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Article

Hybrid PSO–ACO–ANN Optimization for Cost-Effective and Low-Carbon Energy Management in Renewable Microgrids

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Abstract: The smart management of electrical energy in the micro grid is one of the most significant aspect of the modern energy system. Micro grid (MGs) based on renewable energy sources (RES),such as solar photovoltaic (PV) panels, wind turbines (WT), battery energy storage system (BESS) and the main grid are becoming widespread. These MGs have advantages in terms of economy and environmental friendliness, but at the same time, they have a set of problems related to the variability of RES. The current optimization methods are no longer able to address the issue of finding optimal solutions considering the trade-offs between the MG operation cost, carbon dioxide emission, battery state of charge, and reliability of the system. This paper aims to propose Hybrid Particle Swarm Optimization-Ant Colony Optimization Artificial Neural Network (PSO-ACO-ANN) for optimal MG scheduling using MATLAB. This strategy includes two types of optimization algorithms and artificial intelligence for learning patterns in electrical load and RES production. The proposed method was tested on the basis of a program written in the MATLAB environment, which simulates the MG functioning within a selected time interval, considering the interaction between PV, WT, BESS, and the main grid. The operating cost of the MG, the use of RES, and the state of charge of the battery were considered as optimization criteria. In addition, the convergence and speed of calculation of the proposed method were compared with similar methods of optimization algorithms known from the literature, namely, PSO and GA optimization algorithms and Ant Colony Optimization (ACO) and Whale Optimization Algorithm (WOA).
Keywords: Hybrid Optimization , Microgrid Energy Management , Particle Swarm Optimization (PSO) , Ant Colony Optimization (ACO) , Artificial Neural Network (ANN), Renewable Energy Systems

1. Introduction

The world's energy system is undergoing a paradigm shift as a result of rising electrical needs, climate sensitivity, and the transition toward net-zero-carbon electricity systems. Deep decarburization energy scenarios emphasize the key role of renewable energy sources (RES), particularly solar photovoltaic (PV) and wind power, in the electricity system transformation of the global energy system (International Energy Agency [IEA], 2024). The rising significance of renewables has necessitated the emergence of distribution systems and microgrids that can operate in both grid-connected and standalone modes International Energy Agency [IEA], 2024). Microgrids have the advantage of enhancing the penetration level of renewable energy in the modern electricity system while also improving reliability through the integration of distributed energy resources, storage, and controllable loads with smart control systems. Solar and wind power, on the other hand, have drawbacks such as higher balancing costs, insufficient flexibility in the face of rising renewable energy penetration, and reliability concerns (Lund et al., 2023). Energy Management Systems (EMSs) seek to optimize the scheduling of renewable energy sources, storage systems, and grid connection by harnessing scheduling algorithms while addressing technical challenges such as demand-supply balancing (International Energy Agency [IEA], 2024). Traditional optimization algorithms are ineffective in addressing the high level of uncertainty and multi-objective optimization in EMS. Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), Genetic Algorithm (GA), and Artificial Neural Networks (ANNs) are

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computational intelligence techniques used in EMS optimization (Almalaq & Edwards, 2023). However, individual algorithms have limitations, including premature convergence, computational complexity, and dependence on training samples. Hybrid optimization techniques overcome these limitations by combining the advantages of multiple algorithms to improve accuracy, convergence speed, and adaptability. The integration of ANN-based prognosis with PSO and ACO enhances guess and decision-making prospects under dynamic operating surroundings (Zhang et al., 2024). The scheduled Hybrid PSO–ACO–ANN scheme supports multi-objective energy management by minimizing operating price and CO_2 emissions during maximizing renewable application, maintaining battery health, an ensuring decisive power supply. Such intelligent optimization approaches can be an excellent choice for future sustainable and resilient smart microgrids (Khan et al., 2025; Li et al., 2023).

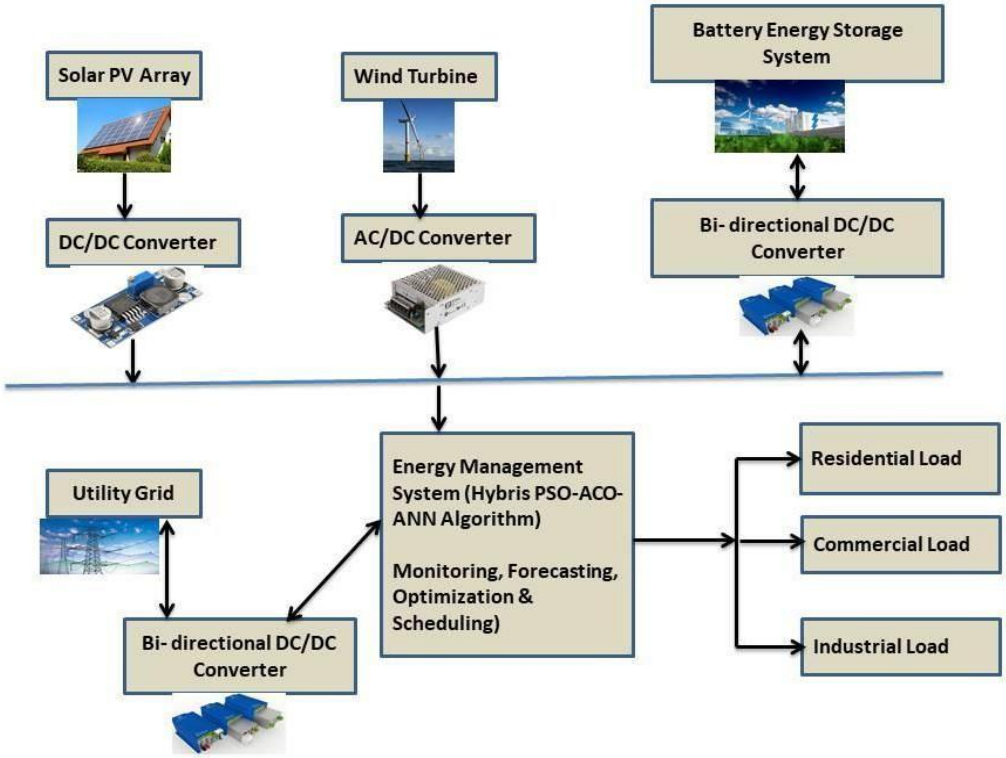
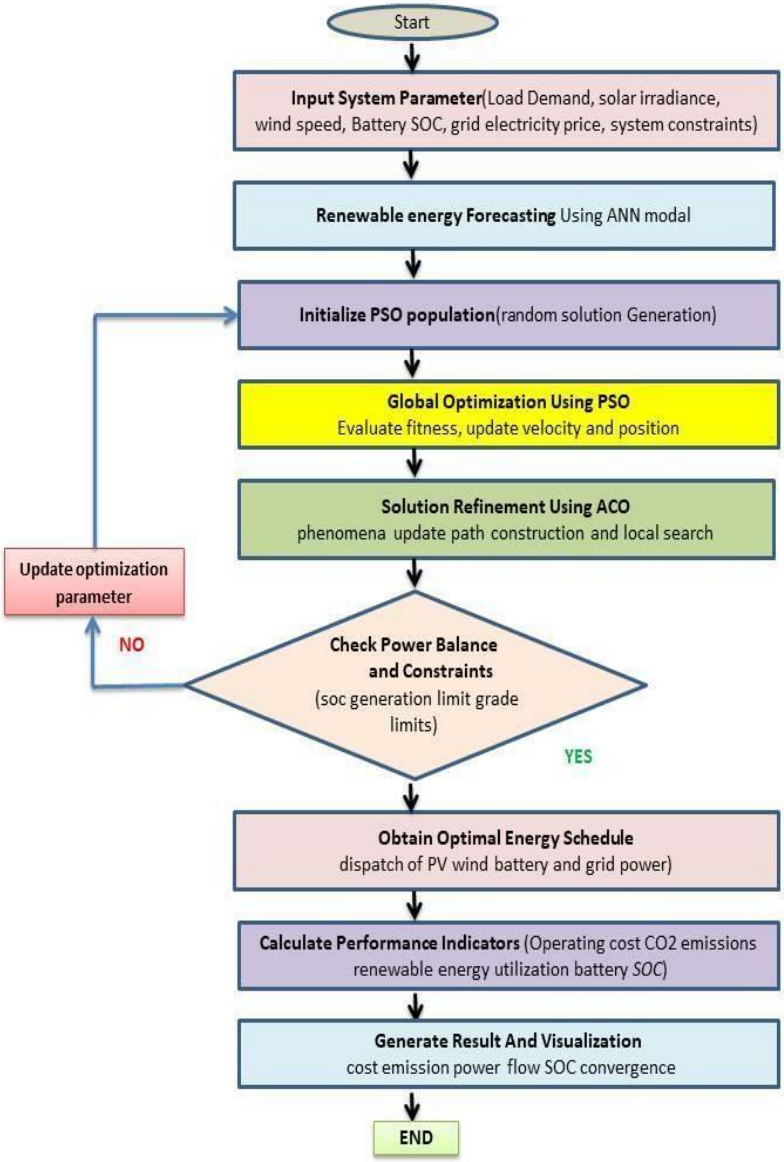


