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Techno-Economic Optimization of a Grid-Connected PV, Battery, Diesel Hybrid Microgrid For Rural Healthcare Facilities Using Grey Lag Goose Optimization

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ABSTRACT

Reliable electricity supply is indispensable for effective healthcare delivery, particularly in developing countries where frequent grid outages disrupt critical medical equipment and increase reliance on diesel generators. Therefore, in other to address this problem and proffer long lasting solution, this paper presents a techno-economic optimization of a grid-connected photovoltaic (PV), battery, diesel hybrid microgrid for General Hospital Sabon Tasha, Kaduna State, Nigeria, employing the Grey Lag Goose Optimization (GLGO) algorithm. The proposed framework enhances power supply reliability while minimizing energy costs and environmental impacts. The hybrid microgrid was modeled in MATLAB/Simulink using the hospital's load profile, NASA solar resource data, local grid availability and diesel fuel costs. Optimal system sizing was determined using GLGO and benchmarked against the conventional Genetic Algorithm (GA). Performance evaluation was conducted using Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP), Energy Efficiency (EE) and carbon dioxide (CO_2) emissions. Results show that GLGO consistently outperformed GA across all indices: reducing LCOE from ₦80/kWh to ₦61/kWh (23.75% reduction), lowering LPSP from 0.06 to 0.01 (83.33% improvement in reliability), increasing EE from 85% to 92% (7.61% gain), and cutting daily CO_2 emissions from 5.8 kg to 3.2 kg (44.80% reduction). These findings demonstrate that GLGO-based optimization provides a cost-effective, reliable, and environmentally sustainable solution for hybrid microgrid planning in healthcare facilities. The methodology offers a robust decision-support tool for strengthening energy resilience and accelerating renewable energy deployment in critical healthcare infrastructure across developing regions.

1. Introduction

Reliable electricity is indispensable for the effective operation of modern healthcare facilities. Hospitals rely on continuous electrical power to operate life-support systems, diagnostic imaging equipment, operating theatres, intensive care units (ICUs), laboratory facilities, vaccine refrigeration systems, sterilization units, and communication infrastructure. Any interruption in electricity supply can compromise patient safety, reduce the quality of healthcare delivery, disrupt emergency medical procedures, and increase operational costs. Consequently, ensuring reliable, affordable, and sustainable electricity for healthcare facilities has become a global priority in achieving the United Nations Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-being) and SDG 7 (Affordable and Clean Energy) [1-3] [4].

Despite significant investments in electricity infrastructure, power supply reliability remains a major

challenge in many developing countries, especially across sub-Saharan Africa. Nigeria continues to experience persistent electricity shortages caused by inadequate generation capacity, ageing transmission infrastructure, distribution network limitations, poor maintenance practices, and increasing electricity demand [5]. As a result, public healthcare facilities frequently depend on diesel generators to ensure continuity of essential medical services. Although diesel generators provide backup power during grid outages, their extensive use is associated with high operating and maintenance costs, greenhouse gas emissions, environmental pollution, excessive noise, and vulnerability to volatile fuel prices [4][6-7]. These limitations have intensified interest in decentralized renewable energy systems capable of providing reliable, cost-effective, and environmentally sustainable electricity for critical healthcare infrastructure.

Among the available renewable energy technologies, solar photovoltaic (PV) system has emerged as one of the most promising in Nigeria due to its modularity, declining installation costs, minimal maintenance requirements, and the abundant solar energy resource available across Nigeria [7]. Nigeria receives an average daily solar radiation ranging from approximately 5.0 to 7.0 kWh/m²/day, making solar PV an attractive solution for distributed electricity generation [8]. However, the intermittent nature of solar irradiation limits the capability of standalone PV systems to satisfy continuous hospital electricity demand, particularly during nighttime and periods of low solar irradiance. To overcome this limitation, photovoltaic systems are commonly integrated with battery energy storage systems (BESS), diesel generators, and utility grid support to form hybrid renewable energy systems (HRES). Such hybrid configurations improve system reliability, increase renewable energy penetration, reduce diesel fuel consumption, and minimize carbon emissions while ensuring uninterrupted power supply for critical healthcare operations [9][10-11].

The optimal design and sizing of hybrid renewable energy systems constitute a complex multi-objective optimization problem involving conflicting economic, technical, reliability, and environmental objectives. The optimal capacities of the photovoltaic array, battery storage system, diesel generator, and inverter must be determined such that the total lifecycle cost is minimized while maintaining high system reliability, maximizing renewable energy utilization, and reducing greenhouse gas emissions. Consequently, numerous optimization techniques have been developed for hybrid energy system design, including Linear Programming (LP), Mixed-Integer Linear Programming (MILP), Dynamic Programming (DP), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Differential Evolution (DE), Grey Wolf Optimizer (GWO), Harris Hawks Optimization (HHO), Whale Optimization Algorithm (WOA), and several other nature-inspired metaheuristic algorithms [12][13-14]. Although these optimization methods have demonstrated satisfactory performance in solving hybrid energy system optimization problems, many suffer from limitations such as premature convergence, inadequate exploration of the search space, sensitivity to algorithm parameters, or entrapment in local optima when addressing highly nonlinear optimization problems [12][15].

Recently, swarm intelligence algorithms inspired by biological systems have attracted considerable attention because of their robust global search capability, adaptive learning mechanisms, and computational efficiency. One of the latest additions to this family is the Grey Lag Goose Optimization (GLGO) algorithm, which emulates the cooperative migratory behavior of grey lag geese through adaptive leadership exchange, coordinated V-shaped flight formation, and collective navigation strategies. These behavioral characteristics enable an effective balance between global exploration and local exploitation, thereby improving convergence accuracy and reducing the probability of trapping in local optima [16]. Compared with conventional evolutionary algorithms, GLGO has demonstrated promising performance in solving complex engineering optimization problems due to its adaptive search mechanism and efficient convergence characteristics. Although considerable research has been conducted on the optimization of hybrid renewable energy systems

using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Differential Evolution (DE), Harris Hawks Optimization (HHO), and other metaheuristic techniques, the application of the recently developed Grey Lag Goose Optimization algorithm to healthcare-oriented hybrid microgrids remains largely unexplored. Furthermore, most existing studies primarily emphasize economic optimization while giving comparatively less attention to the simultaneous assessment of economic, technical, reliability, and environmental performance indicators using actual hospital electricity demand under unreliable grid conditions. This research gap highlights the need for a comprehensive optimization framework capable of improving system performance while ensuring sustainable and reliable electricity supply for critical healthcare facilities [16].

