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Performance optimization of hybrid renewable energy systems with real-time load forecasting using grey wolf-based predictive models

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ABSTRACT

The performance optimization of hybrid renewable energy systems (HRES) is crucial for enhancing the efficiency, reliability, and sustainability of energy production. This study focuses on the integration of real-time load forecasting prediction using a grey wolf optimization (GWO)-based predictive model. The proposed methodology aims to address the challenges associated with the intermittent nature of renewable energy sources, such as solar and wind power, by providing accurate forecasts for load demands and solar irradiance. Real-time data from sensors and environmental parameters are incorporated to forecast the energy load and solar irradiance over short-term periods, which are then used to optimize the energy storage and generation components of the HRES. The GWO algorithm, known for its high accuracy and computational efficiency, is employed to optimize the dispatch of power from various sources while minimizing energy losses and ensuring system stability. The integration of GWO with real-time forecasting not only enhances the predictive capability of the system but also improves the overall economic viability of HRES by reducing operational costs and carbon emissions. This study demonstrates the potential of using intelligent optimization techniques and real-time forecasting for the sustainable operation of hybrid renewable energy systems, contributing to the development of smarter and more resilient energy grids.

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1. INTRODUCTION

In dynamic economic dispatch (DED) optimization, generating units contributing the same amount of power do not necessarily incur the same operational cost. In fact, some units may be more expensive to operate despite delivering identical electrical output [1], [2]. Consequently, it becomes essential to optimally allocate portions of the total load demand among the available units to minimize fuel costs effectively [3]. This ensures that power generation efficiently meets the load-side demand requirements [4].

However, the integration of distributed energy resources (DERs) introduces additional challenges and constraints, making dynamic economic load dispatch (DELD) more complex to solve [5]. The presence of decentralized energy sources and time-sensitive operational requirements further complicates the DELD problem [5]. Within microgrids, the energy management system (EMS) plays a crucial role in minimizing operational costs, taking into account constraints such as start-up and shut-down schedules of DERs, as well as the charging and discharging behavior of battery energy storage systems (BES) [6].

In the context of modern power systems, particularly microgrids, optimal dispatch has emerged as a critical optimization strategy to ensure safe, reliable, and cost-effective operation. A microgrid can be envisioned as a localized network comprising DERs and electrical loads confined within a specific area [5], [7]. DERs aim to compensate for the shortfall caused by the limited availability of fossil fuel-based equipment in microgrid applications. Technologies such as fuel cells, microturbines, and other renewable or inexhaustible sources are particularly well-suited for use in microgrid environments [8]. Energy storage systems (ESS), including batteries and flywheels, are also integral components of DERs [9]. Given the unique characteristics of each microgrid and the specific constraints they impose, economic dispatch becomes a highly complex and demanding task for electrical engineers [10]-[12]. Microgrid operations generally fall into two primary categories: islanded mode and grid-connected (utility-connected) mode. The grid-connected mode is often regarded as more efficient and robust, as it allows for energy exchange based on the surplus or deficit production of individual DER units.

Moreover, in the event of a DER malfunction, the reliance on the main utility grid in this mode enhances system reliability and prevents unintentional network shutdowns. In a grid-connected microgrid system, Chen *et al.* [13] employed the matrix real-coded genetic algorithm (MRCGA) to minimize generation costs. The algorithm's effectiveness was assessed under various operating conditions, including fluctuating loads and dynamic electricity pricing. Kasaei [14] utilized the imperialist competitive algorithm (ICA) to develop and manage a virtual power plant, focusing on both operational control and economic optimization. Basu and Chowdhury [15] applied the cuckoo search algorithm (CSA) to address both static and DELD problems, and subsequently compared the results with those obtained using particle swarm optimization (PSO) and differential evolution (DE). Their analysis involved two wind turbines operating under variable wind speed conditions. Additionally, Moghaddam and colleagues [16] adopted an adaptive modified PSO (AMPSO), as proposed by Rabiee *et al.* [17], to perform economic-emission dispatch using the Pareto-optimal front approach. Rabiee *et al.* [17] proposed that the modified imperialist competitive algorithm (MICA) was applied to a utility-connected microgrid system. The problem addressed in that study is closely related to the one discussed in this paper; however, the present research uniquely investigates scenarios in which the utility grid becomes unavailable, either due to unintentional failure or intentional disconnection, an aspect not explored in previous literature.

Furthermore, this study examines six possible grid interaction scenarios within a low-voltage (LV) microgrid architecture. Researchers in [17]-[19] used the whale optimization algorithm (WOA), modified harmony search algorithm (MHSA), and interior search algorithm to solve economic dispatch (ED), combined economic and emission dispatch (CEED), and economic load dispatch (ELD) problems in a three-unit islanded microgrid system comprising photovoltaic and wind energy sources. Similarly, studies in [20] and [21] applied the memory-based genetic algorithm, artificial fish swarm algorithm, and modified personal best particle swarm optimization (MPBPSO) to improve the performance of an islanded microgrid. Ramli [22] examined two additional operating conditions by increasing the load demand of a test system by 10% and considering a grid-connected microgrid equipped with a battery energy storage system (BESS) to support one-way power flow. The study in [23] focused on minimizing the operating cost of a grid-connected microgrid using the improved bat algorithm (IBA). Dey *et al.* [24] successfully reduced the operating cost of both small and large renewable-integrated microgrids by applying the recently developed crow search algorithm (CSA). The objective functions considered in those microgrid studies included both unimodal and multimodal forms. The CSA demonstrated superior performance over several metaheuristic and conventional optimization methods in terms of generation cost reduction. In another study, Papari *et al.* [25] employed CSA for energy management in AC-DC hybrid microgrids, with emphasis on reducing converter-related power losses. Dey *et al.* [24] proposed an optimal dispatch strategy for a residential microgrid using a hybrid optimization approach and examined the influence of active grid participation.