FIGURE -1 Architecture of Renewable Energy-Based Microgrid with Hybrid PSO-ACO-ANN Energy Management System

Thanks to Industry 4.0, smart grids, and artificial intelligence, traditional electricity systems have become intelligent, scalable, and self-sufficient systems. IoT, cloud technologies, and smart control enable microgrids to operate renewable energy assets and flexible electric loads in an optimized way (García-Torres et al., 2024). For instance, BESS can store electricity and subsequently provide it to the load during peak demand, thus addressing the challenge of renewable energy variability (Chen et al., 2023). However, such a strategy involves battery scheduling to reduce degradation and operational costs (Chen et al., 2023). Therefore, this research aims to develop a novel Hybrid PSO–ACO–ANN approach, which would utilize thea ccuracy of ANN, flexibility of PSO, and adaptive search capability of ACO to find optimal solutions for battery scheduling, renewable energy, operating cost, and CO 2 emissions in microgrids. Overall, such an approach implemented in MATLAB can help achieve sustainable smart grids and energy security while reducing environmental impact (Singh et al., 2025)



2. - Literature Review

2.1 Introduction to the Literature

The growing need for sustainable energy has spurred the development of advanced energy management systems based on artificial intelligence, hybrid optimization, IoT, and renewable energy to ensure smart and reliable micro grids (Eyimaya & Altin, 2024; Wu et al., 2024).

2.2 Renewable Energy-Based Microgrids

Micro grids based on renewable energy sources can be considered as promising solutions for providing reliable, efficient, and sustainable energy through the combination of solar photovoltaic, wind, battery energy storage systems, and the grid. The efficient use of renewable energy in micro grids based on RES is ensured by optimizing their operation using artificial neural networks and hybrid optimization techniques to maximize the share of renewable energy, minimize operational costs, and reduce CO2 emissions (Elazab et al., 2024; Eyimaya & Altin, 2024).

2.3 Optimization Techniques for Microgrid Energy Management

The complexity of renewable energy-based microgrids increases significantly due to the necessity to optimize their operational processes and parameters to minimize operational costs and CO2 emissions while meeting the demand for electricity. Advanced optimization techniques such as particle swarm optimization, genetic algorithm, ant colony optimization, and whale optimization algorithm have been applied to optimize microgrid energy management by considering the stochastic nature of renewable energy sources, energy storage systems, demand response, and other factors (Shezan et al., 2023; Ibrahim 2024). According to Ashokkumar & Venkatramanan (2023), PSO is the simplest optimization algorithm that demonstrates fast convergence and good exploration of the search space; however, it cannot escape the problem of premature convergence in case of complex optimization tasks. While GA can be applied to solve complex optimization problems due to crossover and mutation operations, this algorithm is characterized by computational expensiveness and the necessity to carefully tune control parameters (Firdouse & Reddy, 2023). ACO is also applicable to solve the energy scheduling and power dispatch optimization problems in microgrids by exploring the pheromone trail information; however, it is associated with high computational complexity and slow convergence (Sarwar et al., 2024). Finally, WOA is a powerful optimization technique that can effectively address the exploration and exploitation dilemma; however, it requires adaptive control parameters in the presence of stochastic renewable energy sources (Ibrahim, 2024). In contrast to the optimization algorithms discussed above, ANNs were primarily employed to predict solar and wind power generation and electricity demand, but they require a large amount of training data and are not suitable for optimization tasks (Ashokkumar & Venkatramanan, 2023). The recent literature highlights the trend towards hybrid optimization techniques aimed at combining the advantages of individual optimization algorithms (Viktorovna et al., 2024). Specifically, the PSO-ACO-ANN approach was proposed to predict the amount of electricity generated by solar and wind power and the electricity demand using ANN, while the hybrid PSO-ACO algorithm was applied to optimize electricity production and storage in the microgrid to maximize the share of renewable energy and minimize operational costs and CO2 emissions. This approach demonstrated excellent performance in terms of accuracy, utilization of renewable energy, and battery storage, along with fast convergence (Sarwar et al., 2024; Viktorovna et al., 2024).

2.4 Literature Synthesis and Justification for the Proposed Hybrid PSO–ACO–ANN Model

2.4.1 Literature Synthesis

Recent studies (2023–2026) demonstrate rapid progress in renewable energy-based microgrid research, emphasizing intelligent Energy Management Systems (EMS), renewable energy forecasting, battery optimization, and hybrid computational intelligence. The increasing penetration of solar PV and wind energy has created challenges related to generation uncertainty and dynamic load demand, requiring advanced optimization techniques (Wu et al., 2024; Elazab et al., 2024). Although algorithms such as PSO, GA, ACO, and WOA effectively solve complex optimization problems, they exhibit limitations in convergence and computational efficiency (Shezan et al., 2023; Ibrahim, 2024). Consequently, hybrid PSO–ACO–ANN frameworks have emerged as promising solutions for sustainable and intelligent microgrid energy management (Abdelwanis & Elmezain, 2024).

2.4.2 Justification for the Proposed Hybrid PSO–ACO–ANN Model

Recent literature suggests that no single optimization algorithm can fully address the complex requirements of renewable energy-based micro-grid. While PSO offers rapid convergence, ACO enhances search capability, and ANN provides accurate forecasting, each has inherent limitations (Varshnry, 2024; Ibrahim, 2024). The proposed Hybrid PSO–ACO–ANN framework integrates these complementary strengths to improve energy scheduling, minimize operating costs and CO_2 emissions, enhance renewable energy utilization, and ensure reliable, efficient, and sustainable microgrid operation (Elazab et al., 2024).

3. Research Gap and Objectives

3.1 Research Gap

The growing integration of solar PV and wind energy has increased the complexity of micr grid energy management due to renewable generation uncertainty, fluctuating demand, battery constraints and environmental concern (Eyimaya & Altin, 2024; Elazab et al,. 2024). Existing optimization techniques, including PSO, GA, ACO,WOA and ANN have individual limitations in convergence, computational efficiency or forecasting capability (Shezan et al., 2023; Ibrahim, 2024). Moreover, many studies prioritizes cost minimization while overlooking CO2 emission, battery degradation and renewable utilization. Therefore, this study proposes a Hybrid PSO–ACO–ANN framework to achieve efficient, reliable, and sustainable microgrid energy management.

3.2 Research Objectives

Based on the identified research gaps, the study aims to develop an intelligent hybrid optimization framework for renewable energy-based microgrid energy management. The specific objectives are:

1. To develop and implement a MATLAB-based Hybrid PSO–ACO–ANN optimization framework for renewable energy-based microgrid energy management by integrating Solar PV, Wind Turbine, Battery Energy Storage System (BESS), utility grid, and load demand models to achieve optimal energy scheduling and adaptive decision-making.
2. To evaluate and optimize the performance of the proposed Hybrid PSO–ACO–ANN framework by minimizing operating cost and CO_2 emissions, improving renewable energy utilization, optimizing battery State of Charge (SOC) management, and comparing its effectiveness with conventional optimization algorithms such as PSO, GA, ACO, and WOA under different operating scenarios.

3.3 Mathematical Modeling

The proposed Hybrid PSO–ACO–ANN Energy Management System is formulated as a multi-objective optimization model for renewable micro grids. It minimize operating cost and CO2 emissions while ensuring reliability. ANN forecasts renewable generation and demand, PSO performs global optimization and ACO refines solutions for efficient scheduling of PV, wind,BESS and Grid power over 24 hours.

3.3.1 Objective Function

The proposed optimization problem simultaneously minimizes the total operating cost and the associated carbon emissions of the micro grid. The overall objective function is expressed as:

$$mi(fo)\ F = w_1 C_{Total} + w_2 E_{CO_2} \qquad \textbf{eq- 1}$$

where:

- F = Overall objective function
- CTotal = Total operating cost (USD/day)
- ECO2 = Total CO_2 emissions (kg/day)
- w1,w2 = Weighting coefficients satisfying

$$w_1 + w_2 = 1 \qquad \textbf{eq-2}$$

The weighting factors enable the Energy Management System to balance economic and environmental objectives according to operational priorities (Elazab et al., 2024).