Motivated by these challenges, this study presents the techno-economic optimization of a grid-connected PV–battery–diesel hybrid microgrid designed for General Hospital Sabon Tasha, Kaduna State, Nigeria. The proposed hybrid energy system is developed in MATLAB/Simulink using measured hospital load demand, solar resource data obtained from the NASA POWER database, utility grid availability profiles, and local diesel fuel cost information. The recently developed Grey Lag Goose Optimization (GLGO) algorithm is employed to determine the optimal sizes of the photovoltaic array, battery energy storage system, diesel generator, and inverter. To evaluate its effectiveness, the optimization results are compared with those obtained using the widely adopted Genetic Algorithm (GA). The performance of both optimization approaches is assessed using four widely accepted performance indicators**:** Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP), Energy Efficiency (EE), and carbon dioxide (CO_2) emissions, thereby providing a comprehensive evaluation of the economic, technical, reliability, and environmental performance of the proposed hybrid microgrid.

2. Materials and methods

2.1 Study area

This study investigates the techno-economic optimization of a grid-connected photovoltaic (PV)-battery-diesel hybrid microgrid designed to provide reliable electricity to General Hospital Sabon Tasha, located in Chikun Local Government Area, Kaduna State, Nigeria (Latitude 9.53°N, Longitude 7.57°E). The hospital serves a rapidly growing population and experiences frequent interruptions in electricity supply due to the limited reliability of the Nigerian electricity distribution network. Such interruptions adversely affect the operation of critical medical equipment, including operating theatres, diagnostic laboratories, refrigeration systems for vaccines and medicines, and emergency healthcare services, thereby compromising the quality and continuity of patient care [4-5].

The selection of General Hospital Sabon Tasha as the case study is motivated by its representative electrical load characteristics and the persistent challenges associated with unreliable grid electricity in public healthcare facilities across Nigeria. Previous studies have reported that inadequate power supply remains one of the major barriers to efficient healthcare delivery in many developing countries, resulting in increased dependence on diesel generators with associated high operating costs, greenhouse gas emissions, and maintenance requirements [4][17]. Consequently, the hospital provides a suitable environment for evaluating the technical and economic performance of hybrid renewable energy systems aimed at improving electricity reliability while reducing fossil fuel dependence.

The proposed hybrid microgrid integrates four energy sources: a photovoltaic (PV) array, a battery energy storage system (BESS), the utility grid, and a diesel generator. The system was modelled and simulated using MATLAB R2024a, while the Grey Lag Goose Optimization (GLGO) algorithm was employed to determine the optimal sizes of the system components. For comparative analysis, the widely adopted Genetic Algorithm (GA) was implemented as a benchmark optimization technique. The optimization framework simultaneously minimizes the Levelized Cost of

Energy (LCOE) and the Loss of Power Supply Probability (LPSP) while maximizing the overall Energy Efficiency (EE), subject to operational constraints including battery state-of-charge limits, diesel generator operating limits, and grid availability. This multi-objective optimization framework is consistent with recent studies on hybrid renewable energy system design and sizing [11][17-18].

2.2 Resource assessment

Accurate resource assessment is fundamental to the optimal design, simulation, and operation of hybrid renewable energy systems (HRES), as the performance and economic viability of the system depend largely on the availability of renewable resources and the characteristics of the electrical load [11],[17]. In this study, the required input datasets comprised solar irradiance, ambient temperature, hospital electrical load demand, utility grid availability, and diesel fuel cost. These datasets served as the primary inputs for the mathematical modelling, simulation, and techno-economic optimization of the proposed hybrid microgrid.

2.2.1 Solar resource assessment

Solar resource assessment was performed using long-term meteorological data obtained from the NASA Prediction of Worldwide Energy Resources (NASA POWER) database, which provides reliable satellite-derived climatic data for renewable energy applications worldwide [8]. Monthly average Global Horizontal Irradiance (GHI) values corresponding to General Hospital Sabon Tasha, Kaduna State (Latitude 9.53°N, Longitude 7.57°E), were extracted and processed in MATLAB to estimate the available photovoltaic energy potential.

The study location receives an average annual solar radiation of approximately 5.72 kWh/m²/day, indicating excellent solar energy potential suitable for photovoltaic electricity generation. Maximum solar irradiance occurs during the dry season (March–April), whereas lower irradiance values are experienced during the rainy season (July–August) because of increased cloud cover and atmospheric moisture. These seasonal variations were incorporated into the PV model to improve the accuracy of the simulated hourly power output [19].

The electrical output of the photovoltaic array is expressed as:

$$P_{PV}(t) = A_{PV} \times G(t) \times \eta_{PV} \quad (1)$$

Where A_{PV} is the effective PV array area (m²), G(t) is the incident solar irradiance (W/m²), and ηPV is the PV module conversion efficiency.

2.2.2 Ambient temperature assessment

Ambient temperature data corresponding to the study location were also obtained from the NASA POWER database. The annual average temperature is approximately 27.6 °C, with monthly values ranging from 22 °C to 34 °C.

Since photovoltaic module efficiency decreases as cell temperature increases, ambient temperature was incorporated into the PV performance model to improve the accuracy of the simulation. This approach captures seasonal variations in module operating conditions and provides more realistic estimates of annual energy production [20]

2.2.3 Hospital electrical load assessment

A comprehensive electrical energy audit was conducted to determine the electricity demand of General Hospital Sabon Tasha. The assessment included all major hospital departments, including the emergency unit, operating theatre, laboratory, inpatient wards, pharmacy, radiology department, administration, water supply system, kitchen, laundry and outdoor lighting facilities. Equipment ratings, quantities and daily operating schedules were obtained through field inspection and consultation with hospital technical personnel. Based on these data, the hospital was estimated to have a connected load of approximately 13.2 kW and a total daily electrical energy demand of 366 kWh/day.

Table 1: Hospital Load Demand

Department	Equipment/Loads	Quantity	Power per Unit (W)	Operating Hours/Day	Daily Energy (kWh)
Emergency Room (ER)	Lighting, ventilators, monitors	10	300	24	72
	Split AC units	2	1500	10	30
Operating Theatre	OT Lights, suction, monitors	5	500	6	15
	Anesthesia machines	2	2000	4	16
Laboratory	Centrifuge, fridge, incubator, PC	10	250	8	20
Wards (3 total)	Lighting, fans, nurse station	30	100	24	72
	Bedside outlets (chargers, nebulizer, etc.)	20	150	12	36
Pharmacy	Fridges, PC, lighting	4	300	10	12
Admin/Records	Computers, printers, lighting	10	200	8	16
Radiology	X-Ray, ultrasound machine	2	3000	4	24
Water Supply	Borehole pump (3 HP)	1	2200	2	4.4
Kitchen	Freezer, microwave, lights, extractor fans	5	500	6	15
External Lighting	Floodlights, security lights	8	100	12	9.6
Laundry	Washing & drying machine	2	2000	4	16
Miscellaneous	Misc. plugs, emergency sockets	10	100	8	8
			13200	**142**	**366**

An hourly load profile was subsequently developed in MATLAB to represent the variation in electricity demand over a typical 24-hour period. The profile exhibits two distinct demand peaks. The first occurs during normal clinical activities between 09:00 and 16:00 h, while the second occurs between 18:00 and 22:00 h, corresponding to ward operations, lighting, and other auxiliary loads. This load profile served as the principal demand input during the optimization of the hybrid microgrid [21][22].

