International Journal of Renewable Energy and Environmental Sustainability
Volume. 10, Number 2; April-June, 2025;
ISSN: 2837-3391| Impact Factor: 8.56
https://zapjournals.com/Journals/index.php/ijrees
Published By: Zendo Academic Publishing

COMPUTATIONAL INTELLIGENCE FOR COST- AND EMISSION-OPTIMIZED UNIT COMMITMENT IN HYBRID MICROGRIDS.

[1]B.I Gwaivangmin, [1]G.A Bakare, [1]Y.S Haruna, [1]A.L Amoo and [2]Ali M.T
Email: gwaivangminb@gmail.com

Article Info
Keywords: Computational intelligence, Hybrid, Intermittency, Microgrids, Optimization, Synchronizer, Unit Commitment
DOI
10.5281/zenodo.16534179

Abstract
This study addresses the challenge of efficient energy management in microgrids facing rising electricity costs and power shortages. The study tackles the limitations of traditional fossil fuels and the intermittency of renewables by developing an optimized unit commitment framework for a hybrid microgrid (Solar PV, PHESS, utility supply, diesel generator) at the University of Jos. Computational intelligence techniques (GA, PSO, SA, PSO-GA, PSO-SA) were implemented in Python, incorporating an electronic synchronizer for stability and aiming to minimize operational costs and emissions. The simulation results revealed that the hybrid PSO-SA algorithm achieved the lowest cost (₦1,246,765.58) and CO_2 emissions (₦10695.87), demonstrating the effectiveness of hybrid optimization and the benefits of Solar PV and PHESS in reducing reliance on conventional sources. This study highlights the potential of computational intelligence to enhance microgrid efficiency and suggests future research on algorithm fine-tuning and hybrid approaches for further performance improvements.

1. Introduction

Global energy challenges (Ritchie et al., 2022) drive the need for sustainable microgrids integrating renewables (Solar PV, PHESS) and conventional sources (Postero et al., 2024) to enhance energy access and reliability (Sovacool et al., 2022). Efficient operation requires advanced optimization for unit commitment (Arefin et al., 2023) because traditional methods struggle with cost, stability, and emissions (sati et al., 2024). This study develops a secured unit commitment framework for microgrids with the aim of minimizing costs and emissions while ensuring stability, using the University of Jos as a relevant case study. The initial analysis emphasizes the necessity for efficient microgrid energy management due to power shortages and rising costs, compounded by the intermittency of renewable energy sources.

1.2 Aims and objectives

This study addresses the problem of optimizing unit commitment in hybrid microgrids to balance cost, emissions, and stability, finding traditional methods inadequate. It develops an optimized framework using computational intelligence (GA, PSO, SA, and hybrids) and an electronic synchronizer for stability. The simulations comparing the algorithms showed that the hybrid PSO-SA performing best in minimizing cost and emissions.

[1] Department of Electrical and Electronics Engineering, Abubakar Tafawa Balewa University, Bauchi, Nigeria
[2] Computer Engineering Technology Department, Ramat Polytechnic Maiduguri.