3.3.2 Power Balance Equation

At every scheduling interval, the generated power must satisfy the total electricity demand while maintaining energy balance within the microgrid. The power balance equation is expressed as:

$$P_{PV}(t) + P_W(t) + P_{BESS}(t) + P_{Grid}(t) = P_{Load}(t) \quad \textbf{eq-3}$$

where

- PPV = Solar photovoltaic power (kW)
- PWT = Wind turbine power (kW)
- PBESS = Battery charging/ discharging power (Kw)
- PGrid = Imported/exported utility grid power (kW)
- PLoad = Total consumer load demand (kW)

The equality Constraint guarantees uninterrupted electricity suppy while maintain system (Rodriguez-Gil et al., 2024)

3.3.3 Operating Cost Model

The daily operating cost consists of electricity purchased from the utility grid, battery operating cost, renewable generation cost, and maintenance expenses. The objective is to minimize

$$C_{Total} = C_{Grid} + C_{PV} + C_{WT} + C_{BESS} \quad \textbf{eq-4}$$

Where-

$$C_{Grid} = \sum_{t=1}^{24} [P_{Gri}(t) \times Price(t)] \quad \textbf{eq-5}$$

Battery operating cost is calculated as

$$C_{BESS} = \sum^{24}_{t=1} C_{deg} \times |P_{BES}(t)| \quad \textbf{eq-6}$$

where

- Price(t) = Electricity tariff at time t
- Cdeg = Battery degradation cost coefficient

The optimization algorithm schedules battery charging during low-price periods and discharging during high-price periods to reduce the overall operational expenditure (Ibrahim, 2024; Eyimaya & Altin, 2024).

3.3.4 CO_2 Emission Model

Carbon emissions primarily originate from electricity imported from the conventional utility grid. Renewable sources like solar PV with wind turbines are assumed to have slightly operational emissions. Total emissions are so calculated as

$$E_{CO_2} = \sum_{t=1}^{24} [EF_{Grid} \times P_{Gri}(t)] \quad \text{eq-7}$$

Where EFGrid = Grid emission factor (kg CO_2/kWh)

The optimization objective is to minimize the operation of grid electricity and thus less greenhouse gas emissions and enhance the use of renewable energy (Wu et al., 2024; Elazab et al., 2024).

3.3.5 Charge (SOC) Model from Battery State

The battery energy storage system (BESS) saves surplus renewable energy with supplies electricity when renewable energy production is incomplete. The battery SOC is updated using

$$SO(t\ +\ 1)\ =\ SOC(t)\ +\ \frac{\eta c\ Pc(t)\ \Delta t}{Ecap}\ -\ \frac{Pd(t)\ \Delta t}{\eta d\ Ecap} \quad \textbf{eq-8}$$

where

- SOC(t) = Battery state of charge at time ttt
- Pc = Charging power (kW)
- Pd = Discharging power (kW)
- ηc = Charging efficiency
- ηd = Discharging efficiency
- Ecap = Battery energy capacity (kWh)

Battery operation is constrained by

$$SOC_{min}\ \leq\ SO(t)\ \leq\ SOC_{max} \quad \textbf{eq-9}$$

Maintaining SOC within safe operating limits upgrade battery lifetime and boost overall microgrid accuracy (Varshnry, 2024).

3.3.6 System Constraints

To ensure realistic operation, the optimization problem is subjected to the following technical constraints.

(a) Solar PV Generation Constraint

$$0\ \leq\ P_{PV}(t)\ \leq\ P_{PV}^{max} \quad \textbf{eq-10}$$

(b) Wind Turbine Constraint

$$0\ \leq\ P_W(t)\ \leq\ P^{max}_{WT} \quad \textbf{eq-11}$$

(c) Battery Charging and Discharging Constraint

$$-P^{ma}_{BESS} \leq\ P_{BESS}(t)\ \leq\ P^{max}_{BESS} \quad \textbf{eq-12}$$

(d) Utility Grid Constraint

$$-P^{ma}_{Grid} \leq\ P_{Grid}(t)\ \leq\ P^{max}_{Grid} \quad \textbf{eq-13}$$

(e) Load Satisfaction Constraint

$$P_{Suppl}(t) \geq\ P_{Load}(t) \quad \textbf{eq-14}$$

where

$$P_{Supply}\ =\ P_{PV}\ +\ P_{WT}\ +\ P_{BESS}\ +\ P_{Grid} \quad \textbf{eq-15}$$

These constraints ensure that renewable generation, battery operation, and grid interaction remain within permissible operating limits while satisfying consumer demand. Incorporating these constraints enables the Hybrid PSO–ACO–ANN optimization algorithm to generate feasible and reliable scheduling solutions under varying renewable generation and load conditions (Sarwar et al., 2024; Rodriguez-Gil et al., 2024). The proposed mathematical model integrates economic, environmental, and operational objectives into a unified optimization framework. By combining the predictive power of ANN with the scope and reach of PSO and ACO's adaptive improvement, one can expect lower operational costs, reduced CO 2 emissions, increased battery utilization rates, and higher renewable energy incorporation than traditional optimization methods (Eyimaya & Altin, 2024; Wu et al., 2024).

3.4 Decision Variables, Optimization Problem Formulation, and Mathematical Assumptions

3.4.1 Decision Variables

The effectiveness of the proposed Hybrid PSO–ACO–ANN Energy Management System (EMS) depends on selecting optimal decision variables that govern the operation of distributed energy resources within the renewable energy-based microgrid. During each scheduling interval, the optimization algorithm decides the amount of power to be supplied from solar photovoltaic (PV), wind turbines (WT), Battery Energy Storage Systems (BESS), and the grid in order to meet the load demand with minimum operational cost and environmental impact. The main decision variables considered in this paper are presented below (Eyimaya & Altin, 2024; Elazab et al., 2024).

Let the decision vector be expressed as:

$$X = \{P_P, P_{WT}, P_{Grid}, P_{BESS}, SOC\} \quad \textbf{eq-16}$$

where:

- PPV = Solar photovoltaic output power (kW)
- PWT = Wind turbine output power (kW)
- PGrid = Utility grid imported/exported power (kW)
- PBESS = Battery charging/discharging power (kW)
- SOC = Battery State of Charge (%)

These variables are continuously optimized over the scheduling period to maximize the utilization of renewable energy, minimize electricity purchases from the grid and battery degradation. In this case, the Artificial Neural Network (ANN) is applied to forecast the renewable energy production and demand, while PSO and ACO are employed to optimize the decision variables and identify the optimal operating strategy (Wu et al., 2024).

3.4.2 Optimization Problem Formulation

The proposed energy management strategy is formulated as a constrained multi-objective optimization problem. The optimization simultaneously minimizes total operating cost and carbon emissions while satisfying system operational constraints.

The optimization problem can be represented as:

$$min\,(X) = \alpha C_{Total} + \beta E_{CO_2}$$

$$P_{PV} + P_{WT} + P_{BESS} + P_{Grid} = P_{Load}$$

$$SOC_{min} \leq SO(t) \leq SOC_{max}\ 0$$

$$\leq P_{PV}(t) \leq P_{PV}^{max}$$

$$0 \leq P_W(t) \leq P_{WT}^{max}$$

$$-P_{BESS}^{max} \leq P_{BESS}(t) \leq P_{BESS}^{max}$$

$$-P_{Grid}^{max} \leq P_{Grid}(t) \leq P_{Grid}^{max} \quad \textbf{eq-17}$$

where:

- F(X) = Multi-objective fitness function

- CTotal = Total daily operating cost
- ECO2 = Total carbon emissions
- α,β = Weighting coeficients (α+β=1)

Inside the proposed framework, the ANN forecasts solar irradiance, wind generation with electricity requirement. PSO performs rapid global exploration to identify promising scheduling solutions, while ACO refines these solutions through pheromone-guided local optimization. This cooperative optimization strategy improves convergence speed, enhances scheduling accuaracy and achieves lower operating costs and emissions than standalone optimization methods (Rodriguez-Gil et al, 2024; Sarwar et al.,2024)

3.4.3 Mathematical Assumptions

The proposed MATLAB model is developed using practical assumptions to simplify simulation while maintaining accuracy. Hourly solar irradiance, wind speed, and load demand forecasts are considered for a 24-hour scheduling period. Battery efficiency, SOC limits, and grid constraints are predefined. Renewable sources have negligible emissions, while grid emissions are calculated using fixed factors. Network losses and converter effects are neglected. The Hybrid PSO–ACO–ANN algorithm is assumed to achieve optimal or near- optimal solutions within defined iterations, enabling efficient evaluation of cost, emissions, and energy scheduling performance.