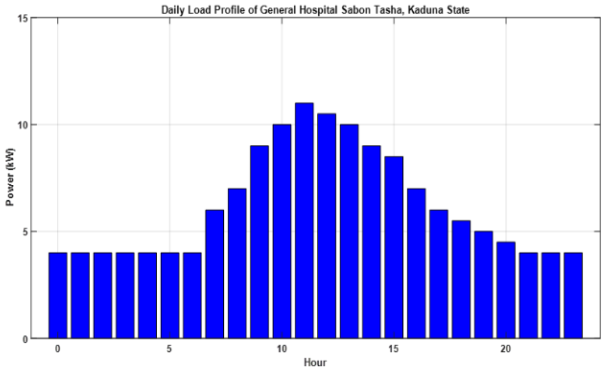

Fig. 1: Hourly electrical load profile of General Hospital Sabon Tasha.

2.3 Hybrid microgrid configuration

The proposed hybrid energy system consists of four complementary energy sources: a photovoltaic (PV) array, a battery energy storage system (BESS), a diesel generator (DG), and the national utility grid. The objective of integrating these energy sources is to ensure a continuous and reliable electricity supply while minimizing energy cost, diesel fuel consumption, and greenhouse gas emissions [17][23]

During periods of high solar irradiance, the PV array serves as the primary source of electricity. The generated power is first used to satisfy the hospital load demand, while any surplus energy is stored in the battery bank. During periods of insufficient solar generation, such as nighttime or cloudy weather conditions, the battery discharges to support the load. If the battery state of charge reaches its minimum allowable limit or renewable generation becomes insufficient, the utility grid supplies the remaining demand whenever it is available. The diesel generator operates only as the last backup source during prolonged renewable energy deficits or grid outages.

This hierarchical energy management strategy maximizes renewable energy utilization, minimizes diesel generator operating hours, reduces fuel consumption and carbon emissions, improves system reliability, and lowers the overall operating cost of the hybrid microgrid. Similar dispatch strategies have been widely adopted in hybrid renewable energy systems because they achieve improved techno-economic

performance while maintaining high supply reliability [11][21]. The complete configuration of the proposed hybrid microgrid is illustrated in Fig. 2.

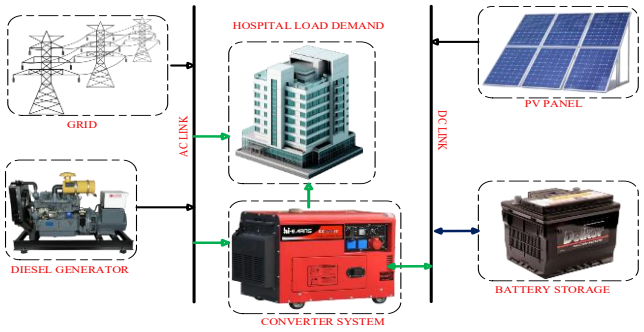

Fig. 2: Configuration of the PV, Battery, Diesel Grid hybrid microgrid.

2.4 Mathematical modelling of hybrid microgrid components

Mathematical models were adopted for each component of the proposed hybrid microgrid to accurately represent their electrical characteristics and operational behaviour during the optimization process. The component models were implemented in MATLAB R2024a and integrated into the Grey Lag Goose Optimization (GLGO) algorithm to determine the optimal system configuration. The adopted models are consistent with those widely reported for hybrid renewable energy system (HRES) analysis [11][18][24].

2.4.1 Photovoltaic system model

The photovoltaic array converts incident solar radiation directly into electrical energy through the photovoltaic effect. The output power of the PV array depends primarily on the available solar irradiance and the operating cell temperature [19].

The hourly PV output power is calculated as:

$$P_{pv}(\mathrm{t}) = Y_d^{\left(\frac{Ig(t)}{I_s}\right)}[1 - \frac{K_p}{100}(T_c(t) - T_{stc})] \quad (2)$$

The influence of temperature on PV output is represented by

$$T_c(\boldsymbol{t}) = T_a(t) + I_g(t)\frac{T_{no}-20}{0.8} \quad (3)$$

Here, Y_d is the PV derating factor, Ig is the incident solar irradiance (kW/m²), Is is the standard solar irradiance (1 kW/m²), Kp is the temperature coefficient of power (%/°C), Ta is the ambient temperature (°C), Tc is the PV cell temperature (°C), TNOCT is the nominal operating cell temperature, and TSTC is the cell temperature under standard test conditions. These equations were adopted to estimate the hourly PV power generation in the proposed hybrid microgrid model.

2.4.2 Battery energy storage system model

The Battery Energy Storage System (BESS) stores surplus photovoltaic energy during periods of excess generation and supplies electricity whenever renewable generation becomes insufficient. Consequently, battery storage enhances supply reliability while minimizing diesel generator operation [17][25].

The battery State of Charge (SOC) is updated according to:

$$SOC(t) = SOC(t-1) + \int_{T-1}^{T} \frac{P_{bt}(t)\eta_{bt}}{V_{bs}} dt \quad (4)$$

Where SOC(t) is the battery state of charge at time *t*, $P_B(t)$ is the battery charging or discharging power (kW), ηB is the battery round-trip efficiency, and V_{DC} is the DC bus voltage (V). Positive values of $P_B(t)$ denote battery charging, whereas negative values represent battery discharging. For discrete-time simulations, the integral expression is replaced by its corresponding summation. To prolong battery lifetime, the battery operation is constrained within predefined minimum and maximum SOC limits throughout the optimization process. The battery bank capacity is calculated using:

$$C_n = \frac{N_{bt}}{N_{bt}^s} C_b \quad (5)$$

Where C_n is the total battery bank capacity, C_C is the capacity of an individual battery unit, N_{bt} is the total number of batteries, and N_{Bt}^s is the number of batteries connected in series. The required number of batteries connected in series is determined from;

$$N_B^s = \frac{V_{DC}}{V_{cell}} \quad (6)$$

Where V_{cell} is the nominal voltage of a single battery. The maximum charging or discharging power of the battery bank is calculated as

$$P_{bt}^{mx} = \frac{N_{bs}V_{bt}I_{mx}}{1000} \quad (7)$$

These models ensure realistic simulation of battery charging, discharging, and energy storage behaviour under varying operating conditions [18][25].