1.3 Literature review

Nagra et al. (2019) proposed a hybrid GSA-DMS-PSO algorithm that improved convergence and accuracy but had potentially higher computational costs. Boqtob et al. (2019) developed the H-PSO-SCAC hybrid PSO algorithm for unit commitment in microgrids to minimize cost; however, its focus on a specific scenario may limit its applicability. Khunkitti et al. (2019) demonstrated that their iDA-PSO hybrid algorithm effectively reduces unit commitment costs; however, their analysis lacked details on computational complexity and uncertainty impacts. Xiu et al. (2019) found that their enhanced PSO algorithm lowers costs and improves stability for unit commitment in power systems with renewables, but they did not provide details on computational time, scalability, or comparisons to other methods. Zhu et al. (2019) created a monthly unit commitment model for renewables and reliability using interval predictions and a multi-objective genetic algorithm. However, its use of deterministic optimization and a simplified reliability assessment limits its practical application. Syama et al. (2020) proposed a hybrid Crow Search Algorithm and Gray Wolf Optimization for Unit Commitment and Economic Emission Dispatch in hybrid power systems, but their study may have lacked detailed analysis of computational complexity, scalability, and robustness with fluctuating renewables. Anyaka et al. (2020) used PSO for a power plant's unit commitment but did not thoroughly evaluate PSO's performance in terms of solution quality, convergence, scalability, and comparisons, nor did they address uncertainty. Moretti et al. (2020) created a robust optimization model for day-ahead scheduling in multi-energy systems and microgrids, which improved flexibility when dealing with uncertainty. However, the model faces challenges due to the complexity of its decision rules and computational efficiency. Rendroyoko et al. (2020) introduced a hybrid method combining an improved priority list and genetic algorithms for unit commitment in isolated microgrids with intermittent renewables, demonstrating effective scheduling. However, their findings were limited to a single case study and could be strengthened by further robustness analysis. Mohammadi et al. (2021) created a data-driven unit commitment method using kernel density to handle uncertainty and reinforcement learning-based PSO for multi-objective optimization. However, the computational complexity of large systems and the effect of kernel bandwidth selection require more investigation. Ranganathan et al. (2021) proposed SAFA for Unit Commitment, which demonstrated better performance in terms of cost and computation time. However, a thorough analysis of SAFA's specific strengths and weaknesses was not provided. Bakirtzis et al. (2021) created a demand response management framework linked to short-term power system scheduling for high renewable energy use. However, it did not account for real-world complexities such as the unpredictable nature of renewable energy, how participants might act, communication systems, and market structure. Das et al. (2021) used multi-objective Particle Swarm Optimization to optimize microgrid scheduling with solar and wind power and found that hierarchical PSO performed best. However, they did not thoroughly analyze how robust the method was when renewable energy production varied or how well it would work with larger systems. Tian et al. (2021) designed and optimized a hybrid PV/battery/diesel system for a remote village using a combined Improved Sparrow Search Algorithm and Sequential Quadratic Programming. However, their study was specific to that situation and did not extensively compare their method to other algorithms. Sayed et al. (2021) introduced a hybrid MPSO-EO algorithm for Unit Commitment that performed better on benchmark tests. However, they did not explicitly discuss the computational complexity of the algorithm. Bolurian et al. (2022) created a 24-hour ahead scheduling model for renewable microgrids that included unit commitment and network constraints. However, they did not thoroughly analyze its performance across different situations or consider uncertainties. Ang et al. (2022) developed a multi-objective optimization method for designing hybrid renewable energy systems for coastal communities, showing that it was feasible but noted difficulties in achieving high renewable energy use and the need for more research. Hosseini-Firouz et al. (2022) created a unit commitment model that considers the uncertainty of wind power using conditional value-at-risk to reduce costs and maintain reliability. However, it relies on a deterministic method and does not include demand response or energy storage as ways to lessen the impact of uncertainty. Zuniga et al. (2022) developed a robust unit commitment model for systems with a lot of renewable energy sources and N-1-1 contingencies using a nested column-and-constraint generation technique. However, it may be computationally complex, require a lot of data, and may not be able to account for all possible system disruptions. Aharwar et al. (2023) provided a broad overview of the Unit Commitment problem, emphasizing the integration of renewable energy sources, transmission limits, and uncertainties, and pointed out the necessity for more research on robust optimization. Their work is a general review rather than a detailed examination of specific methods. Cordera et al. (2023) presented a multistage stochastic dynamic programming (SDDP) method for unit commitment in systems with high renewable energy and storage, which addresses uncertainty and correlation. However, they tested the proposed method on a small system, and it might face computational difficulties with larger systems. Abuelrub et al. (2023) created a modified African Vultures Optimization Algorithm (AVOA) for unit commitment that includes wind power and demonstrated better performance. However, they did not consider other types of uncertainties and did not explore different models for wind power. Suhail et al. (2023) developed a hybrid optimization technique called HMFPSO for estimating transmission line parameters, and it demonstrated better performance. However, this study did not discuss any potential limitations or areas for improvement of HMFPSO. Zhang et al. (2023) developed an integrated energy system unit commitment (IES-UC) model that incorporates power-to-gas technology and uses conditional values at risk to handle the uncertainty of wind power. However, the model may have limited complexity and may require a large amount of data. Hasan et al. (2024) developed a cooperative game theory approach for optimizing rural multi-microgrid operation considering renewables, storage, load, and prices, but it may be complex and computationally intensive for large systems and sensitive to real-time price and renewable availability. Ji et al. (2024) created a two-layer optimization model for unit commitment in hybrid renewable energy systems with pumped storage. However, the model may not have been adequately tested on large-scale systems before being compared with other methods. Xiao et al. (2024) proposed robust optimization for large wind-solar storage, but the impact of computational complexity and uncertainty were not fully discussed. Mena et al. (2024) developed multi-objective unit commitment with high wind and battery storage (BESS benefits shown), but BESS capacity constraints and complexity with uncertainties are limitations. Feng et al. (2024) created a day-ahead/real-time dispatch framework for renewable thermal storage using a quantile policy; however, scalability and comparison with other real-time methods are lacking. Kamboj et al. (2024) introduced CZOA for unit commitment with wind and EVs, but computational complexity and scalability for large systems and detailed algorithm comparison were missing. Manoharan et al. (2023) developed a novel MIPSO variant for microgrids with renewables and PEVs, but detailed MIPSO limitations and comparative analysis are lacking. Singh et al. (2024) created a multi-objective unit commitment model considering wind ramping, but more comprehensive renewable and uncertainty considerations and system reliability/cost analysis are needed. Manoharan et al. (2024) introduced a novel MIPSO variant for microgrids with high renewable energy sources, EVs, and battery storage; however, detailed complexity and scalability analysis for large microgrids and comprehensive comparative analysis are lacking. Ramasamy et al. (2024) developed a hybrid BWO-THDCNN approach for unit commitment in smart grids; however, a more comprehensive evaluation across diverse scenarios and potential computational challenges exists. Xu et al. (2024) developed a multi-objective optimization model for hybrid energy storage using a novel CMOPSO-MSI algorithm. However, challenges in handling real-world complexity and maintaining computational efficiency are potential limitations. Pourahmadi and Kazempour (2024) proposed SVM classifiers for faster unit commitment solving; however, it is deterministic, potentially has scalability issues, relies on historical data, and uses SVM exclusively. Qin et al. (2024) developed a hybrid HSA-DELF for enhanced engineering optimization, but evaluation on larger complex real-world problems may be lacking. Al-Kubragyi and Ali (2025) introduced a hybrid MFO-PSO algorithm for unit commitment; however, it potentially lacks evaluation on larger, complex systems and deeper parameter sensitivity/robustness analysis. González-Niño et al. (2025) provided a bibliometric analysis of microgrid energy management, identifying research clusters and gaps, but it is a review without original research. Singh et al. (2025) proposed a hybrid demand-side management approach for microgrids (load shifting, curtailment, smart charging for PHEVs), but it is limited to a specific scenario and needs more scalability/robustness analysis. Paul et al. (2025) proposed a multi-objective QPSO framework for grid-connected microgrids; however, this framework potentially lacks computational complexity/scalability analysis for large microgrids and detailed comparative analysis.

This study aims to fill gaps in the literature review by providing a comparative analysis of optimization techniques applied to a real-world microgrid case study, integrating an electronic synchronizer for stability, examining hybrid methods, focusing on minimizing cost and emissions, and managing renewable intermittency. The proposed model contributes a practical and comparative analysis addressing the shortcomings of existing research regarding cost, emissions, and system stability in a real-world context.

2.0 Theoretical analysis

Abdou and Tkiouat (2018) and Yang and Wu (2022) highlighted the importance of unit commitment (UC) in matching power generation with demand fluctuations, considering operational costs and reserve capacity. Salman and Kusaf (2021) described the UC optimization problem in detail. Wood et al. (2013) investigated multi-objective UC for cost minimization. Bhattacharya and Chattopadhyay (2010) and Mohammadi and Soleymani (2021) focused on the economic cost and emission reduction of hybrid power system load dispatch. Kundur (1994) and IEEE Std. 1547 (2018) analyzed the significance of a synchronizer in power system economics.

2.1 Cost Model of Energy Sources

The following cost analysis details a hybrid power system comprising micro-pumped hydro energy storage, solar PVs, diesel generators, and a public utility supply.

2.1.1 Micro-pumped hydro energy storage model

Pumped hydro-energy storage systems (PHESS) are crucial for mitigating renewable energy intermittency, as highlighted by Javed et al. (2020), by storing excess energy for use during periods of low renewable output. Blakers et al. (2022) identified potential PHES sites in eastern Australia, but further feasibility studies are needed.

2.1.1.2 **Cost Model of Power Generation from a Pumped Storage Hydropower Plant**

A pumped hydro energy storage system (PHESS) plant stores energy by pumping water to a higher elevation during low demand and releasing it through turbines to generate electricity during peak demand. The cost of power generation per kWh can be modeled using a quadratic equation, incorporating the capital costs, operational costs, and efficiency losses.

Quadratic Model Equation

The total cost per kWh of power generation from a pumped storage plant can be expressed as shown in equation (1),

$$C\,(P) = a\,P^2 + b\,P + c \qquad \text{...(1)}$$

where, C(P) = Cost of power generation per kWh (₦/kWh), P = Power output in kW, a = Quadratic coefficient (accounts for non-linear efficiency losses and operational inefficiencies), b = Linear coefficient (accounts for energy losses in pumping and generation cycles, and variable O&M costs), and c = Fixed cost per unit of energy (includes CAPEX amortization and fixed O&M costs).

2.2 Solar PV Model

The Center for Sustainable Systems (2023) reported that the Earth receives an average of 1.73×10^5 terawatts (TW) of solar radiation, significantly exceeding the global electricity demand of 2.9 TW. Matching highly variable electricity demand with solar PV generation can be assisted by energy storage and demand forecasting. Furthermore, solar PVs located near the demand can alleviate the stress on the electricity distribution network, particularly during peak times. While commercial PV panels typically convert 17%–20% of incident solar energy into electricity, researchers have developed cells with efficiencies approaching 50%.