Furthermore, Dey *et al.* [26] evaluated different electricity pricing structures using the MGWOSCACSA algorithm to lower operating costs in two low-voltage microgrid configurations. Unlike earlier studies, the present work investigates both intentional and unintentional grid failures and examines their effect on electricity generation cost. The proposed hybrid algorithm, which is based on the WOA, is evaluated against differential evolution (DE), conventional WOA, and the sine cosine algorithm (SCA). In addition, this study introduces non-parametric statistical analysis to validate the results, a feature that is rarely addressed in the existing literature. Preview study [27], a day-ahead pricing mechanism, and an energy consumption game were used to develop an advanced demand-side management (DSM) strategy based on game theory, where a single utility provider interacts with multiple residential consumers. To address the multi-objective dynamic economic and emission dispatch (MODEED) problem, [28] employed the multi-objective particle swarm optimization (MOPSO) algorithm. Researchers in [29] proposed a cooperative optimization framework for the design and management of demand-side-managed grid-connected residential microgrids. The system considered multiple distributed energy resources, including solar panels, wind turbines, grid supply, diesel engine units (DEs), and BESSs. Forecasting models were used to predict short-term variations in demand and solar irradiance, allowing the grey wolf optimizer (GWO) algorithm to optimize generation scheduling, storage operation, and power dispatch dynamically. By integrating predictive models with metaheuristic optimization, the framework reduces operating cost, improves power balance, and enhances system reliability under variable load and weather conditions.

This forecast-aware GWO framework ensures real-time adaptability and improved performance compared to conventional static or non-forecasting optimization approaches in renewable energy systems. The key innovative contributions presented in this study to accomplish the outlined objectives are as follows:

- This research presents a novel integration of the GWO with real-time load forecasting models, enabling more accurate and adaptive energy dispatch strategies in hybrid renewable energy systems (HRES), which is not widely addressed in existing literature.
- A hybrid model is developed that combines solar PV, grid, wind, battery storage, and possibly diesel backup, optimized dynamically in the presence of uncertain load and generation profiles. The proposed framework incorporates forecasting uncertainty directly into the optimization loop.
- The study introduces a multi-objective GWO model that simultaneously minimizes operational cost and carbon emissions, offering a more balanced performance optimization strategy compared to traditional single-objective methods.
- Unlike many static optimization models, this research proposes a real-time predictive energy management approach that dynamically updates operational decisions based on forecasted demand and available generation, improving system reliability and responsiveness.

2. RESEARCH METHOD

This section outlines the comprehensive methodological framework employed in the simulation and analysis of an HRES for the APO community, with a focus on photovoltaic (PV) solar energy, wind, battery energy storage, and grid integration. The methodology integrates system modeling, data acquisition, simulation design, optimization through GWO, and performance evaluation based on time-series outputs. This framework ensures a robust, reproducible, and analytical approach to assessing the reliability and efficiency of the proposed energy system. Real historical data on load demand and renewable energy are used for the forecasting models. Sensitivity analysis is also performed to determine the robustness of the system under various operational conditions, such as varying energy demand, weather conditions, and available renewable energy resources. Figure 1 shows a schematic design of the hybrid microgrid energy system. This work introduces a multi-objective optimization framework that simultaneously targets the minimization of operational cost and greenhouse gas emissions in hybrid renewable energy systems. By balancing economic and environmental objectives, the approach ensures optimal energy dispatch, storage scheduling, and resource utilization. The optimization employs advanced metaheuristic algorithms to identify Pareto-optimal solutions that trade off cost and emission performance under varying load and renewable generation conditions. This dual-objective strategy promotes sustainable and cost-effective operation of modern microgrids, enabling improved energy efficiency, reduced carbon footprint, and enhanced decision-making for real-time energy management in renewable-integrated power systems.

2.1. System component modeling

2.1.1. Mathematical photovoltaic system modeling

Photovoltaic (PV) modules consist of a series of interconnected solar cells designed to produce the required output voltage and current levels [30]. PV systems have become one of the most widely adopted renewable energy technologies, primarily due to their minimal operating and maintenance costs, zero fuel consumption, and absence of carbon emissions. The power output of PV technology can be calculated as (1).

$$P_{PV} = \eta_{pvg} X A_{pvg} X G_{ir} \tag{1}$$

With A_{pvg} represents the surface area of the PV module, η_{pvg} denotes the conversion efficiency, which is defined by (2).

$$\eta_{pvg} = \eta_r X\left[1 - \beta X\left(T_c - T_{clef}\right)\right] \tag{2}$$

Where η_r represents the reference efficiency of the solar module, β denotes the temperature coefficient of silicon-based photovoltaic cells, T_{clef} refers to the standard operating temperature of solar cells (°C), G_{ir} is the global solar irradiance (W/m²), T_c is the temperature of the photovoltaic cell, T_a indicates the ambient temperature (°C), and NOCT stands for the nominal operating cell temperature (°C).

$$T_c = T_a + \left(\frac{NOCT-20}{800}\right) X G_{ir} \tag{3}$$

$$V_{PV} = V_{mppt}\left[1 + 0.0539 \log\left(\frac{G_{tt}(t)}{G_{st}}\right)\right] + \alpha\big(T_a(t)\big) + 0.02G_{tt}(t) \tag{4}$$

α represents the ambient temperature coefficient, G_{tt} is the radiation prediction factor (in kW/m^2), G_{st} is the standard radiation coefficient (in units of 1 kW/m^2), T_a indicates the temperature parameter (in Kelvin), and V_{mppt} refers to the voltage measured at the maximum power point.