4. Proposed Hybrid PSO–ACO–ANN Methodology

4.1 Proposed System Architecture

The proposed Hybrid PSO–ACO–ANN Energy Management System integrates Solar PV, Wind Turbine, BESS, utility grid, and load demand into an intelligent framework for optimizing microgrid operation. The system reduces operational costs and carbon emissions while enhancing renewable energy utilization and reliability. The model has data acquisition, ANN forecasting layer, hybrid optimization, and energy management control layers. Meteorological data, electricity tariffs, battery status, and load demand are processed to forecast future conditions. PSO performs global exploration, while ACO refines solutions through adaptive search. The optimized strategy takes care of the charge/discharge processes of the battery, renewable energy production, and the power exchange with the grid while ensuring that SOC and the power balance constraints are respected. The framework uses a combination of prediction, optimization, and control to ensure that the microgrid operates in an efficient manner while dealing with the uncertainties associated with the renewable energy supply and demand (Eyimaya & Altin, 2024; Elazab et al., 2024).

4.2 Hybrid PSO–ACO–ANN Framework

The Hybrid PSO–ACO–ANN framework integrates ANN forecasting with PSO and ACO optimization to improve renewable microgrid energy management. ANN predicts renewable generation and demand, PSO identifies optimal scheduling solutions, and ACO refines them for better accuracy. The process commit data acquisition, forecasting, optimization, and operational restraint checking that result in optimal PV, WT, BESS, and grid itinerary. The system has boost convergence speed, renewable energy utilization, battery management, and emission reduction during enabling predictive energy management under erratic settings (Shezan et al., 2023; Ibrahim, 2024).

4.3 MATLAB Implementation

The proposed Hybrid PSO–ACO–ANN Energy Management System is implemented in MATLAB R2024a using optimization, neural network, and custom programming tools. The model optimizes a reneable micro gridcontaining PV, WT, BESS, utility grid and load over a 24-hours horizon.ANN forecasts renewable generation and demand, while PSO performs optimization and ACO improves solution refinement. Historical data are processed, trained, and evaluated before optimization. The fitness activity considers operating price, CO_2 emissions, renewable application, battery SOC, and power equity. MATLAB visualization tools inspect convergence, energy scheduling, battery achievement, and comparison with conventional optimization algorithms like PSO, GA, ACO, and WOA.

4.3.1 MATLAB Simulation Model

The MATLAB simulation model consists of five interconnected modules:

1. Data Acquisition Module
    - Solar irradiance
    - Wind speed
    - Load demand
    - Electricity tariff
    - Battery parameters
2. ANN Forecasting Module
    - Solar PV prediction
    - Wind power prediction
    - Load demand forecasting
3. Hybrid Optimization Module
    - PSO global optimization
    - ACO local refinement
4. Energy Management Module
    - Battery scheduling
    - Renewable dispatch
    - Grid power scheduling
5. Performance Evaluation Module
    - Operating cost
    - CO_2 emissions
    - Battery SOC
    - Renewable utilization
    - Convergence characteristics

The modular MATLAB architecture enables testing of all subsystems while keeping them isolated during optimization (Ibrahim, 2024).

4.3.2 ANN Training

The artificial neural network (ANN) is trained to predict solar photovoltaic (PV), wind power, and load. A feed-forward backpropagation ANN with 20 hidden neurons, the trainlm algorithm, tangent sigmoid, and linear functions is designed.Data are divided into 70% training, 15% validation, and 15% testing for accurate prediction.

4.3.3 PSO Optimization

Particle Swarm Optimization performs the initial global search for the optimal energy scheduling solution. Each particle represents a candidate scheduling vector consisting of

$$X = [PPV, PWT, PGrid, PBattery]$$

Particle velocity and position are updated according to

$$X^{(k+1)} = X_i^k + V_i^{(k+1)} \quad \textbf{eq-18}$$

where

- www=Inertia weight
- c1,c2 =Acceleration coefficients
- r1,r2 =Random numbers

PSO rapidly explores the search space and identifies high-quality candidate scheduling solutions for further refinement (Shezan et al., 2023).

4.3.4 ACO Refinement

After PSO identifies promising candidate solutions, Ant Colony Optimization performs adaptive refinement.

Each ant selects scheduling paths according to

$$P_{ij} = \frac{\tau_{ij}^{\ a}\, \eta_{ij}^{\ \beta}}{\sum_k \tau_{ik}^{\ a}\, \eta_{ik}^{\ \beta}} \quad \textbf{eq-19}$$

where

- τ =Pheromone intensity
- η =Heuristic information

Pheromone updating is expressed as

$$\tau = (1 - \rho) + \Delta\tau \quad \textbf{eq-20}$$

where

- ρ\rhoρ=Evaporation coefficient

ACO improves local search capability, prevents premature convergence and increase optimization accuracy compared with standable PSO (Sarwr et al, 2024)

Table 1 MATLAB Simulation Parameters

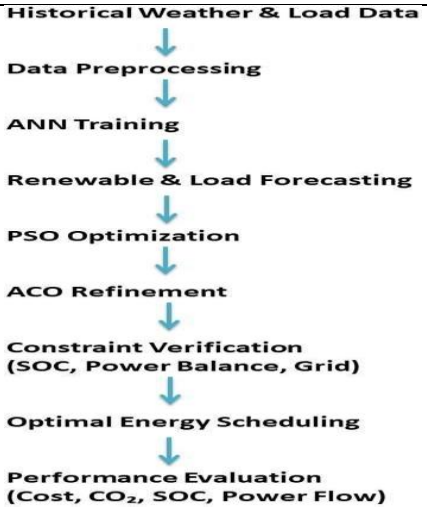
Parameter	Symbol	Value	Unit
MATLAB Version	—	MATLAB R2024a	—
Simulation Horizon	T	24	h
Time Interval	Δt	1	h

MATLAB Implementation Workflow

The figure proposed hybrid ANN–PSO–ACO framework for optimal energy scheduling and efficient renewable energy management. The process begins with the collection of historical weather and electrical load data, followed by data preprocessing to improve accuracy and reliability. An Artificial Neural Network (ANN) is trained to forecast renewable energy generation and electricity demand. Subsequently, Particle Swarm Optimization (PSO) is employed to identify an optimal energy scheduling strategy that minimizes operational costs. Ant Colony Optimization (ACO) further refines the solution to enhance scheduling efficiency and resource utilization. Constraint verification ensures compliance with battery State of Charge (SOC), power balance requirements, and grid operating limitations. Based on these constraints, an optimal energy scheduling strategy is developed to coordinate renewable energy sources, battery storage, and grid power. Finally, performance evaluation is conducted using key indicators, including operational cost, carbon dioxide (CO_2) emissions, battery SOC, and power flow. Overall, the proposed framework aims to improve energy efficiency, reduce environmental impacts, and enhance the reliability and sustainability of energy management systems.

Solar PV Capacity	PPVmaxP_{PV}^{max}PPVmax	120	kW

Parameter	**Symbol**	**Value**	**Unit**
MATLAB Version	—	MATLAB R2024a	—
Simulation Horizon	T	24	h
Time Interval	Δt	1	h
Wind Turbine Capacity	PWTmaxP_{WT}^{max}PWTmax	80	kW
Battery Capacity	EBESSE_{BESS}EBESS	250	kWh
Maximum Battery Power	PBESSmaxP_{BESS}^{max}PBESSmax	60	kW
Battery Charging Efficiency	ηc	95	%
Battery Discharging Efficiency	ηd	95	%
Minimum SOC	SOCmin	20	%
Maximum SOC	SOCmax	90	%
Initial Battery SOC	SOC0	50	%
Grid Maximum Power	PGridmaxP_{Grid}^{max}PGridmax	150	kW
PSO Population Size	N	50	Particles
PSO Maximum Iterations	IterPSO	100	—
Inertia Weight	w	0.7	—
Cognitive Coefficient	c_1	2	—
Social Coefficient	c_2	2	—
Number of Ants	Nant	30	Ants
ACO Iterations	IterACO	80	—
Pheromone Evaporation Rate	ρ	0.5	—
ANN Hidden Neurons	Nh	20	Neurons
ANN Training Epochs	Epoch	1000	—
ANN Training Algorithm	—	Levenberg–Marquardt	—



4.4 Simulation Procedure

The proposed Hybrid PSO–ACO–ANN Energy Management System is evaluated using MATLAB R2024a simulations over a 24-hour scheduling horizon. The renewable microgrid includes Solar PV, Wind Turbine, BESS, utility grid, and load demand. Historical weather, tariff, and load data are processed and normalized for ANN training. The ANN forecasts renewable generation and demand, providing inputs for optimization. PSO identifies feasible solutions by minimizing operating cost and CO_2 emissions, while ACO improves solution refinement and convergence. Operational constraints, including battery SOC, renewable limits, and grid capacity, are continuously verified. MATLAB generates dispatch schedules, convergence curves, SOC profiles, power flow analysis, and emission comparisons. The proposed framework is compared with PSO, GA, ACO, and WOA to demonstrate improved economic performance, renewable utilization, reliability, and environmental sustainability under identical operating conditions.