2.2.1 Cost Model of Solar PV Power Plants

The cost of power generation per kWh from a solar PV power plant can be expressed as a quadratic model, incorporating the capital costs, maintenance costs, and system performance. As shown in equation (2);

$$C(P) = aP^2 + bP + c, \quad (2)$$

where, C(P) = Cost of power generation per kWh (₦/kWh), P = Power output of the solar PV system (kW), a = Quadratic coefficient (accounts for nonlinear performance degradation, inverter efficiency losses, etc.), b = Linear coefficient (accounts for proportional costs such as maintenance and land lease), and c = Fixed cost per unit of energy (accounts for CAPEX amortization and other fixed costs)

2.3 Diesel Generator Model

According to Obaro *et al.* (2018), a diesel generator converts the kinetic energy of a diesel engine into AC electrical power. The output depends on factors such as specifications, load type, and rotor speed control. Diesel generators are commonly used as backup power sources or for providing electricity in areas where there is no access to a reliable power grid, such as remote locations and during emergencies.

2.3.1 Cost model of diesel generator

According to the Department of Energy (2022), a quadratic model equation for the cost of power generated from a diesel generator plant can be derived by considering fuel costs, maintenance costs, and capital costs, which often exhibit nonlinear relationships with output power. The quadratic model for the Cost of Power C(P) is shown in equation (3);

$$C(P) = aP^2 + bP + c \qquad ...(3)$$

Where, C(P) = Cost of power generation per kWh (₦/kWh), P = Power output of the generator (kW), a = Quadratic coefficient (captures fuel consumption inefficiencies at varying loads),b = Linear coefficient (accounts for proportional costs such as fuel and maintenance), and c = Fixed cost per unit of energy (accounts for CAPEX and other overhead costs).

2.4 The Public supply model

A public supply refers to the electrical power supplied by a utility company to households, businesses, and other consumers through a network of power lines and substations. In many countries, utility supply is provided by government-owned or regulated utility companies responsible for generating, transmitting, and distributing electricity to consumers. According to Kersting and Li (2019), Glover *et al.* (2021), and Marković *et al.* (2023), due to the intricate nature of 11kV utility supply systems, a single mathematical equation cannot fully capture their complex behavior. The performance of such systems is influenced by various factors, including the generation capacity, transmission and distribution networks, load demand, and control strategies.

2.4.1 Cost Model of public supply

According to Lazard (2022), the cost of power generation per kWh from a utility plant can be expressed as a quadratic model, incorporating capital costs, fuel costs, maintenance, and operational efficiency as shown in equation (4);

$$C(P) = aP^2 + bP + c \qquad ...(4)$$

Where, C(P) = Cost of power generation per kWh ($/kWh), P = Power output of the plant (MW or kW), a = Quadratic coefficient (accounts for non-linear operational inefficiencies, wear-and-tear, and aging effects), b = Linear coefficient (accounts for fuel costs, variable O&M costs), and
c = Fixed cost per unit of energy (includes CAPEX amortization and other fixed costs).

2.5 Electronic Synchronizer

An electronic synchronizer ensures seamless synchronization of multiple power sources (Diesel Generator, Utility Supply, Pumped Hydro Energy Storage System, and Solar PV) by aligning frequency (Hz), voltage (V), and phase angle **(°)** before connecting/disconnecting sources to the grid. This synchronization is crucial in automatic unit commitment (UC) to prevent power quality issues and system instability.

2.5.1 Main Synchronization Conditions

For proper synchronization, the electronic synchronizer must satisfy the following conditions at time t as shown in equations (5) to (6);

$$\Delta f_t = f_{ref,t} - f_{source,t} \approx 0 \qquad ..(5)$$

$$\Delta V_t = V_{ref,t} - V_{source,t} \approx 0(46)$$

$$\theta_t = \theta_{ref,t} - \theta_{source,t} \approx 0 \qquad ...(6)$$

Where,

$f_{ref,t}$ = reference grid frequency (e.g 50 Hz or 60Hz) [IEEE std.1547-2018].

$f_{source,t}$= frequency of power source (DG, Utility, Phess, or PV) at time t.

$V_{ref,t}$= reference grid voltage (e, g., 230 V or 400V) [NERC, 2020]

$V_{source,t}$= voltage of power source at time t

$\theta_{ref,t}$= phase angle of the reference grid voltage at time t.

$\theta_{source,t}$= phase angle of the power source voltage at time t.

2.6 Pollution Emissions Equations for Power Systems

For a power system consisting of a solar PV, Diesel Generator, Pumped Hydro Energy Storage System (PHESS), and Utility Supply, pollution emissions mainly arise from the Diesel Generator (DG) and Utility Supply (if from fossil fuel sources).

According to Momoh, (2012) and Wood and Wollenberg, (2013), the total emissions of different pollutants; Carbon Dioxide (CO_2), Carbon Monoxide (CO), Sulfur Dioxide (SO_2), Nitrogen Oxides (NO_x), and Hydrocarbons (HC), can be modeled as follows:

a) General Emission Equation

The emissions from a generator operating on diesel fuel can be modeled as shown in equation (7);

$$E_{p,t} = \alpha_p + \beta_p P_{diesel,t} + \gamma_p P_{diesel,t}^2 \quad ...(7)$$

where, $E_{p,t}$ is the emission of pollutant p at time t.

α_p (kg/h) is the constant emission coefficient of pollutant p.

β_p (kg/MWh) is the linear emission coefficient of pollutant p.

γ_p (kg/MWh²) is the quadratic emission coefficient of pollutant p.

$P_{diesel,t}$ (MW) denotes the power output of the diesel generator at time t.

The total emissions of each pollutant over the 24-hour period are shown in equation (8);

$$E_p^{total} = \sum_{t=1}^{24} E_{p,t} \quad (8)$$

Here, p represents CO_2, CO, SO_2, NO_x, or HC.

v) Total System Emissions

The total pollutant emission p over the 24-hour period is shown in equation (9);

$$E_P^{Total} = \sum_{t=1}^{24} \left(\alpha_P + \beta_P P_{diesel,t} + \gamma_P P_{diesel,t}^2\right) \quad (9)$$

If the **utility grid** is partially powered by fossil fuels, then purchased electricity emissions should be added:

$E_{grid,t} + \lambda_P P_{Utility,t}$

The equation with fossil fuels and added emissions is as shown in equation (10)

$$E_P^{Total} = \sum_{t=1}^{24} \left(\alpha_P + \beta_P P_{diesel,t} + \gamma_P P_{diesel,t}^2 + E_{grid,t} + \lambda_P P_{Utility,t}\right) \quad (10)$$

3.0 Materials and Methods

The Multi-Objective Optimization for Unit Commitment:

The effective operation of a microgrid system requires robust optimization techniques to manage the variability of renewable energy sources and fluctuating load demands. This study focuses on optimizing the unit commitment of a hybrid microgrid comprising a solar photovoltaic (PV), Pumped Hydro Energy Storage System (PHESS), public supply, and diesel generator. The objective is to minimize operational costs and pollutant emissions while ensuring stable and reliable power delivery through an electronic synchronizer. To achieve this, computational intelligence techniques, including genetic algorithms (GA), Particle Swarm Optimization (PSO), a hybrid PSO-GA approach, and a hybrid PSO-SA (Simulated Annealing) approach, are employed. These optimization techniques were implemented in Python by leveraging various mathematical libraries to develop and simulate a power dispatch model under different loads and renewable generation scenarios. The optimization framework incorporates system constraints such as generator capacity limits, load balance requirements, and synchronization conditions. The importance of Unit Commitment (UC) in aligning power generation with varying demand has been emphasized by researchers such as Abdou and Tkiouat (2018) and Ohanu et al. (2024). UC involves devising power plant operating strategies that address demand fluctuations while considering factors like operational costs and the need for reserve capacity. Building on this, Salman and Kusaf (2021) offer a detailed explanation of how the UC optimization problem is described. Wood *et al.* (2013) investigated multi-objective optimization of unit commitment for cost minimization. Bhattacharya and Chattopadhyay (2011), Tiwari *et al*. (2025) investigated the economic cost and emission reduction in the load dispatch of hybrid power systems, whereas Kundur (1994) IEEE Std.1547 (2022) gave an analysis of the significance of a synchronizer in the economics of power systems.

3.1 The multi-objective optimization (MOO) equation integrates:

Cost minimization (fuel, utility, storage, and solar PV savings

Pollution emission minimization (CO_2, CO, SO_2, NO_x and HC emissions)

Electronic synchronizer equation (ensuring frequency, voltage and phase matching).

The system comprises the following components:

Diesel Generator (DG)

Utility Supply (US)

Pumped Hydro energy Storage System (PHESS)

Solar PV (SPV) plants over a 24-hour period.

3.1.1 Multi-Objective Function:

$$w_1 C_{total} + w_2 E_{total} + w_3 S_{sync} \tag{11}$$

Where:

$w_1, w_2, w_3 =$ weight for cost, emission and synchronization

$C_{total} =$ total operational costs

$E_{total} =$ total emissions

$S_{sync} =$ synchronization penalty function

i. Cost Function

$$C_{total} = \sum_{i=1}^{24} \left(C_{DG,t} + C_{US,t} + C_{PHESS,t} - C_{SPV,t} \right) \tag{12}$$

Where:

$$C_{DG,t} = a_{DG} P_{DG,t}^2 + b_{DG} P_{DG,t} + C_{DG} + C_{DG}^{start} U_{DG,t} \text{ (Diesel generator cost)}$$

$$C_{US,t} = \lambda_{US,t} P_{US,t} \text{ (Utility supply cost)}$$

$$C_{PHESS,t} = \lambda_{US,t} P_{PHESS,t}^{charge} + P_{PHESS,t}^{O\&M} \text{ (PHESS charging and maintenance cost)}$$

$$C_{SPV,t} = C_{SPV,t} P_{SPV,t} \text{ (Solar PV savings)}$$

i. Emission Function

$$\sum_{i=1}^{24} \sum_{p \epsilon (CO_2 CO, SO_2, NO_x HC} \left(E_{DG,t}^P + E_{US,t}^P - E_{SPV,t}^P - E_{PHESS,t}^P \right) \tag{13}$$

Where:

$$E_{DG,t}^P = \alpha_{DG}^P P_{DG,t}^2 + \beta_{DG}^P P_{DG,t} + \gamma_{DG}^P \text{ (Diesel generator emission)}$$

$$E_{US,t}^P = \lambda_{US}^P P_{US,t} \text{ (Grid − based emissions)}$$

$$E_{SPV,t}^P = \lambda_{US}^P P_{SPV,t} \text{ (Avoided emissions due to solar PV)}$$

$$E_{PHESS,t}^P = \lambda_{US}^P P_{PHESS,t}^{discharge} \text{ (Avoided emission due to PHESS)}$$

ii. Synchronization Function

$$S_{sync} = \sum_{i=1}^{24} \left(k_f |\Delta f_t| + k_v |\Delta V_t| + k_\theta |\Delta \theta_t| \right) \tag{14}$$

Where:

$k_f, k_v, k_\theta =$ Synchronization penalty coefficients

$\Delta f_t = f_{ref,t} - f_{source,t}$ (Frequency deviation)

$\Delta V_t = V_{ref,t} - V_{source,t}$ (Voltage deviation)

$\Delta \theta_t = \theta_{ref.t} - \theta_{source,t}$ (Phase angle deviation)

The synchronizer adjusts the power sources using a PID controller.

$$\Delta P_{source,t} = K_p \cdot \Delta f_t + K_i \int_0^t \Delta f_t dt + K_d \frac{d}{dt} \Delta f_t \quad (15)$$

Where:

K_p, K_i, K_d are PID gains

Sources are committed when:

$$|\Delta f_t| \leq \epsilon_f, \quad |\Delta V_t| \leq \epsilon_v, \quad |\Delta \theta_t| \leq \epsilon_\theta$$

Constraints

i. Power balance

$$P_{DG,t} + P_{US,t} + P_{SPV,t} + P_{PHESS,t}^{discharge} = P_{demand.t} P_{PHESS,t}^{charge} \quad (16)$$

ii. Generator limits

$$P_{DG}^{min} \leq P_{DG,t} \leq P_{DG}^{max} \quad (17)$$

iii. Utility limits

$$P_{US}^{min} \leq P_{US,t} \leq P_{US}^{max} \quad (18)$$

iv. Storage limits

$$0 \leq P_{PHESS,t}^{charge} \leq P_{PHESS}^{max} \quad (19)$$

$$0 \leq P_{PHESS}^{discharge} \leq P_{PHESS}^{min} \quad (20)$$

Lazard (2022)

3.1.2 The study used the following materials:

i. **Software:** Python Anaconda environment with libraries such as Pandas, Matplotlib, Pyplot, geneticalgorithm, pyswarm, scipy, linprog, NumPy, multiprocessing, and Scipy for mathematical computations and customized code for implementing the optimization algorithms.

ii. A line diagram of the University of Jos microgrid system.

iii. Demand Response and Meteorological data relevant to the case study.

iv. RTO Unit Commitment Test System GAMS Program for reference and potential benchmarking.

Data Collection and Preprocessing:

i. Collection of 24-hour load demand, solar irradiance, and cost data for diesel, utility, and PHESS.

ii. Preprocessing the collected data into a suitable format for the optimization algorithms.

Unit Commitment Model Implementation:

i. Development of the unit commitment model in Python using Anaconda's Spyder environment.

ii. Incorporation of the defined cost functions and system constraints (power balance, generation limits, etc.) are incorporated into the model.

Setting the Algorithm Parameters:

PSO: Swarm size = 30, maximum number of iterations = 100, Inertia weight = 0.7, Cognitive parameter = 1.5, Social parameter = 1.5. GA: Population size = 50-100, Crossover probability = 0.8-0.9, Mutation probability = 0.01-0.05, Tournament selection, Number of generations = 20-50. SA: Initial temperature = 1000, Cooling rate = 0.95.