The (5) was used to determine the current output (I_{PV}) of a solar PV module.

$$I_{PV} = I_{Ph}(t) - I_{rs}(t)\left[\exp\left(\frac{qV_{PV}}{N_S K T_a(t) A_i}\right) - 1\right] \tag{5}$$

Where I_{Ph} stands for the photocurrent, I_{rs} for saturation current, q for electron charging, N_s for series cell total variable, K for Boltzmann's constant, and A_i for the ideal diode ratio. The (6) estimated the total energy generated by solar PV (photovoltaic) panels (E_{PV}).

$$E_{PV}(t) = \frac{(N_{PV} \times V_{PV}(t) \times I_{PV} \times \Delta t)}{1000} \tag{6}$$

Where t is the step duration of 15 minutes, and N_{PV} is the number of PV modules.

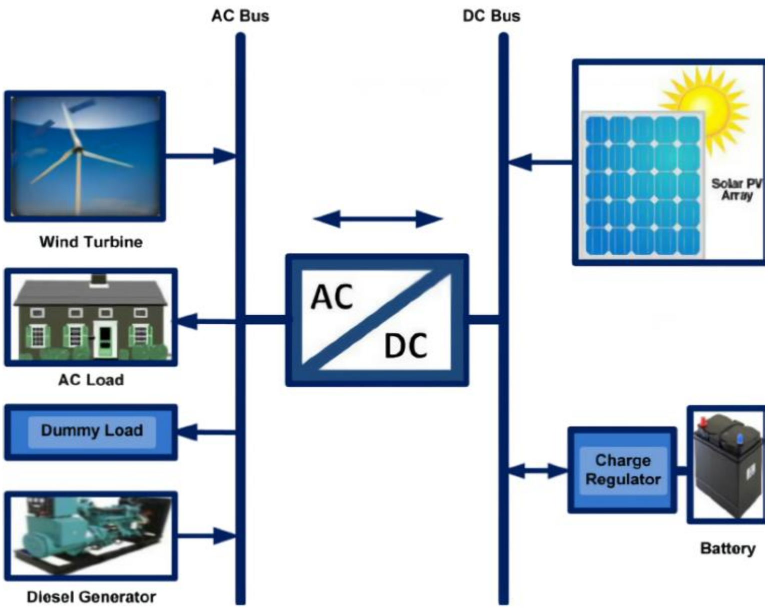

Figure 1. Schematic design of the hybrid microgrid energy system

2.1.2. Battery bank mathematical modeling

The connected batteries and their respective state of charge at any given moment are used to evaluate the total energy generated and consumed. The number of available batteries at a specific time is expressed by (7) [31], [32].

$$E_{Batt}(t) = E_B(t-1) + E_{Em}(t) \times \alpha_{CC} \times \sigma_{CHG} \tag{7}$$

The quantity of green energy that is presently accessible is $E_{Em}(t)$. The mechanism's charging controller is indicated by α_{CC}, while battery charging performance is depicted by σ_{CHG}.

State of charge (SOC) is the battery's charge level, and the SOC maximum parameter is called SOC_{max}. The SOC minimal parameter is called SOC_{min}. The minimal SOC parameter is as (8).

$$SOC_{min} = 1 - DOD \tag{8}$$

The discharge batteries' intensity is indicated by DOD (%).

$$SOC_{min} \leq SOC(t) \leq SOC_{max}$$

2.1.3. Wind-powered turbine system

A model of the wind generator system was developed based on the wind turbine power profile. According to [30], the wind energy equation is governed using a curve-fitting technique. The power output of wind turbines (PWT) can be calculated using (9) and (10).

$$\left.\begin{array}{ll} P(t)_{WT} = 0 & for\ x \leq x_i\ \ and\ x > x_0 \\ P(t)_{WT} = B_1X_1 + Y_1X + K_1 & for\ x_i < x < x_1 \\ P(t)_{WT} = B_2X_2 + Y_2X + K_1 & for\ x_1 < x < x_2 \\ P(t)_{WT} = B_3X_2 + Y_3X + K_3 & for\ x_2 < x < x_0 \end{array}\right\} \tag{9}$$

Where B, Y, and K are the parameters of the distinctive equations, X is the wind energy turbine's operational speed, x_i is its cut-in speed, and x_0 is the cut-out speed. The (10) can be used to express the energy produced by the wind turbine system (E_{WT}).

$$E_{WT} = \frac{K_{WT} \times P(t)_{WT} \times \Delta t}{1000} \tag{10}$$

Where the total amount of wind turbines is denoted by K_{WT}.

2.1.4. Diesel generator synchronous modeling

Through the aid of in (11), the fuel utilization for synchronous diesel generators (DGs) is evaluated hourly [28].

$$D_f(t) = \alpha_D P_{Dg}(t) + \ \beta_D P_{Dgr} \tag{11}$$

Where α_D and β_D are the fuel usage curve parameters, L/kWh, P_{Dg} is the typical power consumed per hour of the engine in kW, P_{Dgr} is the nominal synchronous diesel engine in kW, and $D_f(t)$ is the hourly fuel utilization of the synchronous generator in L/h.