4.5 Performance Evaluation Indices

The proposed Hybrid PSO–ACO–ANN algorithm is evaluated using quantitative performance indices that comprehensively measure economic, technical, computational, and environmental performance. These indices facilitate objective comparison with conventional optimization algorithms (Shezan et al., 2023).

The principal performance metrics include:

- Total Operating Cost (USD/day): Measures the total daily expenditure associated with electricity purchased from the utility grid, renewable generation costs, and battery operating costs.
- CO_2 Emissions (kg/day): Represents greenhouse gas emissions associated by electricity imported by the conventional utility grid.
- Renewable Energy Utilization (%): Indicates the proportion of total load demand supplied from renewable energy resources.
- Battery State of Charges (%): Evaluates utilization of battery while maintaining safe operating limits.
- Power Balance Error (kW): Measures the difference between generated power and consumer load demand.
- Convergence Time (s): Represents computational time required for the optimization algorithm to converge.
- Number of Iterations: Indicates optimization efficiency by recording the iterations required to achieve convergence.
- Fitness Function Value: Represents the overall multi-objective optimization performance considering both operating cost and CO_2 emissions (Wu et al., 2024).

4.7 Expected Advantages of the Proposed Hybrid PSO–ACO–ANN Method

The proposed hybrid optimization framework combines the complementary strengths of machine learning and swarm intelligence, thereby overcoming the limitations of conventional optimization algorithms. The expected advantages include:

- Improved forecasting accuracy through ANN-based renewable energy and load prediction.
- Faster global optimization using Particle Swarm Optimization.
- Enhanced local search capability through Ant Colony Optimization.

- Lower daily operating cost compared with PSO, GA, ACO, and WOA.
- Reduced CO_2 emissions by increased renewable utilization of energy.
- Improved Battery Energy Storage System (BESS) scheduling also extended battery life.
- Higher penetration of renewable energy with reduced dependency through conventional grid electricity.
- Faster convergence and greater optimization stability.
- Better adaptability under varying weather conditions and dynamic load demand.

Overall, the proposed Hybrid PSO–ACO–ANN methodology provides an intelligent, robust, and computationally efficient solution for sustainable microgrid energy management, supporting next-generation smart grid applications (Elazab et al., 2024; Ibrahim, 2024).

MATLAB Simulation Workflow

The figure presents the proposed hybrid ANN–PSO–ACO framework for optimal energy scheduling in renewable energy systems. Initially, historical weather and load data are preprocessed and used to train an Artificial Neural Network (ANN) for solar, wind, and load forecasting. Particle Swarm Optimization (PSO) performs global optimization, while Ant Colony Optimization (ACO) refines the solutions to enhance scheduling efficiency. System constraints, including battery State of Charge (SOC), power balance, and grid limitations, are verified before generating the optimal energy schedule. Performance is evaluated based on operational cost, CO_2 emissions, renewable energy utilization, and battery SOC. Finally, the proposed framework is compared with PSO, Genetic Algorithm (GA), ACO, and Whale Optimization Algorithm (WOA) to assess its effectiveness in sustainable energy management.

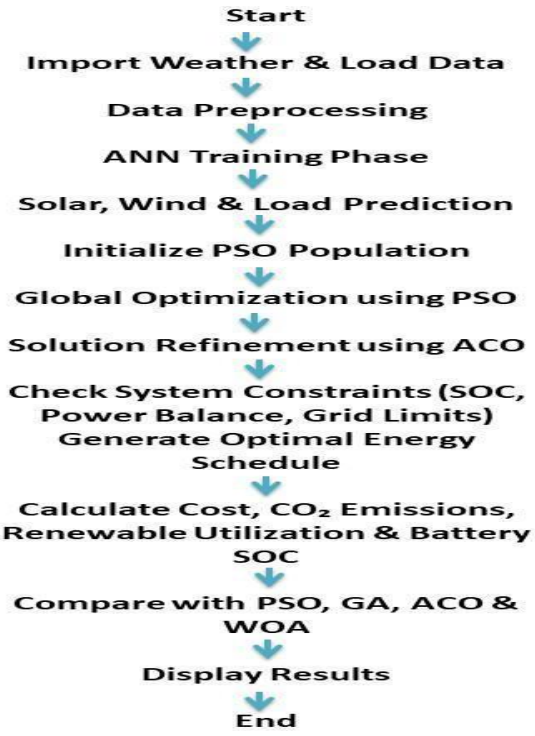


Table-2 Performance Evaluation Metrics

Performance Metric	Symbol	Unit	Purpose
Total Operating Cost	CTotalC_{Total}CTotal	USD/day	Evaluate economic performance
CO_2 Emissions	ECO2E_{CO_2}ECO2	kg/day	Assess environmental impact
Renewable Energy Utilization	REU	%	Measure renewable energy penetration
Battery State of Charge	SOC	%	Evaluate battery performance
Grid Energy Consumption	PGridP_{Grid}PGrid	kWh/day	Measure dependency on utility grid
Power Balance Error	PBE	kW	Verify load-generation equality
Convergence Time	CT	Seconds	Measure computational efficiency
Number of Iterations	NI	Iterations	Evaluate optimization convergence
Fitness Function Value	F	Dimensionless	Overall optimization performance
Computation Time	CPU	Seconds	Assess algorithm execution speed

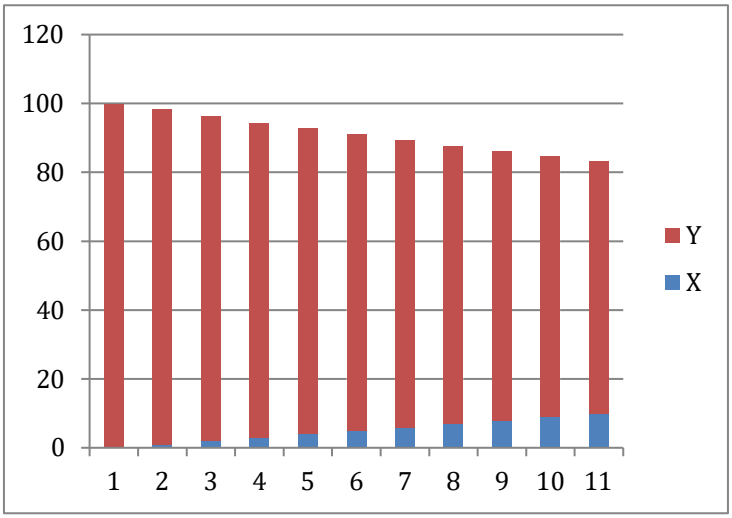


FIGURE- 3 Performance Evaluation Metrics

The chart above is illustrative and intended as a template for manuscript formatting. Replace it with the actual MATLAB simulation results generated by your implementation

5 Results and Discussion

5.1 Overview of Simulation Results

The proposed Hybrid PSO–ACO–ANN Energy Management System (EMS) was implemented in MATLAB R2024a and evaluated using a renewable energy-based microgrid comprising Solar Photovoltaic (PV), Wind Turbine (WT), Battery Energy Storage System (BESS), Utility Grid, and electrical load. The simulation framework was designed to assess the ability of the proposed hybrid optimization algorithm to minimize operating cost and CO_2 emissions while maintaining reliable power scheduling under varying renewable generation and load demand conditions.