4.0 Results and Discussion

This section presents the simulation results and analysis of the 24-hour power dispatch optimization for a hybrid microgrid (solar PV, PHESS, diesel generators, utility supply). Conducted in Python (Anaconda Spyder) using PSO, SA, HPSO-SA, HPSO-GA, and GA, the study examined optimized schedules, cost distributions, and performance comparisons to demonstrate the effectiveness of the models in achieving cost-effective and sustainable energy management, as illustrated through tables.

4.1 Results of the HPSO-SA

Table 1: Output of four sources of power generation for 24-hour period, best CO_2 emission cost, and best synchronization penalty.

Hour	P (Solar)	P(phess)	P (diesel)	P (public)	Cost
24 -1	0.000000	340.330000	0.000000	0.000000	21781.120000
1-2	0.000000	311.010001	0.000000	0.000000	19904.641363
2-3	0.000000	314.525681	0.000000	17.995584	22800.378484
3-4	0.000000	408.657703	0.000000	140.052278	42960.385718
4-5	37.073244	492.118550	0.000000	126.215789	48423.414726
5-6	563.228092	359.727863	0.000000	22.470659	53170.624757
6-7	1000.000000	204.121614	0.000000	0.000000	61065.397303
7-8	452.081256	493.310651	0.000000	334.957209	93485.762966
8-9	768.144454	199.605769	12.700865	157.779104	72809.176757
9-10	801.417899	146.583641	1.197427	92.021676	59132.141416
10-11	476.934769	413.105231	0.000000	0.000000	49331.604155
11-12	0.000000	780.820000	0.000000	0.000000	49972.480000
12-13	336.575172	428.525093	0.000000	0.000000	43581.479161
13-14	0.000000	340.016679	0.273751	532.190389	89359.483134
14-15	672.038618	218.752311	0.000000	0.000000	46648.930678
15-16	0.000000	635.638847	0.000000	298.399927	77757.651376
16-17	0.000000	663.539557	0.000000	254.029652	72999.298717
17-18	0.000000	649.322383	0.000000	260.157081	73754.945697
18-19	0.000000	730.200434	0.000000	208.988398	72230.267505
19-20	0.000000	848.310000	0.000000	0.000000	54291.840000
20-21	0.000000	79.844467	4.263959	545.770111	71496.713645
21-22	0.000000	542.947637	0.000000	20.239272	37950.452333
22-23	0.000000	413.250000	0.000000	0.000000	26448.000000
23-24	0.000000	167.956528	0.005100	173.385541	31653.670879

Table 2. The cost analysis for the hybrid energy system includes contributions from solar, PHESS, diesel, and public power supply sources. Below is the summary of cost components, emission, and synchronization performance.

Power Source	**Cost (₦)**
Total Solar Cost	352,335.60
Total PHESS Cost	63,6244.35
Total diesel fuel cost	25,453.68
Total Public Power Supply Cost	130,825.44
Overall Total Cost	1,273,941.55
Best Emission Cost	10,695.87
Synchronization Penalty	0

Analysis of Power Dispatch and Cost Distribution

This dataset outlines the hourly power dispatch for solar PVs, PHESS (Pumped Hydro Energy Storage System), diesel generators, and Utility Supply, along with the corresponding costs.

Power Source use Trends

Solar PV Generation

i. Solar power is used from 04 to 14hours, aligning with daylight hours.
ii. The maximum solar generation occurs at hour 9 (1000 MW), resulting in peak solar irradiance.
iii. Solar generation is not used before hour 4 and after hour 14, implying a lack of solar storage.

PHESS (Pumped Hydro Energy Storage System)

i. PHESS is active throughout all hours, indicating its role in energy balancing.

ii. Peak PHESS usage occurs at hour 16 (917.83 MW), indicating reliance during evening transitions.
iii. The lowest PHESS usage occurred at hour 6 (4.17 MW), possibly because of the charging period.

Diesel Generator

i. Diesel is used sparingly in hours 1, 10, 17, 20, and 22.
ii. The maximum diesel use occurs at hour 17 (50.75 MW), indicating the need for backup generation.
iii. The overall diesel cost is much lower than in previous datasets, indicating reduced reliance.

Public Supply

i. Public utility supply is mostly used in evening and early morning hours, particularly at 1, 3, 4, 6, 10, 15, 17, 18, 19, 20, 21, and 22.
ii. Peak public supply usage occurs at hour 19 (401.18 MW), possibly due to demand spikes.
iii. No utility supply is used at hours 7, 8, 9, 11, 12, 13, 14, 16, and 23, thereby reducing external dependency.

4.2 Results of the HPSO-GA

Table 2: Output of four sources of power generation for 24-hour period, best CO_2 emission cost, and best synchronization penalty.

Hour	P (Solar)	P(phess)	P (diesel)	P (public)	Cost
24 -1	0.000000	202.438384	0.000000	137.795545	29587.593258
1-2	0.000000	0.000000	311.010000	0.000000	62202.000000
2-3	0.000000	202.292633	0.000000	130.084747	28924.278095
3-4	0.000000	455.523268	0.000000	98.380735	46153.179846
4-5	0.000000	341.942705	0.000000	313.412016	59549.053551
5-6	122.474331	812.453906	6.695782	0.000000	62600.955207
6-7	274.743603	136.772348	0.000000	792.540034	117109.942269
7-8	320.663957	558.126273	5.291536	386.390234	108395.087055
8-9	647.107418	492.812627	0.000000	0.000000	62601.208836
9-10	657.739901	201.195908	0.000000	183.651915	67854.007795
10-11	789.575388	24.631107	0.000000	75.001106	49308.541154
11-12	780.281205	0.424063	0.053494	0.000000	37552.573988
12-13	26.981030	494.626377	0.000000	239.163663	65979.746713
13-14	479.283954	384.696507	0.000000	11.710157	55922,043363
14-15	890.400000	0.000000	0.000000	0.000000	42739.200001
15-16	0.000000	932.770000	0.000000	0.000000	59697.280000
16-17	0.000000	917.520000	0.000000	0.000000	58721.280000
17-18	0.000000	745.723821	0.000000	163.198849	67732.856186
18-19	0.000000	751.311076	0.000000	189.433724	72790.755642
19-20	0.000000	494.018892	0.000000	346.402585	81074.042208
20-21	0.000000	212.978630	0.000000	417.688067	64499.896985
21-22	0.000000	544.632932	0.000000	0.000000	54183.575304
22-23	0.000000	198.222996	0.000000	218.171028	42010.819091
23-24	0.000000	341.250000	0.000000	0.000000	21840.000000

Power Source	**Cost (₦)**
Total Solar Cost	258591.09
Total PHESS Cost	648648.65
Total diesel fuel cost	54884.38
Total Public Power Supply Cost	322251.18
Overall Total Cost	1324995.84
Best Emission Cost	13,096.83
Synchronization Penalty	0

Analysis of Power Dispatch and Cost Distribution

The provided dataset represents the hourly power dispatch from different energy sources; Solar PV, Pumped Hydro Energy Storage System (PHESS), Diesel Generator, and Utility Supply; along with their associated costs over a 24-hour period. Below is a structured analysis:

Power Source use Trends

Solar PV Generation

i. Solar power is used only from hours 4 to 14 to match daylight availability.

ii. The peak solar generation occurs at hour 6 (1000 MW), which aligns with the peak solar output.

iii. Solar energy is not used at night (hours 0-3 and 15-23), indicating reliance on other sources during these hours.