2.4.3 Diesel generator model

The diesel generator serves as the dispatchable backup power source within the hybrid microgrid. Its primary function is to maintain uninterrupted electricity supply whenever the photovoltaic system, battery storage, and utility grid cannot satisfy the hospital load demand.

The hourly diesel fuel consumption is represented by:

$$F_{dg}(t) = \alpha_{dg} P_{dg,g}(t) + \beta_{dg} P_{dg,r}(t) \quad (8)$$

where

- $F_{dg}(t)$= hourly fuel consumption (L/h),
- $P_{dg,g}(t)$= generator output power,
- $P_{dg,r}(t)$ = rated generator capacity,
- α and β are fuel consumption coefficients.

The objective of the optimization algorithm is to minimize diesel generator operating hours while maintaining the required reliability of electricity supply [26].

2.4.4 Utility Grid Model

The national electricity grid is incorporated as a supplementary energy source whenever electricity is available. Grid availability is represented by a binary operating state based on the observed supply reliability for the study area. When the grid is available, it supplies any remaining demand after photovoltaic generation and battery discharge have been utilized. During grid outages, the hybrid system relies on the battery bank and diesel generator to maintain uninterrupted electricity supply. The inclusion of grid support improves operational flexibility and reduces diesel fuel consumption during normal operating conditions.

2.4.5 Power Converter Model

A bidirectional power converter (inverter) is employed to facilitate energy exchange between the DC components (PV array and battery bank) and the AC hospital load. The inverter converts direct current generated by the photovoltaic array into alternating current suitable for hospital electrical equipment while also enabling battery charging during periods of excess PV generation. The inverter efficiency is assumed to remain constant throughout the simulation, and its capacity is selected to satisfy the maximum instantaneous hospital load demand with an adequate design margin. This power delivered by the inverter is expressed as:

$$P_{AC}(t) = \eta_{inv} P_{DC}(t) \quad (9)$$

Where $P_{AC}(t)$ is the inverter output power at time (t), $P_{DC}(t)$ is the DC input power supplied by the PV and η_{inv} is the inverter efficiency

2.5 Grey Lag Goose Optimization (GLGO)

Grey Lag Goose Optimization (GLGO) is a recently developed nature-inspired swarm intelligence algorithm that emulates the cooperative migratory behaviour of grey lag geese. During migration, grey lag geese periodically exchange leadership positions, maintain adaptive V-shaped formations, and cooperate to minimize aerodynamic energy losses while navigating long distances. These biological behaviours are mathematically translated into an optimization framework capable of balancing global exploration and local exploitation [16].

Unlike conventional evolutionary algorithms such as Genetic Algorithm (GA), which primarily rely on crossover and mutation operators, GLGO employs adaptive position updating, cooperative search mechanisms, and dynamic leadership exchange to improve convergence speed while maintaining population diversity. Consequently, GLGO demonstrates strong capability for solving nonlinear constrained optimization problems associated with hybrid renewable energy system sizing [16][17].

The optimization objective can be expressed as

$$X_i^{K+1} = X_i^k + r_1\left(X_{leader} - X_i^k\right) + r_2\left(X_{best} - X_i^k\right) \quad (10)$$

where

X_i^{K+1} = updated position of thei^{th}goose at iteration $k+1$

X_i^k = current position of the ith goose at iteration k

X_{leader}= position of the current flock leader

X_{best} = globally best solution found so far

r_1 and r_2 = uniformly distributed random numbers in the interval

The optimization continues iteratively until either the maximum number of iterations or the convergence criterion is satisfied. The optimal solution minimizes the Levelized Cost of Energy (LCOE) and Loss of Power Supply Probability (LPSP) while maximizing overall system energy efficiency.

2.6 Genetic Algorithm

The Genetic Algorithm (GA) was implemented as the benchmark optimization technique because of its widespread application in the optimal sizing and operational scheduling of hybrid renewable energy systems. GA is a population-based metaheuristic inspired by the principles of natural selection and genetics, offering robust global search capability for solving complex nonlinear optimization problems [17][18]. The algorithm begins by generating an initial population of candidate solutions randomly within the predefined design constraints. Successive generations are produced through the evolutionary operators of selection, crossover, and mutation, which promote the inheritance of desirable characteristics while maintaining population diversity. Individuals with superior fitness values have a higher probability of surviving and contributing to subsequent generations, leading to progressive improvement toward the optimal solution [12][17].

For a fair comparison, both GLGO and GA were executed using identical system models, optimization constraints, and stopping criteria. Their performances were evaluated using the Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP), Energy Efficiency (EE), and carbon dioxide (CO_2) emissions.

2.7 Objective Functions

The optimal sizing of the proposed grid-connected PV–battery–diesel hybrid microgrid was formulated as a multi-objective optimization problem. The optimization simultaneously minimizes the economic cost of electricity generation and the probability of power interruption while maximizing the overall energy efficiency of the system [15][17]. Three objective functions were therefore considered.

2.7.1 Levelized Cost of Energy (LCOE)

The Levelized Cost of Energy (LCOE) represents the average cost of generating one unit of electrical energy over the lifetime of the hybrid energy system. It incorporates all lifecycle expenditures, including capital investment, replacement costs, operation and maintenance costs, fuel consumption, and salvage value, thereby providing a comprehensive measure of economic performance [7][18].

The LCOE is expressed as

$$C_{ann-total} = C_{initial\ capital} + C_{Replacement} + C_{maintenance\ \&\ operation} \quad (11)$$

$$F_1 = \min\{LCOE\} = \min\{\frac{C_{ann-total}}{\sum_{t=1}^{N} E_{load,t}}\} \quad (12)$$

where

- C_{ann} is the total annualized system cost;
- $E_{load,t}$ is the total annual electrical energy supplied to the hospital load.

The optimization objective is, $F_1 = \min\{LCOE\}$, Lower LCOE values indicate improved economic performance and greater long-term financial viability.

2.7.2 Loss of Power Supply Probability (LPSP)

The Loss of Power Supply Probability (LPSP) is used to quantify the reliability of the hybrid microgrid. It represents the proportion of the total electrical demand that cannot be satisfied by the available energy sources during the simulation period. A lower LPSP corresponds to higher system reliability and improved continuity of electricity supply, which is particularly important for critical healthcare facilities [10][27]. The LPSP is calculated as in equation (13).

$$F_2 = \min\left\{\frac{\sum_{t=1}^{8760}[P_{load}(t)+P_{bt-ch}(t)-(P_{pv}(t)+P_{bt-disc}+P_{grid}(t)+P_{dg}(t))]}{\sum_{t=1}^{8760} P_{load}(t)}\right\} \quad (13)$$

The optimization objective is, $F_2 = \min$ {LPSP}, an LPSP value approaching zero indicates that the hybrid system can reliably satisfy the hospital electricity demand throughout the study period.