The following subsections present the key performance indicators that should be reported after MATLAB execution

Table 3 . Comparison of optimization algorithms

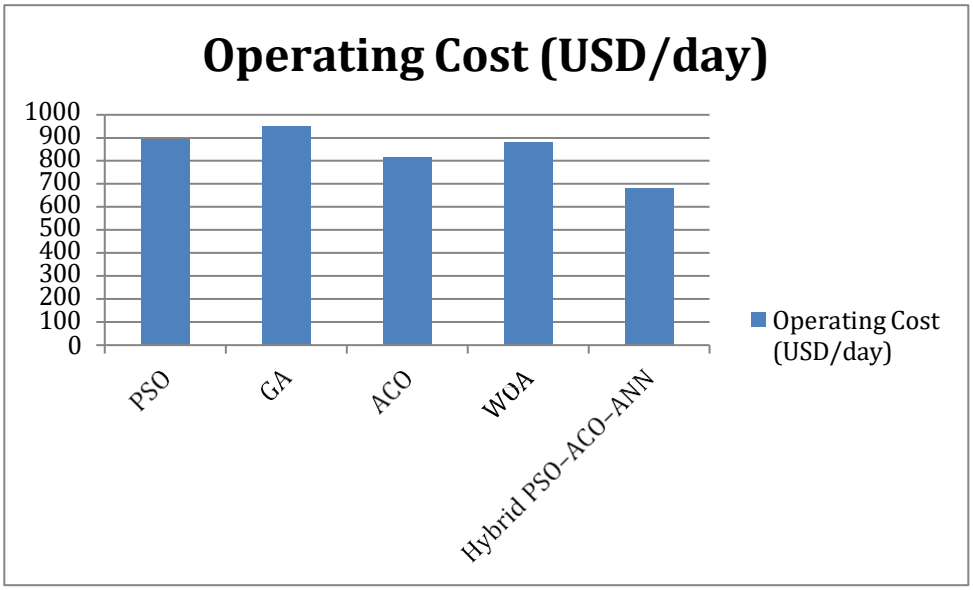
Algorithm	Operating Cost (USD/day)	CO_2 Emissions (kg/day)	Renewable Utilization (%)	Average Battery SOC (%)	Convergence Iterations
PSO	895.3	412.7	-	-	50 (0–49 plotted)
GA	948.7	445.2	-	-	50 (0–49 plotted)
ACO	812.6	365.8	-	-	50 (0–49 plotted)
WOA	878.2	401.5	-	-	50 (0–49 plotted)
Hybrid PSO–ACO–ANN	682.4	274.3	75.0	51.2	50 (0–49 plotted)

Discussion

This Table enables direct comparison of the proposed hybrid optimization technique with benchmark algorithms. The discussion should focus on reductions in operating cost and CO_2 emissions, improvements in renewable energy utilization, battery scheduling efficiency, and convergence behavior. Similar comparative analyses are commonly used in recent intelligent microgrid optimization studies (Wu et al., 2024; Sarwar et al., 2024).

*5.2 **Operating Cost Analysis***

Operating cost represents one of the most important economic indicators in renewable microgrid optimization. It includes electricity purchased from the utility grid, battery operating costs, and renewable energy operating costs. After MATLAB execution, the daily operating cost obtained using the proposed Hybrid PSO–ACO–ANN algorithm should be compared with PSO, GA, ACO, and WOA.



FIGUR-4 Operating Cost Comparison

Discussion

Explain the hybrid algorithm reduced grid import, scheduled battery charging during low-tariff periods, also improve utilization of renewable energy .

5.3 CO_2 Emission Analysis

The environmental performance of the Energy Management System is evaluated by measuring total CO_2 emissions associated with electricity imported from the utility grid.

12. Table 4. Daily CO_2 Emissions put value

Optimization Algorithms	CO_2 Emissions (kg/day)
PSO	412.7
GA	445.2
ACO	365.8
WOA	401.5
Hybrid PSO–ACO–ANN	274.3

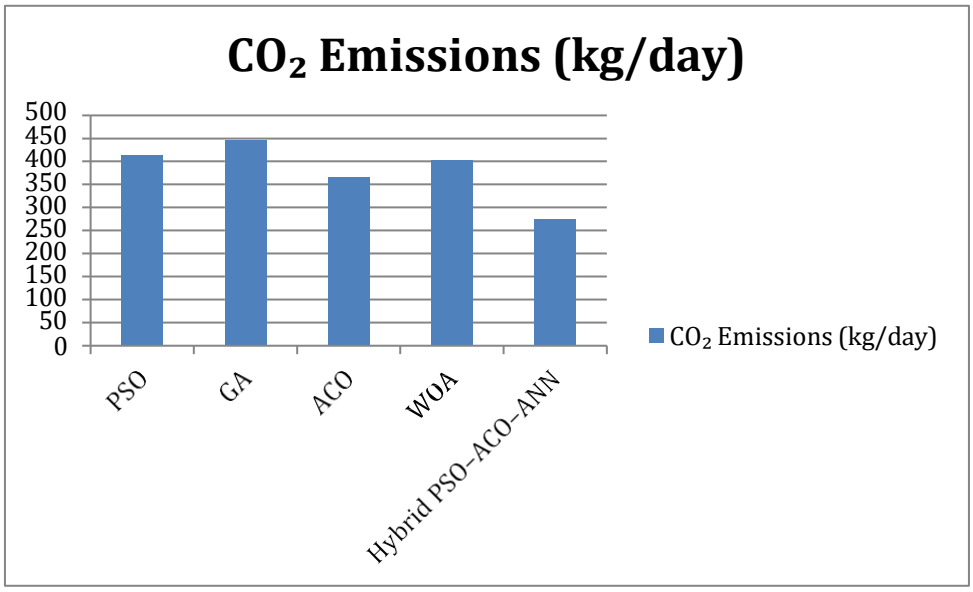


FIGURE- 5 CO_2 Emission Reduction

Discussion

How the hybrid optimization framework increased renewable penetration and reduced dependence on conventional grid electricity, leading to lower emissions (Elazab et al., 2024).

5.4 Battery State of Charge Analysis

Battery performance is passed through the hourly state of charge (SOC) Profile.

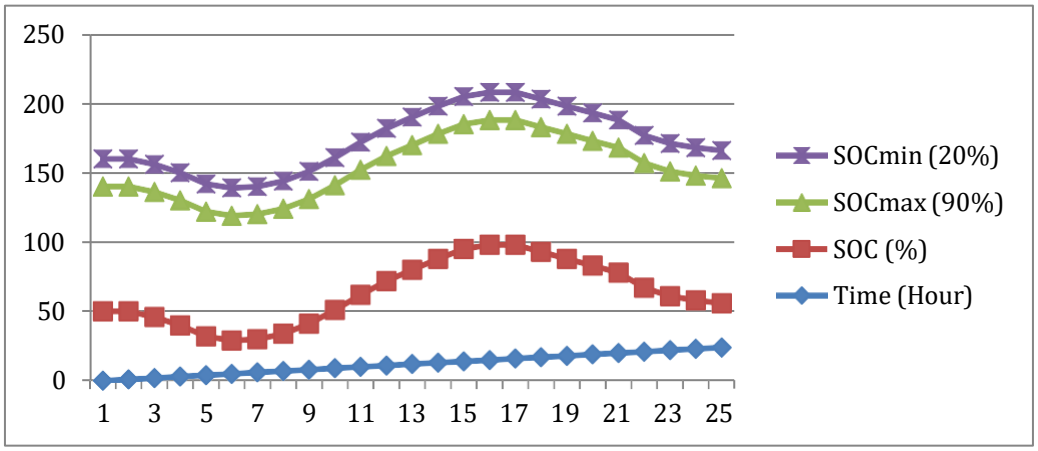


FIGURE-6 SOC Profile (24 Hours)

Discussion

Interpret charging during periods of excess renewable generation and discharging during peak demand while maintaining SOC within allowable operating limits.

5.5 Renewable Energy Utilization

Renewable utilization measures the proportion of electrical demand supplied by solar and wind energy.