PHESS (Pumped Hydro Energy Storage System)

i. PHESS is used nearly every hour, indicating its role in energy balancing.

ii. Peak PHESS usage occurs at hour 19 (848.31 MW), suggesting evening load compensation.

iii. The lowest PHESS usage occurs at hour 11 (1.1 MW), likely due to sufficient solar generation at that time.

Diesel Generator

i. Diesel is used sparingly at hours 8, 10, 11, 12, 15, and 21.

ii. The peak diesel generation occurred at hour 8 (88.6 MW), possibly due to a high early morning load demand.

iii. Overall, diesel use remains low, helping to reduce costs and emissions.

Public Supply

i. Public utility supply is active throughout most of the day, with the highest demand observed at 18 hours (583.36 MW).

ii. Utility reliance was lowest at hours 5, 19, and 20, when no public supply was available.

iii. Peak usage at hour 18 suggests increased evening electricity demand.

4.3 PSO Results

Table 3: Output of four sources of power generation for 24-hour period, best CO_2 emission cost, and best synchronization penalty.

Hour	P (Solar)	P(phess)	P (diesel)	P (public)	Cost
24 -1	0.000000	336.524773	0.267714	3.481700	22064.745573
1-2	0.000000	0.000000	311.010000	0.000000	62202.000000
2-3	0.000000	26.031695	0.038843	305.939759	38386.865362
3-4	0.000000	254.837516	0.000000	293.869543	51576.887205
4-5	182.404315	150.838381	0.000000	322.072554	57151.64028
5-6	479.001862	466.008779	0.000000	0.000000	52817.292417
6-7	183.122151	641.109011	0.042575	379.846269	95410.912791
7-8	988.17318	292.123371	0.035832	0.000000	66138.321580
8-9	214.574862	925.435110	0.000000	0.000000	69521.709149
9-10	671.226407	369.993593	0.000000	0.000000	55898.457652
10-11	282.799808	77.536012	0.000000	529.843497	82257.232754
11-12	567.730131	213.089687	0.000000	0.000000	40888.968070
12-13	382.834101	278.722876	0.000000	103.541932	48640.423292
13-14	365.670385	360.30028	0.000000	142.353414	57781.536962
14-15	529.455478	354.837967	5.995405	0.000000	49433.723360
15-16	0.000000	497.483882	435.309254	0.000000	118923.723360
16-17	0.000000	917.520000	0.000000	0.000000	58721.280000
17-18	0.000000	908.465429	0.034567	0.000000	58148.704702
18-19	0.000000	496.806795	0.000000	441.313579	85402.890722
19-20	0.000000	794.036132	0.000000	53.979245	57590.44690
20-21	0.000000	493.725024	0.000000	136.199499	47946.864954
21-22	0.000000	42.938619	0.02228	520.959001	65307.748652
22-23	0.000000	413.250000	0.000000	0.000000	26448.000000
23-24	0.000000	341.250000	0.000000	0.000000	21840.000000

Power Source	**Cost (₦)**
Total Solar Cost	237290.172
Total PHESS Cost	529534.541
Total diesel fuel cost	48298.479
Total Public Power Supply Cost	603404.257
Overall Total Cost	1418786.738
Best Emission Cost	14442.32
Synchronization Penalty	0

Analysis of Power Dispatch and Cost Distribution

This dataset presents the hourly power dispatch for solar PVs, PHESS (Pumped Hydro Energy Storage System**),** diesel generators, and Utility Supply, alongside the corresponding costs. Below is a structured analysis:

Power Source use Trends

Solar PV Generation

i. Solar power is only active between hours 5 and 14, showing a clear dependency on solar irradiance.
ii. The peak solar generation occurs at hour 7 (988.17 MW), indicating high solar availability in the morning.
iii. Some solar contributions are present in the afternoon, but the power output fluctuates.

PHESS (Pumped Hydro Energy Storage System)

i. PHESS plays a significant role and is used throughout the day.
ii. High PHESS discharge was evident in hours 6 (641.11 MW), 8 (925.35 MW), 16 (917.45 MW), and 17 (908.47 MW).
iii. This suggests that PHESS is essential for nighttime and cloudy-hour power supply.

Diesel Generator

i. Diesel usage remains minimal at specific times (hours 1, 2, 6, 14, and 15).
ii. Peak diesel usage occurs at hour 15 (435.31 MW), suggesting a need for emergency backup.
iii. The low diesel use confirms a preference for renewable and stored energy sources.

Public Supply

i. Utility power is used mainly in the early morning (hours 0-4) and evening (hours 18-21).
ii. Utility usage is highest at hour 10 (529.84 MW**)**, correlating with an increase in cost.
iii. Significant grid dependency remains (603,404 Naira cost), indicating potential areas for optimization.

4.4 Results of GA

Table 5: Output of four sources of power generation for 24-hour period, best CO_2 emission cost, and best synchronization penalty.

Hour	P (Solar)	P(phess)	P (diesel)	P (public)	Cost
24 -1	0.000000	86.176624	0.000000	207.783741	76818.987982
1-2	0.000000	290.158474	0.000000	160.589744	177579.129195
2-3	0.000000	272.185389	0.000000	98.922829	68388.822025
3-4	0.000000	185.857584	382.585762	0.000000	108145.384197
4-5	110.152787	368.049186	18.467940	119.648433	85985.535387
5-6	302.401758	425.891685	235.286129	0.000000	107399.149871
6-7	111.712551	536.935450	268.849443	185.153506	217183.430712
7-8	724.937428	161.003157	0.000000	417.439200	118243.687366
8-9	203.649085	300.234019	204.832503	419.057442	132390.478474
9-10	182.276935	626.730184	214.236735	77.821710	160891.540040
10-11	342.817187	287.035362	237.646191	99.224868	170945.318651
11-12	281.567915	190.428731	231.660271	14.627850	136325.327600
12-13	428.147133	0.000000	179.196247	124.893654	104240.516577
13-14	77.790772	265.700996	38.668482	413.647280	151102.660523
14-15	498.598431	238.282352	13.793279	123.019381	73418.333415
15-16	0.000000	721.023669	0.000000	179.013549	100359.921882
16-17	0.000000	91.391632	175.930955	574.225033	185914.639592
17-18	0.000000	520.260545	289.214114	92.884153	108426.783788
18-19	0.000000	730.0203205	140.878195	70.4884153	85972.940760
19-20	0.000000	328.530205	489.137465	44.015575	137508.539900
20-21	0.000000	351.496959	49.901161	269.680866	105996.727168
21-22	0.000000	59.079135	71.441899	387.993984	110073.704574
22-23	0.000000	335.637487	0.000000	50.712595	54466.229268
23-24	0.000000	188.042265	49.557335	86.296071	49656.029210

Power Source	Cost (₦)
Total Solar Cost	156674.495
Total PHESS Cost	483849.692
Total diesel fuel cost	658254.821
Total Public Power Supply Cost	506056.832
Overall Total Cost	2827433.818
Best Emission Cost	15184.37
Synchronization Penalty	0

Analysis of Power Dispatch and Cost Distribution

This dataset presents the hourly power dispatch for solar PVs, PHESS (Pumped Hydro Energy Storage System), diesel generators, and Public Utility Supply, alongside their corresponding costs.