2.7.3 Energy Efficiency (EE)

Energy Efficiency (EE) evaluates the effectiveness with which the hybrid microgrid converts available renewable energy resources into useful electrical energy delivered to the hospital. Higher efficiency indicates improved utilization of renewable resources, lower conversion losses, and enhanced overall system performance [6][17].

The overall system efficiency is expressed in (14).

$$F_3 = \min\left\{\frac{\sum_{t=1}^{8760}\left(P_{pv}^{out}(t) + P_{dg}^{out}(t) + P_{grid}^{in}(t) + P_{battery}^{discharge}(t)\right)\Delta t}{\sum_{t=1}^{8760} P_{load}(t)\Delta t}\right\} \quad (14)$$

The optimization objective is $F_3 = \min\{\text{EE}\}$, higher energy efficiency reflects better utilization of renewable resources, lower conversion losses, and improved operational performance.

2.7.4 Multi-Objective Optimization Formulation

Since minimizing LCOE, minimizing LPSP, and maximizing EE are inherently conflicting objectives, the optimization problem was formulated as a weighted multi-objective function. The weighted-sum approach combines the individual objective functions into a single scalar objective while allowing decision-makers to assign relative importance to economic, reliability, and efficiency considerations [10][18].

The optimization problem is expressed as, $F_1 = \min\{LCOE\}$, $F_2 = \min\{\text{LPSP}\}$ and $F_3 = \min\{\text{EE}\}$

- minimizing the Levelized Cost of Energy;
- minimizing the Loss of Power Supply Probability;
- Maximizing the overall Energy Efficiency.

To obtain a single optimization function, a weighted-sum approach is adopted.

$$F(x) = [F_1(x), F_2(x), F_2(x)]^T \quad (15)$$

$$J(x) = w_1\frac{F_1(x)}{F_1^{ref}} + w_2\frac{F_2(x)}{F_2^{ref}} + w_3\frac{F_3(x)}{F_3^{ref}} \quad (16)$$

where:

$w_1+w_2+w_3=1$, $w_i \geq 0$ *are weights reflecting stakeholder priorities,*

F_i^{ref} *are reference values used for normalization*

The weighting coefficients allow the optimization algorithm to balance conflicting objectives according to the desired operational priorities [10][18].

The weighting coefficients adopted are 0.35 for LCOE(w_1), 0.35 for LPSP(w_2,) 0.15 for energy efficiency(w_3), and 0.15 for CO_2 emissions, giving a total weight of 1.00. These weights were selected to prioritize economic affordability and power-supply reliability, which are critical considerations for healthcare facilities, while also accounting for operational efficiency and environmental sustainability.

2.8 System Constraints

To ensure realistic operation of the hybrid microgrid, the optimization process was performed subject to several technical and operational constraints.

2.8.1 Battery State-of-Charge Constraint

To ensure realistic operation of the proposed hybrid microgrid, the optimization process was performed subject to several technical and operational constraints. These constraints guarantee that all system components operate within their allowable limits while maintaining system reliability and extending component lifetime [10][18].

2.8.1 Battery State-of-Charge Constraint

The Battery State of Charge (SOC) was maintained within the manufacturer's recommended operating limits throughout the simulation period.

$$SOC_{min}(t) \leq SOC(t) \leq SOC_{max}(t) \quad (17)$$

This constraint prevents excessive charging and deep discharging, thereby prolonging battery lifespan, maintaining storage efficiency, and improving the overall reliability of the hybrid microgrid [6][28].

2.8.2 Photovoltaic Capacity Constraint

The installed photovoltaic (PV) array capacity was constrained within feasible design limits to ensure practical installation, prevent excessive system oversizing, and maintain realistic investment costs while maximizing the utilization of available solar resources [9][10]. The maximum PV capacity was determined based on the available installation area,

local solar resource potential, and the electrical demand of the healthcare facility. The constraint is expressed as

$$0 < P_{pv} \leq P_{pv}^{max} \quad (18)$$

where:

- P_{pv} is the installed photovoltaic array capacity (kW);
- P_{pv}^{max} Is the maximum allowable PV capacity (kW), determined by the available installation area, system design requirements, and investment limitations.

This constraint prevents unrealistic PV sizing during the optimization process while ensuring that the selected PV capacity remains technically feasible and economically justifiable.

2.8.3 Diesel Generator Constraint

The diesel generator (DG) was constrained to operate within its permissible loading range to improve fuel efficiency, reduce greenhouse gas emissions, and prevent excessive engine wear caused by prolonged operation under very low or overloaded conditions [10][36]. The operational constraint is expressed as

$$P_{DG}^{min} \leq P_{DG}(t) \leq P_{DG}^{rated} \quad (19)$$

where:

- $P_{DG}(t)$ is the diesel generator output power at time (t) (kW);
- P_{DG}^{min} is the minimum stable operating power (kW);
- P_{DG}^{rated} is the rated generator capacity (kW).

This constraint ensures that the diesel generator operates only within its recommended loading limits, thereby improving operational reliability, extending equipment lifespan, and reducing fuel consumption and carbon emissions during hybrid microgrid operation**.**

2.8.4 Battery power balance constraint

The charging and discharging power of the battery energy storage system (BESS) was governed by the power balance equation to ensure that electricity generation and storage satisfy the instantaneous hospital load demand. This constraint guarantees that the combined power supplied by the photovoltaic (PV) array, diesel generator, utility grid and battery in satisfying the hospital load demand, while accounting for battery charging or discharging requirements. Maintaining power balance is essential for reliable microgrid operation, minimizing loss of power supply probability (LPSP) and preventing unnecessary battery degradation due to excessive cycling [10][25]. The system power balance is expressed as

$$\mathrm{P_{pv}}(t) + P_{grid}(t) + P_{bt}(t) + P_{dg}(t) = P_{load} \quad (20)$$

where:

- $\mathrm{P_{pv}}(t)$ is the photovoltaic output power (kW)
- $P_{dg}(t)$ is the diesel generator output power (kW)
- $P_{grid}(t)$ is the utility grid power supplied (kW)
- $P_{bt}(t))$ is the battery power (kW), which is positive during battery discharge and negative during battery charging; and
- P_{load} Is the hospital electrical demand (kW).