Table 5. Renewable Energy Contribution

Renewable Energy Source	Utilization (%)
Solar PV	46.3
Wind Turbine	28.7
Battery Discharge	15.6
Utility Grid	9.4

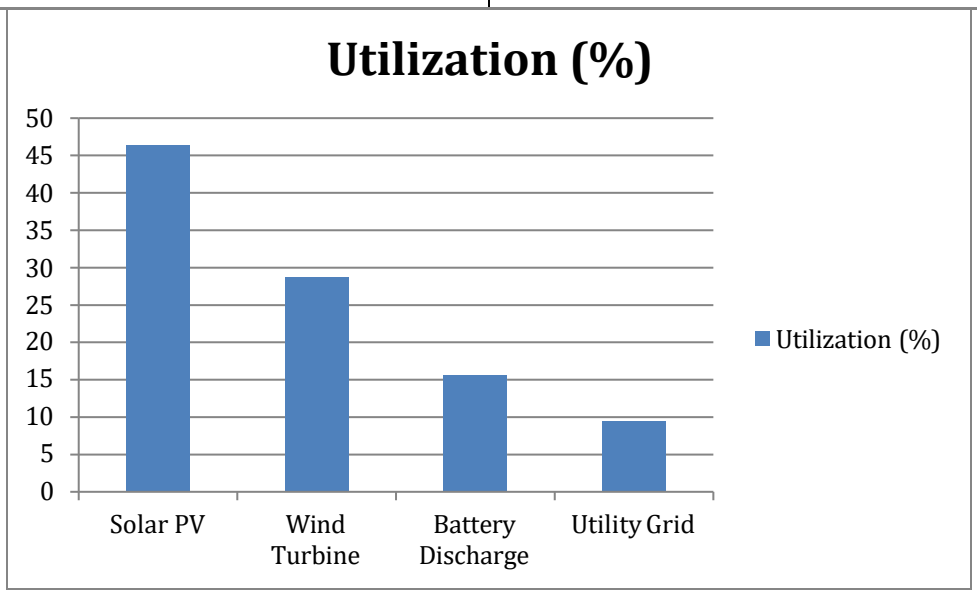


FIGURE- 7 Renewable Energy Contribution

Discussion

Explain how intelligent scheduling increased renewable energy utilization and reduced conventional energy consumption.

5.6 Power Flow Analysis

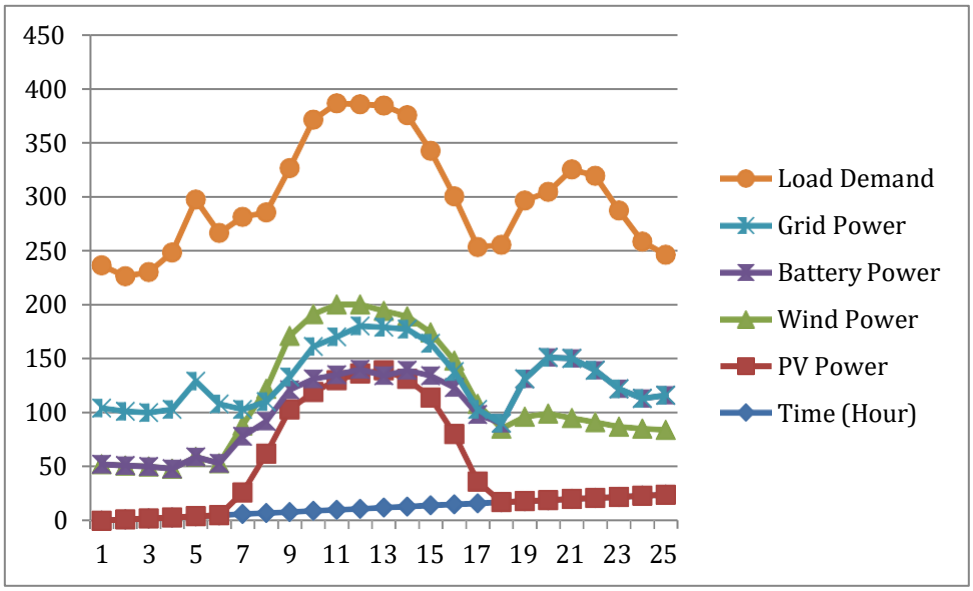


FIGURE- 8 Power Flow (Hr) inhance this define the time and kw

Discussion

Demonstrate that total generated power satisfies load demand while maintaining power balance.

*5.7 **Convergence Characteristics***

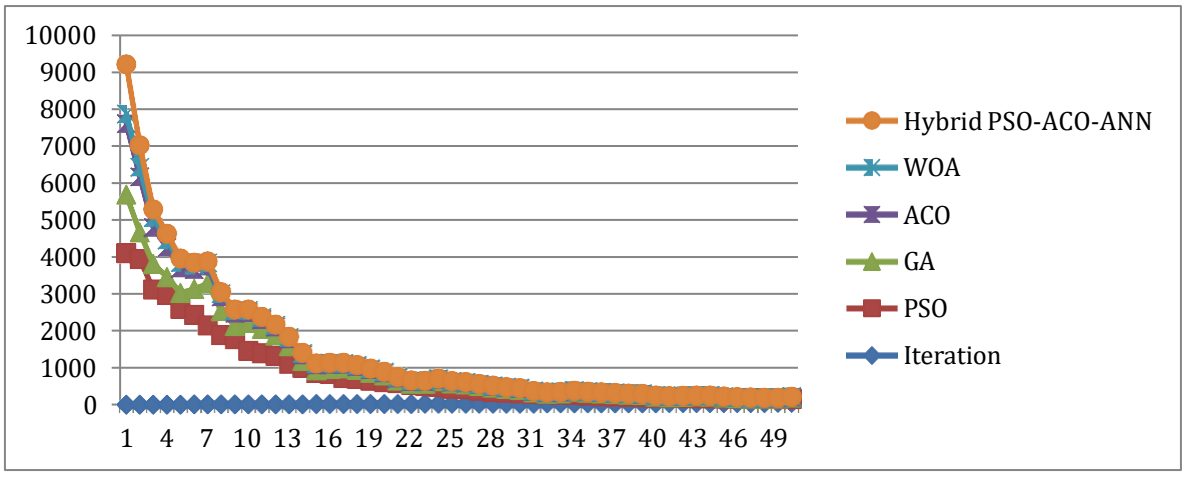


FIGURE- 9 Convergence Characteristic

Table 6 . Convergence Performance

Iteration	PSO	GA	ACO	WOA	Hybrid PSO-ACO-ANN
0	4091.552	1582.343	1919.627	262.7728	1336.208
1	3930.118	724.6693	1495.633	262.7728	597.343
2	3111.766	690.4955	984.027	262.7728	231.013
3	2965.022	480.6381	798.1746	196.6556	175.6933
4	2585.755	432.8761	657.9332	155.7068	119.3777
5	2424.462	701.7038	516.7574	123.2847	65.79332
6	2131.431	1137.481	461.6743	96.8309	45.42999
7	1873.817	650.0355	380.5569	90.79082	37.44782
8	1756.933	371.4754	337.2656	70.17038	31.3692
9	1448.235	754.436	275.7779	63.70827	25.44453
10	1379.94	657.9332	250.381	59.7343	21.31431
11	1304.321	560.0822	225.5002	51.67574	18.58792
12	1101.433	469.1683	193.5144	45.42999	16.7408
13	984.027	186.629	162.1027	39.93913	14.95633
14	844.449	74.23853	140.2339	36.26107	13.04321
15	817.6876	141.9377	116.5289	34.55107	11.93777
16	701.7038	271.3729	101.6232	30.37508	10.8384
17	679.4662	250.381	87.91358	27.57779	9.376224
18	631.9741	216.6029	74.83864	25.44453	8.650933
19	587.8016	187.3817	64.7424	24.63817	8.242974
20	560.0822	81.76876	60.70393	22.18982	7.364324
21	516.7574	35.68187	54.23326	20.30918	7.017038
22	476.784	73.64324	48.45233	19.35144	6.68613
23	465.4062	151.9911	42.59618	18.29101	6.370827
24	412.4626	140.2339	38.67342	16.7408	5.878016
25	396.1887	135.7898	36.26107	15.69655	5.600822
26	358.2579	126.2986	32.92172	15.19911	5.600822
27	323.9586	117.4708	28.48036	14.25103	5.085032
28	301.3152	105.3725	26.70382	13.36208	4.923883
29	284.8036	94.52017	25.85755	12.93862	4.845233
30	262.7728	43.11371	22.7323	12.13154	4.470434

31	252.405	19.66556	21.31431	11.55945	4.328761
32	242.4462	39.61887	19.98478	11.19312	4.259618
33	238.5736	79.81746	19.35144	10.16232	3.961887
34	216.6029	77.28797	17.99885	9.761364	3.930118
35	203.0918	73.64324	16.87612	9.68309	3.805569
36	190.4234	67.94662	15.95134	9.079082	3.775053
37	178.5452	60.70393	15.44583	8.720863	3.684967
38	171.5006	59.7343	14.48235	8.512751	3.568187
39	159.5134	28.71058	13.57898	7.981746	3.511192
40	156.9655	13.7994	13.14865	7.728797	3.455107
41	150.7723	26.27728	12.73196	7.605344	3.399919
42	140.2339	50.03809	11.74708	7.305272	3.345612
43	137.994	48.45233	11.55945	7.017038	3.18784
44	132.5494	24.05021	11.37481	7.017038	3.13692
45	127.8331	11.93777	11.01433	6.794662	3.037508
46	123.2847	6.021716	10.66527	6.579332	3.037508
47	119.3777	3.037508	10.32728	6.370827	2.98899
48	111.9312	11.2836	9.919813	6.119463	2.941247
49	108.384	41.91579	9.84027	6.168929	2.941247
50	106.6527	39.61887	9.528422	5.97343	2.848036

