W. Wang, "Zero-Vector-Regulation-Based Closed-Loop Power Distribution Strategy for Dual-DC-Port DC–AC Converter-Connected PV–Battery Hybrid Systems," *IEEE Transactions on Power Electronics,* vol. 38, pp. 6956-6968, 2023-06-01 2023, https://doi.org/10.1109/TPEL.2023.3242839.
23. M. Fayyazi *et al.*, "Artificial Intelligence/Machine Learning in Energy Management Systems, Control, and Optimization of Hydrogen Fuel Cell Vehicles," *Sustainability,* 2023-03-15 2023, https://doi.org/10.3390/su15065249.
24. M. Hashish *et al.*, "Monte Carlo Simulation and a Clustering Technique for Solving the Probabilistic Optimal Power Flow Problem for Hybrid Renewable Energy Systems," *Sustainability,* 2023-01-01 2023, https://doi.org/10.3390/su15010783.
25. K. Sivamayil, E. Rajasekar, B. Aljafari, S. Nikolovski, S. Vairavasundaram, and I. Vairavasundaram, "A Systematic Study on Reinforcement Learning Based Applications," *Energies,* 2023-02-03 2023, https://doi.org/10.3390/en16031512.

26. Y. Ran, H. Hu, Y. Wen, and X. Zhou, "Optimizing Energy Efficiency for Data Center via Parameterized Deep Reinforcement Learning," *IEEE Transactions on Services Computing,* vol. 16, pp. 1310-1323, 2023-03-01 2023, https://doi.org/10.1109/TSC.2022.3184835.
27. L. Yang, X. Li, M. Sun, and C. Sun, "Hybrid Policy-Based Reinforcement Learning of Adaptive Energy Management for the Energy Transmission-Constrained Island Group," *IEEE Transactions on Industrial Informatics,* vol. 19, pp. 10751-10762, 2023-11-01 2023, https://doi.org/10.1109/TII.2023.3241682.
28. Q. Li, X. Meng, F. Gao, G. Zhang, W.-R. Chen, and K. Rajashekara, "Reinforcement Learning Energy Management for Fuel Cell Hybrid Systems: A Review," *IEEE Industrial Electronics Magazine,* vol. 17, pp. 45-54, 2023-12-01 2023, https://doi.org/10.1109/MIE.2022.3148568.
29. M. Behera and L. Saikia, "A Novel Resilient Control of Grid-Integrated Solar PV-Hybrid Energy Storage Microgrid for Power Smoothing and Pulse Power Load Accommodation," *IEEE Transactions on Power Electronics,* vol. 38, pp. 3965-3980, 2023-03-01 2023, https://doi.org/10.1109/TPEL.2022.3217144.
30. A. Alsharif *et al.*, "Impact of Electric Vehicle on Residential Power Distribution Considering Energy Management Strategy and Stochastic Monte Carlo Algorithm," *Energies,* 2023-01-27 2023, https://doi.org/10.3390/en16031358.
31. S. Gheouany, H. Ouadi, and S. E. Bakali, "Hybrid-integer algorithm for a multi-objective optimal home energy management system," *Clean Energy,* 2023-03-29 2023, https://doi.org/10.1093/ce/zkac082.
32. C. Jia, J. Cui, W. Qiao, and L. Qu, "Real-Time Model Predictive Control for Battery-Supercapacitor Hybrid Energy Storage Systems Using Linear Parameter-Varying Models," *IEEE Journal of Emerging and Selected Topics in Power Electronics,* vol. 11, pp. 251-263, 2023-02-01 2023, https://doi.org/10.1109/JESTPE.2021.3130795.
33. M. R. Islam, M. A. Hossain, J. Hasan, T. K. Roy, and M. A. H. Sadi, "Double integral sliding mode controller based bridge-type flux-coupling non-superconducting fault current limiter to protect DFIG-based multi-machine power system under transient-state," *International Journal of Electrical Power & Energy Systems,* vol. 142, p. 108271, 2022, https://doi.org/10.1016/j.ijepes.2022.108271.
34. H. Borhanazad, S. Mekhilef, V. G. Ganapathy, M. Modiri-Delshad, and A. Mirtaheri, "Optimization of micro-grid system using MOPSO," *Renewable energy,* vol. 71, pp. 295-306, 2014.
35. P. Stackhouse. "NASA POWER | Prediction Of Worldwide Energy Resources." https://power.larc.nasa.gov [Accessed: Mar. 15, 2025].
36. S. Puchalapalli, S. K. Tiwari, B. Singh, and P. K. Goel, "A microgrid based on wind-driven DFIG, DG, and solar PV array for optimal fuel consumption," *IEEE Transactions on Industry Applications,* vol. 56, no. 5, pp. 4689-4699, 2020, https://doi.org/10.1109/TIA.2020.2999563.
37. M. Ashari and C. Nayar, "An optimum dispatch strategy using set points for a photovoltaic (PV)–diesel–battery hybrid power system," *Solar energy,* vol. 66, no. 1, pp. 1-9, 1999, https://doi.org/10.1016/S0038-092X(99)00016-X.
38. M. K. Deshmukh and S. S. Deshmukh, "Modeling of hybrid renewable energy systems," *Renewable and sustainable energy reviews,* vol. 12, no. 1, pp. 235-249, 2008, https://doi.org/10.1016/j.rser.2006.07.011.
39. S. D. Tavakoli *et al.*, "Grid-forming services from hydrogen electrolyzers," *IEEE transactions on sustainable energy,* vol. 14, no. 4, pp. 2205-2219, 2023, https://doi.org/10.1109/TSTE.2023.3270295.
40. L. Xu, X. Ruan, C. Mao, B. Zhang, and Y. Luo, "An improved optimal sizing method for wind-solar-battery hybrid power system," *IEEE transactions on Sustainable Energy,* vol. 4, no. 3, pp. 774-785, 2013, https://doi.org/10.1109/TSTE.2012.2228509.

41. A. Osama, D. Allam, and M. B. Eteiba, "A Novel Real-Time Fuzzy-Based Optimal Control of the Charging Cycle of a Renewable Energy Microgrid Storage System," *International Journal of Fuzzy Systems,* pp. 1-15, 2025, https://doi.org/10.1007/s40815-024-01924-8.

Paper submitted: 19.01.2025
Paper revised: 20.04.2025
Paper accepted: 21.04.2025