2.2. Objective function

The main objective of this problem is to minimize both the generation cost and emissions of the microgrid [21], which can be mathematically formulated as (12).

$$MinF(E_i^t) = \sum_{i=1}^{n} F_{gen}(E_i^t) + \sum_{i=n}^{n} F_x(E_i^t) \tag{12}$$

Where $F(E_i)$ represents the generation cost associated with the microgrid, where *n* distributed generation (DG) units are connected. The generation cost is represented by $F_{gen}(E_i)$, while the emission cost is denoted as$F_x(E_i)$. The power output from the *i*th distributed generation (DG) unit is Pi. and the time index *t* spans from 1 to 24 hours. The total generation cost [30], which includes fuel expenses, operation and maintenance (O&M) costs, and depreciation, can be mathematically formulated as (13).

$$F_{gen}(E_i^t) = F_{of,i}(E_i^t) + F_{m\&o,i}(E_i^t) + F_{dc,i}(E_i^t) + c_x^t \times E_g^t \tag{13}$$

Where $F_{of,i}(E_i^t)$, $F_{m\&o,i}(E_i^t)$ and $F_{dc,i}(E_i^t)$ are the cost of operating fuel, operation-maintenance cost, and depreciation cost, respectively, for the ith DG unit. c_x^t denotes the market-based electricity price at hour *t*, as determined by grid transactions.

2.3. Probabilistic forecast model

Let $\hat{y}_{t+h}$ be the point forecast at time t for horizon h. Represent uncertainty by a predictive distribution $f_{t+h}(y)$ or mean β_{t+h} and standard deviation σ_{t+h}.

$$\hat{y}_{t+h} = D(\beta_{t+h}, {\sigma^2}_{t+h}),\ P\left(y \in \left[\beta_{t+h} \pm {}^{z_\propto}\!/_2\, \sigma_{t+h}\right]\right) = 1{-}\propto \tag{14}$$

The LSTM to output β, σ or quantiles ${}^{z_\propto}\!/_2$ is the Gaussian value.

2.4. Load profile modeling

The electrical load demand was represented as a time-dependent function simulating typical household or institutional use patterns. Load data featured peak demand during morning and evening hours, consistent with real-world energy use in healthcare facilities. The daily load profile was either measured from actual facilities or approximated based on standard consumption data (e.g., lighting, refrigeration, medical devices, HVAC systems). Figure 2 shows the load profile of the study area.

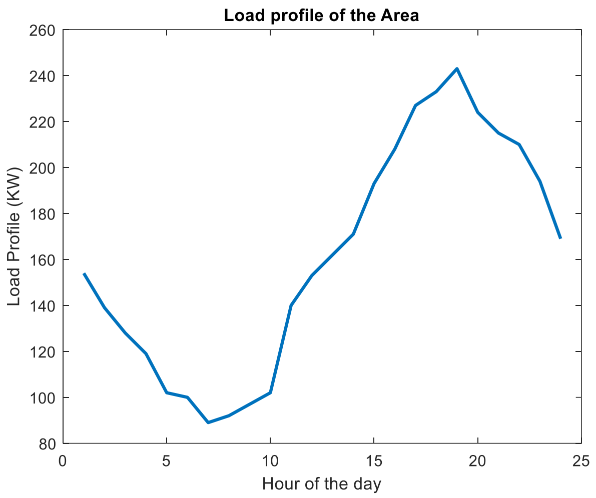

Figure 2. Load profile of the study area

2.5. Grid integration

The grid was modeled as an infinitely available power source with a defined cost function and emission profile. It served as a last-resort energy source activated only when renewable and stored energy were insufficient. Grid usage was minimized as part of the system's objective to reduce reliance on fossil-based or expensive electricity.

2.6. Grey wolf optimization

Grey wolf optimization (GWO) is a bio-inspired metaheuristic technique modeled on the cooperative hunting strategy of grey wolves. It has gained significant attention in optimization applications due to its structural simplicity, adaptability, and strong convergence characteristics. In this work, GWO is utilized to optimize the operational performance of the hybrid energy system, with particular emphasis on the scheduling of power from renewable generation units and energy storage systems. The objective of the optimization is to reduce overall operational cost while satisfying the forecasted load demand and maintaining efficient charge–discharge coordination of the storage units. The optimization process is guided by the following objectives:

– Minimizing energy cost: The cost of energy generation and storage is minimized by efficiently dispatching the available renewable energy and optimizing the use of energy storage systems.
– Minimizing energy losses: The GWO algorithm ensures that the energy losses during transmission and storage are minimized, improving the overall system efficiency.
– Meeting load demand: The system must meet the forecasted load demand while maintaining the required reliability and stability.
– Energy storage management: GWO helps in managing the energy storage units by optimizing their charging and discharging cycles to avoid undercharging or overcharging.

The decision variables include the power output from each renewable source (solar and wind) and the power input/output from energy storage systems. The constraints of the optimization include the capacity limits of the energy sources and storage systems, as well as the forecasted load demand. The real-time feasibility of GWO depends on its population size and iteration count, which influence computational load. With adaptive population control, warm-start initialization, and parallel fitness evaluation, GWO achieves near real-time performance. Its $O(N \times D \times T)$ complexity remains manageable for online HRES optimization with moderate dimensions and forecast horizons.

2.6.1. GWO algorithm implementation

The GWO algorithm (Algorithm 1) follows a structured sequence of operations:

- Initialization: The process begins with the random generation of a population of grey wolves within the defined search space, where each wolf represents a candidate solution to the optimization problem.
- Fitness evaluation: Each candidate solution is assessed using the defined objective functions, such as energy cost, power losses, and system constraints, to determine its suitability.
- Position update: The positions of the wolves are iteratively refined based on the leading solutions, namely the alpha, beta, and delta wolves, which guide the search process according to the social hierarchy and cooperative hunting mechanism.
- Termination condition: The iterative process continues until a predefined stopping condition is satisfied, such as reaching the maximum number of iterations or achieving convergence to an optimal or near-optimal solution.