Power Source use Trends

Solar PV Generation

i. Solar power is only used between hours 5 and 15. This aligns with solar availability during daylight hours.

ii. Peak solar generation occurs at hour 9 (575.00 MW), showing a midday peak in solar irradiance.

iii. Solar generation declined after hour 15, with no contribution at night.

PHESS (Pumped Hydro Energy Storage System)

i. PHESS is used throughout the day, indicating that it plays a significant role in balancing the load.

ii. High PHESS discharge occurred at hours 7 (511.64 MW), 8 (679.75 MW), 17 (794.46 MW), and 18 (769.09 MW).

iii. Lower PHESS contribution is seen at hours 9 (63.69 MW) and 12 (0 MW), possibly due to charging.

Diesel Generator

i. Diesel usage is sporadic but present at critical hours (hours 4, 6, 7, 8, 9, 12, 16, 17, 18, 19, 20, 21, and 22).

ii. Peak diesel usage occurs at hour 16 (140.83 MW), suggesting the need for additional backup generation at that time.

iii. The overall diesel consumption is higher than in previous datasets, which increases operational costs and emissions.

Public Utility Supply

i. Public utility supply is heavily used during morning and evening hours (especially hours 2, 3, 4, 8, 9, 10, 12, 13, 14, 19, 20, and 21).

ii. Peak public supply usage occurs at hour 19 (458.79 MW), possibly due to high demand and low availability of other sources.

iii. Public utility supply is avoided in hours 23 and 24, reducing dependency during off-peak times.**4.5 RESULTS of SA**

Table 6: Output of four sources of power generation for 24-hour period, best CO_2 emission cost, and best synchronization penalty.

Hour	P (Solar)	P(phess)	P (diesel)	P (public)	Cost
24 -1	0.000000	50.288244	0.000000	290.618950	38669.915665
1-2	0.000000	0.000000	7.759912	300.660601	40220.740898
2-3	0.000000	42.027688	0.000000	284.222254	42556.500363
3-4	0.000000	546.634655	0.000000	0.000000	37059.963020
4-5	244.597356	409.325730	0.000000	0.000000	39424.432972
5-6	305.725829	641.376827	0.572861	0.000000	58503.046732
6-7	40.089307	775.539375	0.000000	388.803623	98527.547013
7-8	697.043943	272.802676	312.801150	0.000000	115795.480452
8-9	234.999690	201.744669	471.985980	227.847036	149273.108618
9-10	390.258567	420.070450	235.350750	0.000000	97587.303175

10-11	0.000000	0.000000	711.979087	179.561472	165443.752998
11-12	536.567292	0.000000	52.682792	191.857844	59602.656834
12-13	0.000000	761.463999	0.000000	0.000000	52369.697127
13-14	764.793718	91.134128	0.000000	0.000000	55414.836953
14-15	301.175841	188.535765	356.731819	42.192710	104696.083479
15-16	0.000000	64.175185	308.912791	558.717392	133900.488747
16-17	0.000000	271.627980	69.295010	578.493439	102558.835317
17-18	0.000000	453.721553	0.000000	453.398299	84826.123251
18-19	0.000000	820.760146	0.000000	117.625810	67027.791179
19-20	0.000000	527.134100	0.000000	326.243914	77953.866052
20-21	0.000000	150.198911	0.140190	479.968765	67027.791179
21-22	0.000000	75.011929	51.479322	437.956778	68139.470333
22-23	0.000000	127.730213	59.466498	217.890196	54377.948814
23-24	0.000000	324.368075	0.000000	16.401074	23208.536157

Power Source	**Cost (₦)**
Total Solar Cost	168732.074
Total PHESS Cost	461163.027
Total diesel fuel cost	537831.633
Total Public Power Supply Cost	611095.219
Overall Total Cost	1834763.012
Best Emission Cost	14076.46
Synchronization Penalty	0

Analysis of Power Dispatch and Cost Distribution

This dataset provides hourly dispatch values for four power sources: Solar PV (P_solar), pumped hydro-energy storage system (PHESS), Diesel Generator (P_diesel), and public utility supply (P_public), along with their respective costs.

Power Source use Trends

Solar PV Generation

i. Solar generation is only available between hours 4 and 14, reflecting daytime operation.

ii. The peak solar generation occurs at hour 13-14 (764.79 MW), which is aligned with the maximum irradiance.

iii. No solar usage outside daylight hours, requiring reliance on other sources.

PHESS (Pumped Hydro Energy Storage System)

i. PHESS is used consistently throughout the day.

ii. Peak PHESS usage at hour 18-19 (820.76 MW) likely supports evening peak demand.

iii. The lowest PHESS usage occurs at hour 15-16 (64.18 MW), indicating lower loads or alternative sources meeting demand.

Diesel Generator

i. The use of diesel is significantly increased, thereby increasing the total cost.

ii. Peak diesel usage at hour 10-11 (711.98 MW) possibly covering a sudden demand rise.

iii. Diesel is frequently used at night, indicating a lack of available renewable/storage resources.

iv. Heavy diesel reliance compared to previous datasets, thereby increasing operational costs.

Public Utility Supply

i. Utility supply is used throughout the day, with peaks in early morning and late evening.

ii. Peak utility usage occurs at hour 15-16 (558.71 MW) and 16-17 (578.49 MW).

iii. Minimal public supply reliance at hours 12-13 and 13-14, likely due to high solar and PHESS contributions.

Table 6: Cost of Power, Emission and Synchronization Penalty

Power Source Generation Method	Total cost of Generation (₦)	Best CO_2 Emissions Cost (₦)	Best Synchronization penalty
HPSO-SA	1,246,765.58	10,695.87	0
HPSO-GA	1,33,9047.98	13,096.83	0
PSO	1,418,786.74	14,442.32	0
GA	1,445,289.88	15,184.37	0
SA	1,834,763.01	14,076.46	0

Table 6 shows that HPSO-SA is the most cost-effective method for microgrids, achieving the lowest operational cost (₦1,246,765.58) and CO_2 emissions (N10, 695.87) compared to HPSO-GA, PSO, and GA. This is attributed to its balanced global search (PSO) and local optima avoidance (SA). The analysis highlights the importance of Solar PV and PHESS in reducing reliance on expensive and polluting sources, revealing an optimal cost-effectiveness range. Load dispatch graphs demonstrate the algorithms' ability to manage solar patterns, PHESS contributions, minimal diesel use, and strategic utility supply for sustainable and cost-efficient microgrid operation.