2.8.5 Grid Availability Constraint

The utility grid was represented using an availability schedule derived from the operational characteristics of the study area. During periods of utility outage,

$$P_{grid}(t)=0 \quad (21)$$

where $P_{grid}(t)$ is the power supplied by the utility grid at time (t). Under this condition, the hospital electrical demand was met entirely by the photovoltaic (PV) array, battery energy storage system (BESS), and diesel generator (DG) in accordance with the system power balance constraint. This modeling approach accurately represents the intermittent nature of electricity supply commonly experienced in developing countries and enables the hybrid microgrid to maintain continuous power delivery to critical healthcare loads during utility outages. Incorporating grid availability constraints into hybrid energy system optimization improves system reliability, minimizes the Loss of Power Supply Probability (LPSP), and enhances operational resilience under uncertain grid conditions [6][29].
The grid availability can therefore be expressed as

$$\mathrm{P_{grid}(t)} = P_{sn}\begin{cases} P_{grid\,max} & \text{if utility grid is available} \\ 0 & \text{if utility grid is unavailable} \end{cases} \quad (22)$$

Where $P_{grid\,max}$ denotes the maximum power that can be imported from the utility grid.

2.8.6 Inverter capacity constraint

The inverter was sized to ensure adequate conversion of the direct current (DC) power produced by the

photovoltaic (PV) array and battery energy storage system (BESS) into alternating current (AC) required by the hospital loads. To guarantee uninterrupted operation, the inverter rated capacity was constrained to be greater than or equal to the maximum instantaneous electrical demand of the hospital, while also accounting for short-duration surge loads and system reliability requirements [10][30-31]. The inverter capacity constraint is expressed as

$$P_{inv} \geq P_{peak,load} \quad (23)$$

where:

- P_{inv} = inverter rated capacity (kW);
- $P_{peak,load}$ = Peak hospital electrical load demand (kW).

This constraint ensures that the inverter can continuously supply the maximum hospital demand without overloading, thereby improving system reliability, reducing conversion losses and maintaining stable operation of the hybrid PV, battery, diesel microgrid during both grid-connected and islanded operating modes.

2.9 Simulation Procedure

The proposed hybrid microgrid was modelled and simulated using MATLAB R2024a, which provides a flexible environment for modelling renewable energy systems and implementing optimization algorithms [32]. The simulation framework integrated the photovoltaic array, battery energy storage system, diesel generator, utility grid, inverter, and hospital load profile into a unified optimization platform. Similar simulation frameworks have been widely adopted for techno-economic optimization of hybrid renewable energy systems [10-11].

The simulation procedure consisted of the following steps:

1. Collection of solar irradiance, ambient temperature, and hospital load demand data.
2. Development of mathematical models for all hybrid microgrid components.
3. Initialization of the Grey Lag Goose Optimization (GLGO) and Genetic Algorithm (GA).
4. Generation of candidate solutions representing different hybrid system configurations.
5. Hourly simulation of system operation throughout the study period.
6. Evaluation of the objective functions, namely Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP), and Energy Efficiency (EE).
7. Verification of all operational and design constraints.
8. Iterative updating of decision variables until convergence was achieved.
9. Selection of the optimal hybrid microgrid configuration corresponding to the minimum objective function value.

3. Results and Discussion

3.1 Optimal Hybrid Microgrid Configuration

The optimization produced an optimal hybrid microgrid comprising an 80 kW photovoltaic array, a 140 kWh battery energy storage system, a 20 kW inverter, and a 25 kVA diesel generator. This configuration provided an appropriate balance between renewable energy penetration, storage capacity, and backup generation to ensure uninterrupted electricity supply. Similar optimal sizing strategies have been reported for healthcare microgrids where photovoltaic generation is complemented by battery storage and standby diesel generation to achieve reliable and cost-effective operation.

During daytime operation, the photovoltaic system supplied the majority of the hospital electrical demand. Excess photovoltaic energy generated during periods of high solar irradiance was stored in the battery bank for later use. During periods of low solar irradiance or nighttime operation, the battery supplied the load until its minimum state-of-charge limit was reached. The utility grid supplied additional energy whenever available, while the diesel generator operated only during prolonged renewable energy deficits or grid outages. This operational strategy is consistent with the energy management practices commonly adopted in hybrid renewable microgrids for critical infrastructure, where renewable energy is prioritized to minimize fuel consumption and greenhouse gas emissions.

The optimized configuration significantly reduced dependence on diesel generation, improved renewable

energy utilization, and enhanced overall system reliability, demonstrating the effectiveness of GLGO for hybrid microgrid planning in critical healthcare applications. These findings are consistent with previous studies indicating that advanced nature-inspired optimization algorithms outperform conventional evolutionary methods in identifying globally optimal hybrid energy system configurations with lower operating costs and improved reliability.

3.2 Convergence Analysis of Grey Lag Goose Optimization and Genetic Algorithm

The convergence characteristics of the Grey Lag Goose Optimization (GLGO) algorithm were compared with those of the conventional Genetic Algorithm (GA) over 500 optimization iteration.

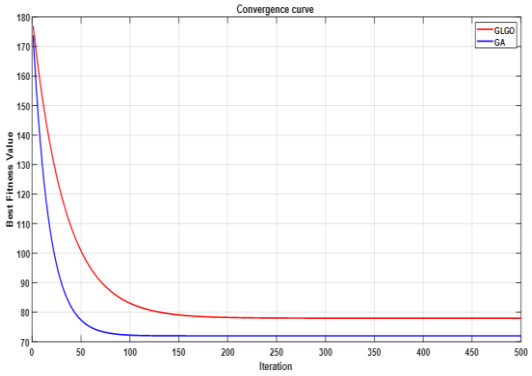

Fig. 3: Convergence characteristics of Grey Lag Goose Optimization (GLGO) and Genetic Algorithm (GA) over 500 iterations

As illustrated in Fig. 3, both algorithms rapidly reduced the objective function during the initial search stage, indicating effective exploration of the solution space. However, their convergence behaviours differed considerably as the optimization progressed. Similar convergence trends have been observed in comparative studies involving modern metaheuristic optimization techniques applied to hybrid renewable energy system design.

The GLGO algorithm exhibited smooth and continuous convergence towards the global optimum, whereas the Genetic Algorithm converged prematurely after relatively few iterations. Premature convergence limited the ability of GA to continue exploring improved solutions, resulting in a higher objective function value. Premature convergence is a well-recognized limitation of conventional genetic algorithms, particularly when solving highly nonlinear and multi-modal optimization problems.

The superior convergence behaviour of GLGO can be attributed to its adaptive leadership exchange mechanism and cooperative search strategy, which effectively balance exploration and exploitation throughout the optimization process. These mechanisms enable the algorithm to avoid local optima while maintaining adequate population diversity. Such adaptive exploration–exploitation mechanisms have been identified as critical characteristics of modern swarm intelligence algorithms for solving complex engineering optimization problems.