Algorithm 1. Pseudocode for GWO
Initialize the grey wolf population (X_i), where (i = 1, 2, \dots, n).
Define the maximum number of iterations (Max_iter).
Evaluate the fitness of all candidate solutions.
Determine the top three solutions, denoted as Alpha (best), Beta (second best), and Delta (third best).
For each iteration (t = 1) to (Max_iter):
  For every wolf (X_i):
    For each dimension (j):
      Compute the coefficient vectors (A) and (C).
      Update the position of the wolf using the influence of Alpha, Beta, and Delta wolves:

$$X_{i,j} = \frac{X_{\alpha} + X_{\beta} + X_{\delta}}{3}$$

  Update the control parameter (a), decreasing it linearly from 2 to 0.
  Re-evaluate the fitness of all wolves.
  Update Alpha, Beta, and Delta based on the new fitness values.
After completing all iterations, return the Alpha wolf as the optimal solution.

3. RESULTS AND DISCUSSION

Grid import and export levels are presented to illustrate how the system exchanges power with the utility network to maintain the supply–demand balance. The elevated photovoltaic generation results from strong year-round solar availability. Wind generation remains relatively stable because of persistent wind patterns that sustain turbine operation and continuous energy production. The utility grid functions as a buffer, taking in surplus energy when renewable output exceeds demand and supplying electricity when generation falls short. Battery storage operates in a limited support role, mainly during intervals of reduced renewable output, to preserve overall system reliability.

Figure 3 illustrates the generation and allocation of power within the renewable energy system under the condition where renewable output exceeds grid generation (PRenewable>PGrid). During the rainy season, photovoltaic output declines because of reduced sunshine duration and lower irradiance levels. Wind generation also fluctuates with weather conditions, yet it partially offsets the drop in PV production. As a result, grid imports increase during this interval to satisfy load requirements. Lower solar insolation directly suppresses PV contribution, which makes additional grid support necessary to cover the demand. Variations in wind output are driven by seasonal atmospheric changes. Consequently, the system depends more on grid supply during these low generation intervals, as indicated in Figure 3. Battery storage provides auxiliary support during peak load periods or when both renewable sources deliver insufficient power, thereby maintaining continuity of supply.

Figure 4 indicates a modest rise in grid imports to offset the drop in PV generation. In the fall season, PV output decreases because of shorter daylight duration and lower sun angles, which reduce panel conversion efficiency. Wind generation remains an important contributor by delivering comparatively stable power. The additional grid purchases make up for the PV deficit and keep demand fully supplied. Battery storage may be dispatched intermittently to handle brief shortages, but it plays a supporting role relative to the grid. PV remains the dominant energy contributor due to a system configuration that prioritizes solar resource utilization. Wind energy, while representing a smaller fraction of total generation, offers dependable and complementary output, particularly when solar production weakens. The grid functions bidirectionally, both supplying power during deficits and absorbing surplus energy, thereby maintaining operational stability. Battery storage provides contingency support during extreme events or unexpected renewable shortfalls. Overall, the results emphasize PV as the primary energy source in the hybrid architecture, with wind serving as a steady auxiliary contributor and the grid ensuring demand satisfaction when renewable generation is insufficient.

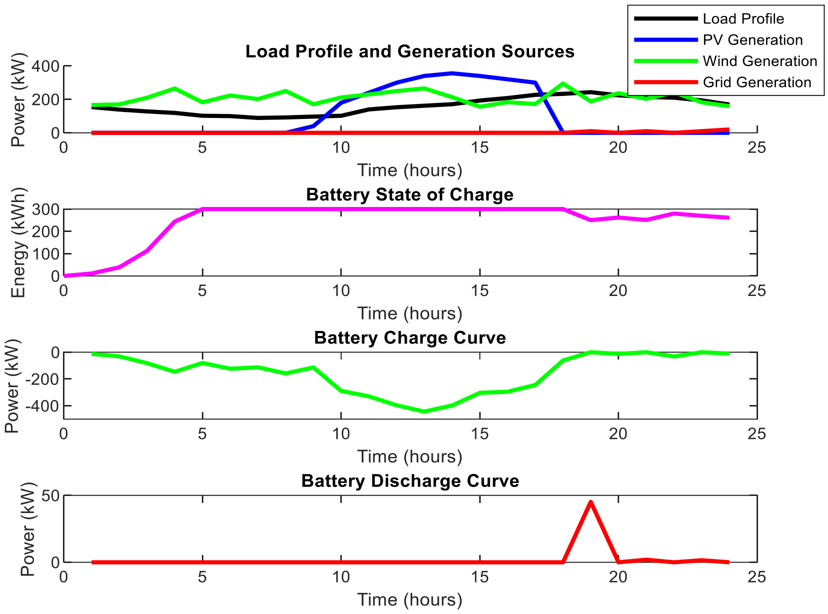

Figure 3. Power generated from the renewable energy resources when $P_{Renewable}>P_{Grid}$