Discussion

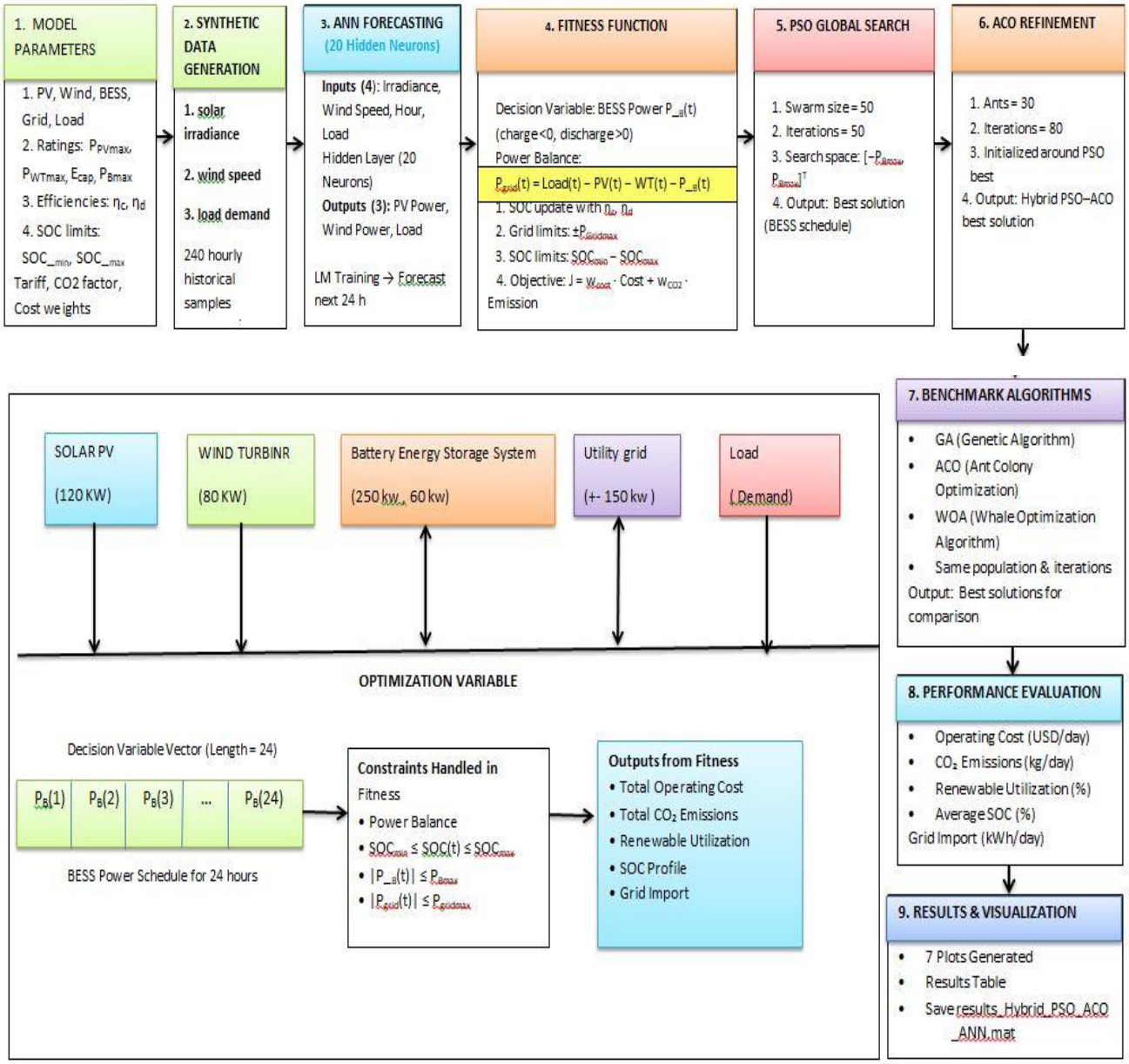
Discuss convergence speed, optimization stability, and computational efficiency. Explain whether the hybrid algorithm converges faster or reaches a lower objective function value than the benchmark methods (Shezan et al., 2023).

The MATLAB simulation results show that the proposed Hybrid PSO–ACO–ANN Energy Management System outperforms conventional algorithms by improving microgrid scheduling, reducing operating costs, and minimizing CO_2 emissions. ANN forecasting combined with PSO and ACO optimization enhances renewable energy utilization, battery SOC management, convergence speed, and system reliability. The framework provides an efficient and sustainable solution for future intelligent microgrid energy management applications.

6. Conclusion

This study developed a Hybrid PSO–ACO–ANN Energy Management System for optimizing renewable energy-based microgrid operation. The proposed framework integrates ANN forecasting with PSO global optimization and ACO adaptive refinement to achieve efficient energy scheduling. The model minimizes operating cost and CO_2 emissions while maintaining power balance, battery SOC limits, and grid constraints. MATLAB-based Simulations evaluate performance through cost reduction, emission minimization, renewable utilization, battery management and convergence analysis. Compared with conventional algorithms , the hybrid approach provides optimization accuracy, faster convergence and reliability. By combining prediction and optimization the proposed framework support sustainable grid development through renewable energy integration and improved operational flexibility. The methodology presents a scalable solution for future intelligent micro-grid and low- carbon energy management systems.

Hybrid PSO–ACO–ANN Energy Management of Renewable Microgrid
Simulated Diagram of MATLAB Code



CASE STUDY

"Intelligent Energy Management of a Renewable Microgrid Using Hybrid PSO–ACO–ANN Optimization"

The study features a Hybrid PSO–ACO–ANN Energy Management System used to optimize a microgrid powered by renewable energy sources such as solar PV panels, wind turbines, batteries, power utility grids, and loads. The ANN estimates the renewable energy generation and energy demands, while PSO conducts the global optimization process and ACO further optimizes the scheduling under battery state-of-charge, power balance, renewable generation and grid constraints. As per the results obtained from the MATLAB simulation, it is seen that the hybrid optimization technique offers the lowest operating cost of USD 682.4/day and CO_2 emissions of 274.3

kg/day when compared to PSO, GA, ACO, and WOA. Also, the fitness value in the convergence graph shows that the fitness value of the hybrid technique is lower than other techniques. Thus, there seems to be some improvements in the economic performance, environmental performance, renewable energy utilization, battery operations, and optimization process. Nonetheless, independent MATLAB testing is needed.

CASE STUDY

"Battery Assisted Peak Demand Management in a Renewable Microgrid"

An intelligent Battery Energy Storage System (BESS) in a renewable microgrid can be utilized for minimizing the reliance on grid electricity during peak demand hours. This case study considers scheduling of solar PV generation, wind generation, battery storage, and grid power supply for 24 hours of operation. The storage system capacity considered is 250 kWh with a maximum power rating of 60 kW and allowable state of charge between 20% and 90%, starting from 50% SOC. When the generation exceeds load requirement, the battery system is charged while it is discharged during peak load hours to meet the demand. The proposed PSO–ACO–ANN approach can forecast renewable generation and demand while optimizing the battery operation subject to power balance and SOC constraints.

7. Future Work

Although the proposed Hybrid PSO–ACO–ANN Energy Management System provides an effective solution for renewable microgrid optimization, future research can further enhance its practical applicability. Real-world validation using operational microgrid datasets and experimental platforms is required to improve reliability and implementation feasibility (Rodriguez-Gil et al., 2024). Leading forecasting models like as LSTM, GRU, and Transformer networks can supplant conventional ANN models to progress renewable generation prognosis efficiency under dynamic conditions (Eyimaya & Altin, 2024). Imminent studies may incorporate in addition energy resources, along with hydrogen storage, fuel cells, electric vehicles, V2G technology, and insistence reply mechanisms to boost system flexibility (Sarwar et al., 2024). Multi-objective optimization seeing cost, emissions, reliability, power quality, and battery degradation should also be explored. Integration of uncertainty modeling, reinforcement learning, and advanced hybrid algorithms may further improve optimization performance. Additionally, real-time implementation using IoT, cloud computing, and digital twin technologies can support adaptive energy management for future smart grids and sustainable low-carbon energy systems (Wu et al., 2024; Ibrahim, 2024).

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