Consequently, GLGO produced a superior combination of photovoltaic capacity, battery storage, diesel generator rating, and inverter size compared with the Genetic Algorithm. The improved convergence performance translated directly into lower LCOE, improved energy efficiency, and enhanced supply reliability, confirming the suitability of GLGO for optimal hybrid microgrid planning in healthcare facilities where uninterrupted power supply is essential [5][29].

3.3 Photovoltaic output power tracking performance

The photovoltaic output power obtained using GLGO and GA was evaluated against the ideal reference power under varying operating conditions.

Figure 4, demonstrates that both optimization methods successfully tracked changes in photovoltaic output. Nevertheless, the GLGO algorithm exhibited considerably faster transient response, reduced oscillations, and negligible steady-state error compared with GA.

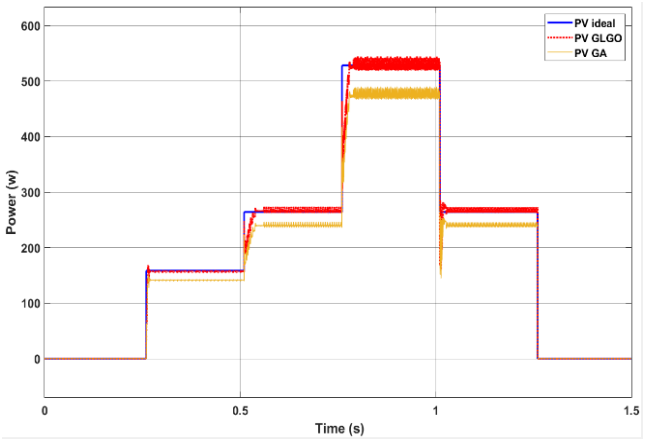

Fig. 4: Photovoltaic output power tracking performance using GLGO and GA compared with ideal reference power.

The improved tracking performance enhanced photovoltaic energy harvesting and reduced fluctuations in battery charging and diesel generator operation. Consequently, renewable energy utilization increased while fossil fuel consumption decreased. Similar observations have been reported in previous studies, where improved optimization techniques enhanced renewable energy penetration and minimized auxiliary generator utilization in hybrid microgrid applications.

Furthermore, the smoother power response achieved by GLGO contributes directly to improved operational stability of the hybrid microgrid by reducing frequent switching of energy sources and mitigating unnecessary battery cycling. This operational stability not only extends battery lifespan but also improves the overall efficiency and reliability of the hybrid renewable energy system, making it particularly suitable for healthcare facilities where uninterrupted power supply is essential.

3.4 Techno-Economic Performance Analysis

The performance of the optimized hybrid microgrid was evaluated using four key indicators:

1. Levelized Cost of Energy (LCOE)
2. Loss of Power Supply Probability (LPSP)
3. Energy Efficiency (EE)
4. Carbon dioxide (CO_2) emissions

These indicators collectively assess the economic, technical, reliability, and environmental performance of the proposed energy system.

3.4.1 Levelized Cost of Energy

The GLGO algorithm achieved an LCOE of ₦61/kWh, whereas the Genetic Algorithm produced an LCOE of ₦80/kWh, corresponding to a 23.75% reduction in electricity cost, which can be seen in Figure 5.

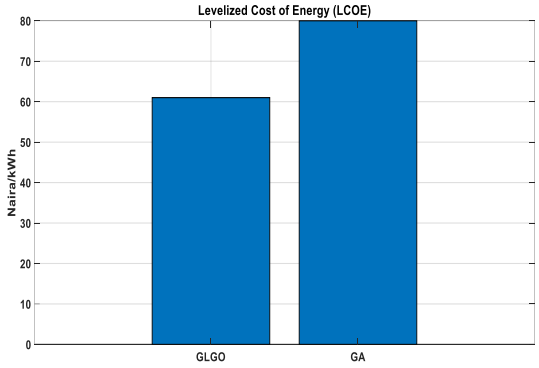

Fig. 5: Levelized Cost of Energy (LCOE) comparison between GLGO and GA.

The lower LCOE obtained using GLGO results from more effective sizing of the photovoltaic array and battery storage system, together with reduced diesel generator operating hours and improved renewable energy utilization. The reduction in lifecycle electricity cost enhances the long-term financial viability of hybrid microgrids for healthcare facilities operating under limited budgetary resources.

3.4.2 Reliability Assessment

Reliability was evaluated using the Loss of Power Supply Probability (LPSP). The optimized GLGO system achieved an LPSP of 0.01, whereas the GA-based system produced an LPSP of **0.06**, representing an 83.33% improvement in supply reliability. This can be seen in figure 6, below.

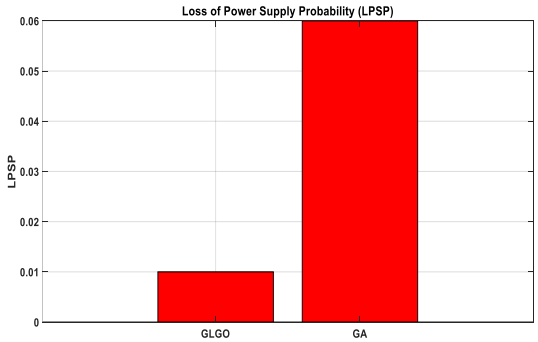

Fig. 6: Loss of Power Supply Probability (LPSP) comparison between GLGO and GA

This substantial improvement demonstrates the superior capability of GLGO to coordinate photovoltaic generation, battery storage, utility grid interaction, and diesel backup generation, thereby minimizing unmet electrical demand and ensuring continuous operation of critical healthcare equipment.

3.4.3 Energy Efficiency

The optimized hybrid microgrid achieved an overall Energy Efficiency of **92%** using GLGO compared with **85%** using GA. The result reveals that GLGO achieves an efficiency level slightly above 0.9, while GA records a marginally lower value just below 0.9. The figure 7, below show that.

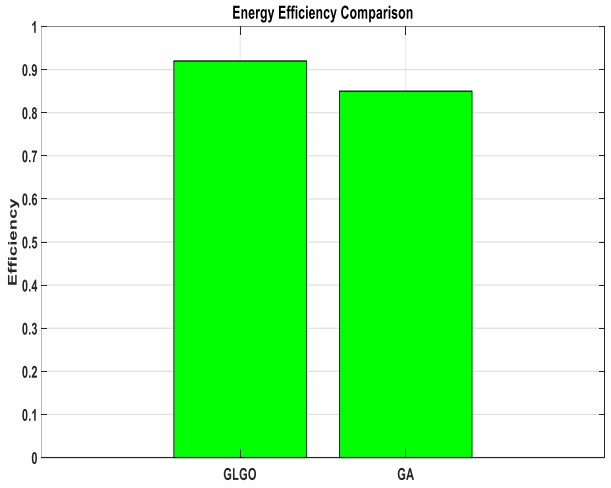

Fig. 7: Comparative energy efficiency of hybrid microgrid optimization using GLGO and GA.