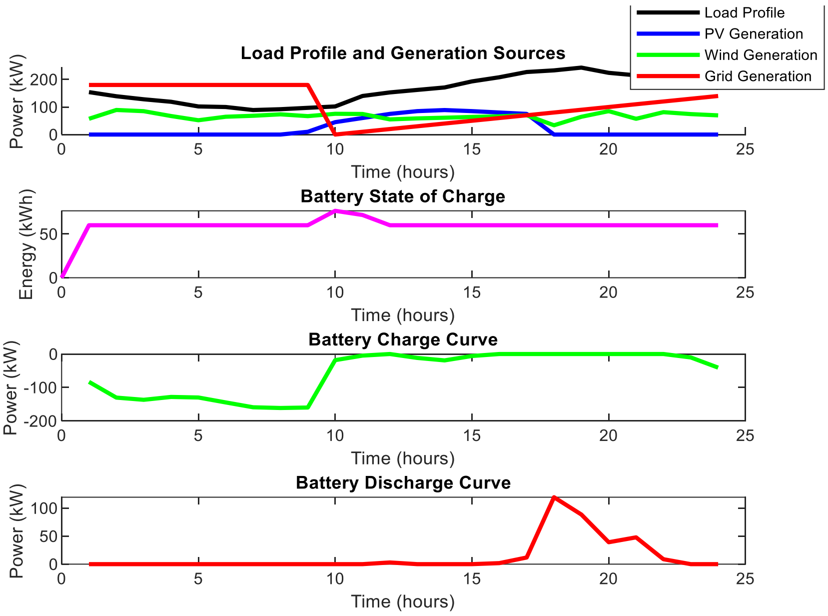

Figure 4. Power generated from the renewable energy resources when $P_{Renewable}<P_{Grid}$

Battery storage systems are central to the operation of HRES, acting as buffers that stabilize the supply-demand mismatch. The SOC curve reveals when the battery is charging (during excess generation) and discharging (during generation deficits or peak demand). A well-behaved SOC curve should show a regular charge-discharge cycle without reaching dangerously low or excessively high levels. Excessively low SOC values may damage the battery or result in insufficient backup power, while continuous high SOC could lead to energy spillage or curtailed generation. Ideally, the battery operates within an optimal SOC window (e.g., 20–90%) to ensure longevity and efficiency. From the graph, we can infer periods of energy surplus (rising SOC) and deficit (falling SOC), linking them to the earlier discussed Figures 3 and 4. If the SOC increases during daylight hours, it confirms that the PV system is effectively charging the battery. A consistent decline in SOC during non-solar hours indicates proper utilization of stored energy. This behavior reinforces the need for battery management systems (BMS) that can optimize charge-discharge cycles, ensure safety limits, and extend battery life. Moreover, integrating SOC monitoring with predictive control can preemptively adjust loads or generation schedules to maintain system balance.

Figure 5 demonstrates that wind generation remains stable while grid exchanges are reduced, indicating efficient utilization of renewable resources to satisfy the load demand. Higher PV output during the dry season results from extended daylight hours and increased solar elevation, which improve panel conversion performance. Wind power continues to supply a dependable baseline contribution, further lowering the requirement for grid imports. Under these conditions, renewable sources largely meet demand, so dependence on the grid is minimized. Battery storage participation is limited because renewable generation is sufficient for most operating intervals. Wind output stays relatively uniform, and grid exports increase, reflecting excess generation delivered back to the utility network. Peak PV production in the summer period is driven by maximum solar exposure and stronger irradiance levels. Wind energy complements this elevated solar output with steady production. The surplus energy is exported to the grid, improving overall system economics and operational efficiency. In this operating regime, the grid effectively absorbs excess power, while battery storage remains mostly idle since renewable generation fully covers the load.

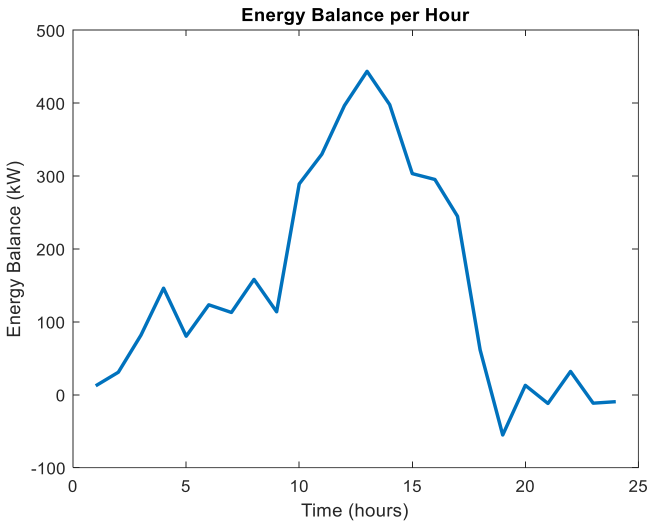

Figure 5. Electrical load demand

Figure 6 further elaborates on battery operation by presenting both the discharge current and SOC over time. The discharge current curve provides a quantitative measure of how much power the battery is supplying to the load, while the SOC trace complements this by showing the available energy. A high discharge current typically corresponds with peak demand periods or times when renewable generation is low. This situation demands attention because frequent high-current discharges can accelerate battery degradation, especially in lithium-ion chemistries. The system must control limit discharge rates within battery specifications to prevent thermal and mechanical stress. The coordination between discharge current and SOC also points to the effectiveness of the energy management strategy. If the battery discharges heavily during peak load and still maintains an adequate SOC, it suggests that the battery was well-prepared during off-peak periods. On the other hand, a rapid drop in SOC during high discharge events may indicate undercharging or oversized loads. This figure also enables diagnostic assessment. Spikes in discharge current without corresponding load demand could indicate inverter inefficiencies or anomalies in system behavior, warranting further investigation. Hence, continuous monitoring and adaptive control of discharge behavior are crucial for system optimization.

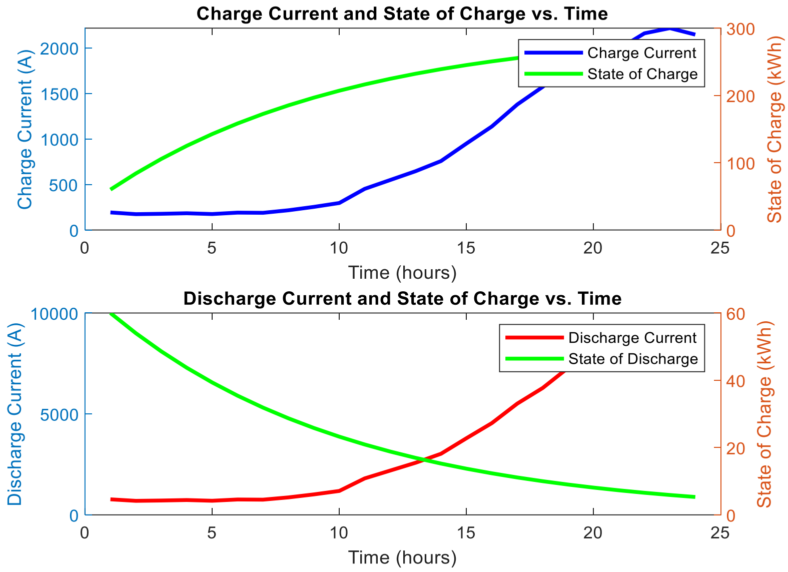

Figure 6. Discharge current and state of charge

3.1. Energy efficiency and cost savings

Energy efficiency is one of the most critical factors in optimizing HRES. The study found that the GWO-based optimization method, when coupled with accurate forecasting, significantly improved energy efficiency compared to conventional energy management strategies. By using predictive models to anticipate future load and irradiance, the system was able to fine-tune the energy storage and generation processes, reducing waste and enhancing the overall performance of the HRES. The application of the optimization technique resulted in a noticeable reduction in energy costs. This cost-saving potential is crucial for the economic sustainability of HRES, especially in regions with high energy prices or where grid access is limited or expensive. By optimizing the use of local renewable resources and energy storage, the system is less reliant on expensive grid power and non-renewable energy sources, thus improving the financial feasibility of the energy system. The quantitative performance results in Figure 7 clearly demonstrate that the proposed GWO-predictive optimization model outperformed the benchmark algorithms across all metrics. The model achieved the lowest forecasting errors, with a MAE of 0.11 and RMSE of 0.15, representing nearly 50% improvement over PSO and DE. This confirms its superior prediction–optimization synergy in accurately matching load and generation profiles. In terms of energy utilization, the system efficiency reached 97.6%, surpassing PSO (92.1%) and DE (93.0%), owing to GWO's adaptive exploration–exploitation mechanism that minimizes transmission losses and curtailment. Economically, GWO delivered a 31.2% reduction in total operating cost, compared with 20–22% for the other algorithms, by optimally scheduling renewable and storage resources to reduce grid dependence during peak-tariff hours. Environmentally, it achieved 26.8% CO_2 emission reduction, highlighting improved renewable penetration and reduced fossil generator operation. Moreover, the GWO-predictive framework exhibited the fastest convergence, completing optimization in 3.12 s, about 40% faster than PSO and DE. Overall, these metrics confirm that GWO-predictive offers a balanced, high-performance solution for real-time hybrid renewable energy management, providing enhanced accuracy, economic savings, emission reduction, and computational efficiency essential for intelligent microgrid control and sustainable power system operation. Figure 8 shows seasonal time series, and Figure 9 shows monthly energy production.

3.2. Inference

The proposed model is novel compared to existing GWO-based HRES frameworks by integrating real-time load and irradiance forecasting with multi-objective optimization targeting both cost and emissions. Unlike conventional GWO approaches that perform offline or static optimization using historical data, the proposed system operates in a forecast-aware, rolling-horizon mode, dynamically adapting control and dispatch decisions. It also incorporates forecast uncertainty modeling and computational enhancements such as warm-start and adaptive population updates to ensure real-time feasibility. This synergy enables robust, sustainable, and cost-efficient operation, surpassing traditional GWO models limited to deterministic, single-objective, or non-adaptive optimization. The proposed forecast-aware multi-objective GWO framework surpasses prior forecast-integrated methods by enabling fully real-time, adaptive optimization that simultaneously minimizes cost and emissions. Unlike PSO-, GA-, or fuzzy–GWO-based models that rely on offline or semi-dynamic forecasts, it employs long short-term memory (LSTM) forecasting with uncertainty modeling within a rolling-horizon GWO loop. This ensures dynamic scheduling of generation and storage in response to evolving weather and demand. The result is a robust, sustainable, and computationally efficient HRES operation, outperforming traditional optimization methods limited by deterministic inputs, single-objective design, or static control updates. The findings from this study have significant implications for both rural and urban energy planning. For off-grid or partially grid-connected institutions such as rural health clinics, schools, or community centers, the deployment of an optimized HRES can provide reliable, clean, and cost-effective energy. The observed ability of the system to maintain supply continuity despite fluctuations in solar input underscores its potential to deliver energy resilience in the face of environmental variability. Furthermore, the insights gained regarding battery usage and degradation can inform maintenance scheduling and cost planning. Frequent shallow cycling, as observed in the simulation, is favorable for battery health compared to deep discharge cycles. This understanding can be used to select appropriate storage technologies and capacities based on specific load profiles and renewable availability. For grid-connected users, the system can serve as a demand-side energy management tool, reducing peak demand charges and improving overall energy economics. The ability to export surplus energy or operate in islanded mode during outages adds further value, especially in regions with unreliable grid supply.