The increase in efficiency reflects improved renewable energy penetration, reduced conversion losses, and more effective energy management throughout the hybrid system. Although the numerical improvement appears moderate, its cumulative effect over the project lifetime results in significant reductions in operating cost and fuel consumption.

3.4.4 Environmental Performance

The environmental performance of the proposed hybrid microgrid was assessed using daily carbon dioxide emissions and can be seen from the figure 8, below.

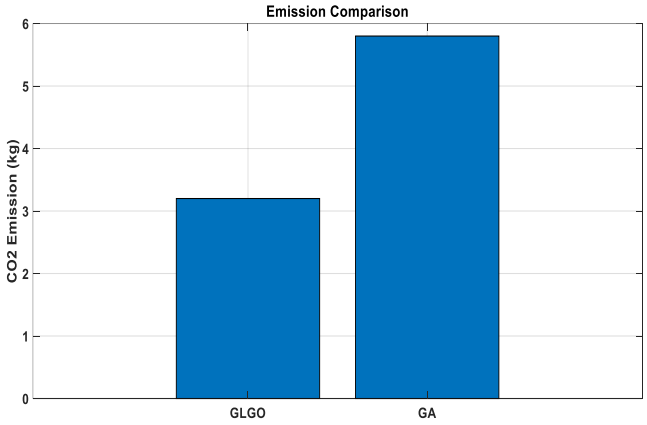

Fig. 8: Daily carbon dioxide (CO_2) emissions comparison between GLGO and GA

The GLGO-optimized system emitted only 3.2 kg/day of CO_2 compared with 5.8 kg/day obtained using GA, representing a 44.80% reduction in greenhouse gas emissions.

The reduction in emissions is primarily attributed to increased photovoltaic energy utilization and reduced diesel generator operation. These findings demonstrate that the proposed optimization framework contributes not only to economic benefits but also to environmental sustainability.

3.5 Overall Performance Comparison

Table 2 summarizes the comparative performance of GLGO and GA across all evaluation criteria.

S/N	Performance metric	GLGO	GA	Percentage improvement (%)
1	Levelized cost of energy (~~N~~)	61	80	23.75
2	Loss of power supply probability	0.01	0.06	83.33
3	Energy efficiency (%)	92	85	7.61
4	Carbon emission (kg/day)	3.2	5.8	44.8

4. Comparative Analysis of GLGO and Genetic Algorithm (GA)

To evaluate the effectiveness of the proposed optimization framework, the obtained results were compared with findings reported in recent studies on hybrid renewable energy systems for rural electrification and healthcare applications. Previous

investigations have employed optimization techniques such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Harris Hawks Optimization (HHO), and Differential Evolution (DE) to determine the optimal sizing of hybrid microgrids. While these approaches have demonstrated satisfactory performance, many studies have reported challenges related to premature convergence, local optima, and reduced solution diversity when solving highly nonlinear multi-objective optimization problems.

In this paper, the Grey Lag Goose Optimization (GLGO) algorithm demonstrated superior performance compared with the conventional Genetic Algorithm. The optimized hybrid microgrid achieved a 23.75% reduction in the Levelized Cost of Energy (LCOE), an 83.33% reduction in the Loss of Power Supply Probability (LPSP), a 7.61% improvement in Energy Efficiency (EE), and a 44.80% reduction in daily carbon dioxide (CO_2) emissions. These improvements indicate that GLGO provides a more effective balance between global exploration and local exploitation, enabling better identification of optimal component sizes and energy dispatch strategies and table 2 shows that.

The results are consistent with the growing body of literature demonstrating that advanced swarm-intelligence algorithms can outperform conventional evolutionary optimization techniques in hybrid renewable energy system design. The findings therefore support the application of GLGO as a promising optimization approach for complex multi-objective energy planning problems.

5. Practical Implications

Reliable electricity remains a major challenge for healthcare facilities across many developing countries, particularly in rural communities where frequent grid outages disrupt essential medical services. The optimized hybrid microgrid proposed in this paper provides a practical solution capable of ensuring continuous electricity supply while reducing long-term operating costs and environmental impacts.

The optimized system significantly reduces dependence on diesel generators by maximizing photovoltaic energy utilization and intelligently coordinating battery storage, utility grid interaction and backup generation. Consequently, hospitals can improve the reliability of life-support equipment, operating theatres, laboratories, vaccine refrigeration systems, and emergency medical services.

Beyond healthcare applications, the proposed optimization framework can also be adapted for schools, rural communities, research institutions and other critical infrastructure requiring reliable and sustainable electricity. The methodology therefore provides valuable guidance for engineers, policymakers, investors, and government agencies involved in renewable energy deployment and rural electrification programmes.

6. Conclusion

This paper presented the techno-economic optimization of a grid-connected photovoltaic (PV)-battery-diesel hybrid microgrid for General Hospital Sabon Tasha, Kaduna State, Nigeria, using the Grey Lag Goose Optimization (GLGO) algorithm. A comprehensive MATLAB-based optimization framework was developed to determine the optimal sizing of the photovoltaic array, battery energy storage system, diesel generator, and inverter while simultaneously minimizing the Levelized Cost of Energy (LCOE) and Loss of Power Supply Probability (LPSP) and maximizing Energy Efficiency (EE).

Simulation results demonstrated that GLGO consistently outperformed the conventional Genetic Algorithm. The optimized system reduced the LCOE from ₦80/kWh to ₦61/kWh (23.75%), decreased the LPSP from 0.06 to 0.01 (83.33%), increased the overall energy efficiency from 85% to 92%, and reduced daily carbon dioxide emissions from 5.8 kg to 3.2 kg (44.80%). These improvements confirm the capability of GLGO to achieve a superior balance between economic performance, supply reliability, renewable energy utilization, and environmental sustainability.

The proposed optimization framework offers a practical and scalable solution for improving electricity reliability in healthcare facilities located in regions with unreliable grid infrastructure. The methodology can support policymakers, engineers, and healthcare

planners in designing cost-effective and resilient hybrid renewable energy systems that contribute to national energy transition objectives and the achievement of the Sustainable Development Goals.

Future research should extend the proposed framework by incorporating battery degradation models, stochastic renewable energy forecasting, demand-side management strategies, and real-time energy management systems. Comparative evaluation with other state of the art metaheuristic optimization algorithms and validation using field implementation data would further strengthen the applicability of the proposed approach.

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