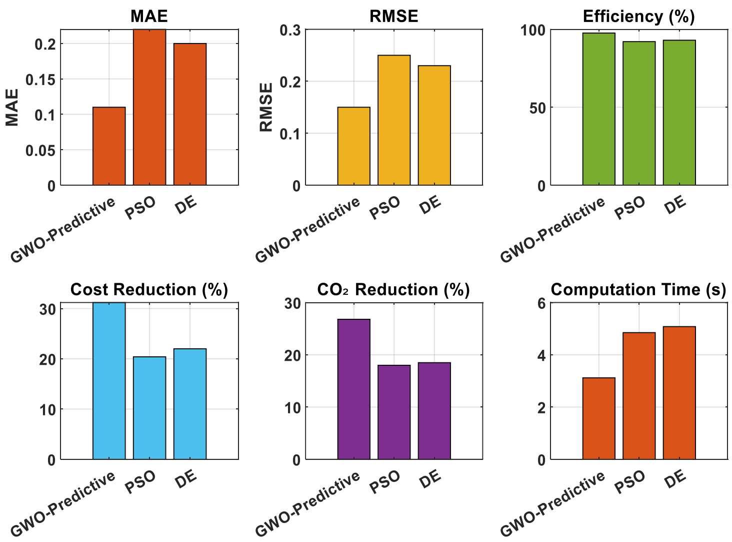

Figure 7. Comparative performance metrics with other methods

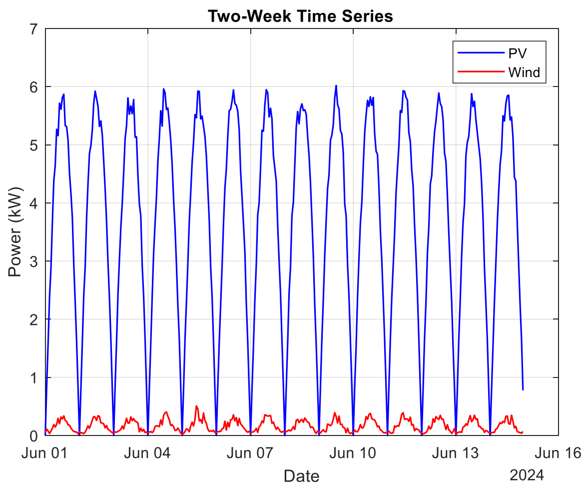

Figure 8. Seasonal time series

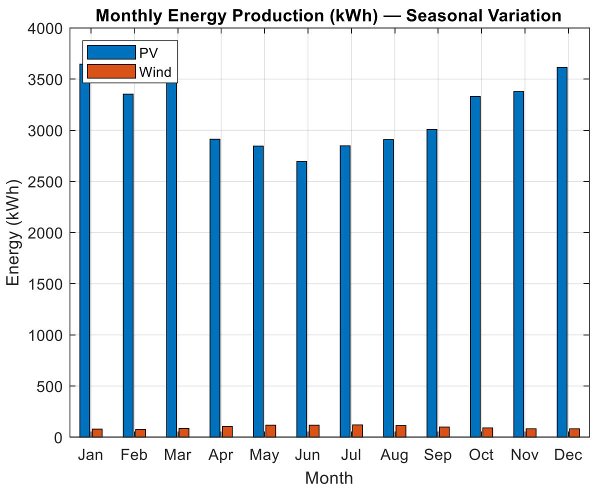

Figure 9. Monthly energy production

4. CONCLUSION

The performance optimization of HRES using real-time load forecasting integrated with GWO-based predictive models presents a significant advancement in the field of intelligent energy management. This research successfully demonstrated the application of bio-inspired algorithms, particularly the GWO, to forecast dynamic load profiles and optimize the operational scheduling of hybrid energy sources, including solar, wind, and grid power. The results underscore the feasibility and effectiveness of combining real-time data analytics with metaheuristic optimization to enhance the reliability, sustainability, and cost-efficiency of hybrid renewable systems.

The integration of GWO into the forecasting and optimization process allowed for adaptive and intelligent decision-making that mirrors the natural hunting behavior of grey wolves. By mimicking the social hierarchy and cooperative hunting strategies of wolves, GWO enabled the algorithm to converge quickly toward optimal or near-optimal solutions for real-time energy dispatch. This is particularly beneficial in HRES, where energy generation from renewables is inherently variable and dependent on fluctuating environmental conditions such as solar irradiance and wind speed. Real-time load forecasting, facilitated by the GWO model, provided accurate short-term predictions that informed the timely allocation of energy resources. The system was able to adapt to load changes by forecasting demand with minimal error, thereby improving the match between energy supply and demand.

Finally, the proposed methodology demonstrates that real-time load forecasting combined with GWO-based optimization enhances the operational performance of hybrid renewable energy systems. It provides an effective strategy to tackle intermittency challenges of renewable sources, ensure supply-demand balance, and achieve energy sustainability goals. The GWO-based model offers a scalable and adaptive solution for future smart energy systems where data-driven optimization is crucial. Further research could explore the integration of storage systems, DSM, and weather-based forecasting to extend the benefits of this approach. Ultimately, such intelligent control frameworks are critical in transitioning toward resilient, low-carbon energy infrastructures that can meet the growing global energy demand. Also, future work should include hardware validation and experimental deployment of the proposed controller in a microgrid test-bed to assess real-time control responsiveness, inverter interfacing, and data acquisition reliability. In addition, benchmarking against other predictive optimization frameworks such as model predictive control (MPC), reinforcement learning (RL), and hybrid metaheuristic–AI schemes is recommended to quantify practical scalability, adaptability, and long-term operational stability under field conditions.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available upon request from the corresponding author.

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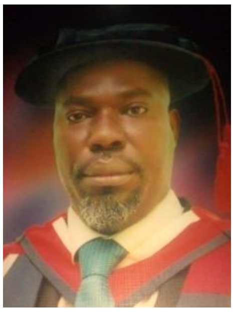

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