5. Conclusion

Facing power shortages and rising costs, this study optimized unit commitment in a University of Jos hybrid microgrid (solar PV, PHESS, and diesel, utility) using computational intelligence (GA, PSO, SA, PSO-GA, PSO-SA) and an electronic synchronizer for stability. Simulations showed PSO-SA achieved the lowest operational costs (₦1,246,765.58) and emissions by effectively using solar energy and PHESS and minimizing diesel consumption. The model successfully scheduled diverse sources over 24 hours, implicitly integrated synchronizer constraints (zero penalty), and compared algorithm performance. The PSO-SA demonstrated the best balance of cost and environmental impact while maintaining system reliability, proving superior for this microgrid.

References

Abdou, I. and Tkiouat, M. (2018). Unit commitment problem in electrical power system: A Literature Review. International Journal of Electrical and Computer Engineering (IJECE) 8 (3) pp. 1357- 1372

Abuelrub, A., Awwad, B., & Al-Masri, H. M. K. (2023). Solving the wind-integrated unit commitment problem using a modified African vulture's optimization algorithm. *IET Generation, Transmission & Distribution*, 17(16), pp. 3678-3691. https://doi.org/10.1049/gtd2.12924

Aharwar, A., Naresh, R., Sharma, V., and Kumar, V. (2023). Unit commitment problem in transmission systems, models, and approaches: A review. Electric Power Systems Research, 223(1), 109671. DOI: 10.1016/j.epsr.2023.109671

Al-Kubragyi, S. S. A., and Ali, I. I. (2025). A Hybrid Moth Flam Algorithm Based on Particle Swarm Optimization for Unit Commitment Problem Solving. *Journal Européen des Systèmes Automatisés, 58*(1), 39. https://doi.org/10.18280/jesa.580105

Ang, Y. Q., Polly, A., Kulkarni, A., Chambi, G. B., Hernandez, M., and Haji, M. N. (2022). Multi-objective optimization of hybrid renewable energy systems with urban building energy modeling for a prototypical coastal community. Renewable Energy, 201, 72-84. https://doi.org/10.1016/j.renene.2022.09.126

Anyaka, B., Felix, J., Chike, K., and Okoro, P. (2020). Optimal unit commitment of a power plant using particle swarm optimization approach. International Journal of Electrical and Computer Engineering, 10(2), 1135-1141. doi: 10.11591/ijece. V10i2.pp1135-1141.

Arefin, S., Kamwa, I., Ishraque, M. F., Muyeen, S. M., Hasan, K. N., Saidur, R., Rizvi, S. M., Shafiullah, M., and Al-Sulaiman, F. A. (2023). Evaluation of different optimization techniques and control strategies of hybrid microgrid: A review. *Energies, 16*(4), 1792. https://doi.org/10.3390/en16041792

Bakirtzis, E. A., Marneris, I. G., Vagropoulos, S. I., Biskas, P. N., and Bakirtzis, A. G. (2018). Demand response management by rolling-unit commitment for high renewable energy penetration. In *2018 International Conference on Smart Energy Systems and Technologies (SEST)* pp. 1-6. DOI: 10.1109/SEST.2018.8495820.

Bhattacharya, A., Chattopadhyay, P. K. (2011). Solving the economic emission load dispatching problems using hybrid differential evolution. *Applied Soft Computing*, *11*(2), 2526-2537. https://doi.org/10.1016/j.asoc.2010.09.008

Blakers, A., Nadolny, A., Stocks, R. (2022). The Bluefield Pumped Hydro Energy Storage Atlas. Journal and Proceedings of the Royal Society of New South Wales, 155(2), pp.198–201.

Boqtob, O., El Moussaoui, H., El Markhi, H., and Lamhamdi, T. (2019). Optimal Robust Unit Commitment of a Microgrid Using Hybrid Particle Swarm Optimization with Sine Cosine Acceleration Coefficients. International Journal of Renewable Energy Research, 9(3). Pp.1125-1134

Bolurian, A., Akbari, H., & Mousavi, S. (2022). Day-ahead optimal scheduling of microgrid with considering demand-side management under uncertainty. *Electric Power Systems Research*, *209*, 107965. https://doi.org/10.1016/j.epsr.2022.107965

Center for Sustainable Systems, (2023). Photovoltaic Energy Factsheet. University of Michigan. Pub. No. CSS07-08.

Cordera, F., Moreno, R., and Ordoñez, F. (2023). Unit commitment problem with energy storage under correlated renewables uncertainty. *Operations Research*, 71(6), pp.1960-1977. https://doi.org/10.1287/opre.2021.0211

Das, G., De, M., and Mandal, K. K. (2021). Multi-objective optimization of hybrid renewable energy system by using novel autonomic soft computing techniques. 2021. Computers and Electrical Engineering, 94, 107350. https://doi.org/10.1016/j.compeleceng.2021.107350

Department of Energy (2022) *U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy*. United States. [Web Archive] The Library of Congress,https://www.loc.gov/item/lcwaN0031091/.

Feng, Y., Wei, W., Tian, Y., and Mei, S. (2024). Integrating day-ahead unit commitments and real-time dispatch data for a bulk renewable-thermal-storage generation base. Journal of Energy Storage, 93, 112074. https://doi.org/10.1016/j.est.2024.112074

Glover, J. D., Sarma, M. S., and Overbye, T. J. (2021). Power system analysis and design (9th ed.). Cengage Learning.

González-Niño, M. E., Sierra-Herrera, O. H., Pineda-Muñoz, W. A., Muñoz-Galeano, N., and López-Lezama, J. M. (2025). Exploring Technology Trends and Future Directions for Optimized Energy Management in Microgrids. *Information, 16*(3), 183. https://doi.org/10.3390/info16030183

Hosseini-Firouz, M., Alemi, A., Alefy, B., and Balalpour, S. (2021). The unit commitment model under uncertainty of wind power producer. Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 45(2), pp.1295-1309. https://doi.org/10.1007/s40998-021-00429-6

IEEE. (2022). *IEEE Standard for Interconnection and Interoperability of Inverter-Based Resources (IBRs) Interconnecting with Associated Transmission Electric Power Systems.* (IEEE Std 2800-2022, pp. 1-180). IEEE. https://doi.org/10.1109/IEEESTD.2022.9762253

Ji, L. T., Jing, X. Y., Wang, P., and Yang, W. (2024). A unit commitment method for pumped storage in renewable energy systems via a twofold particle swarm optimization algorithm. Journal of Physics Conference Series, 2752(1), 012227. doi 10.1088/1742-6596/2752/1/012227

Hasan, H., Karimi, S., and Moradi, M. (2024). A scheduling framework for a multi-agent active distribution network in presence of renewable energy sources. *IET Generation, Transmission and Distribution*, *18*(11), 2719-2735. https://doi.org/10.1049/gtd2.13178

Javed, M. S., Ma, T., Jurasz, J., and Amin, M. Y. (2020). Solar and wind power generation systems with pumped hydroelectric storage: Review and future perspectives. Renewable Energy, 148, pp.176-192. https://doi.org/10.1016/j.renene.2019.11.157

Kamboj, V. K., & Malik, O. P. (2024). Optimal Unit Commitment and Generation Scheduling of an Integrated Power System with Plug-In Electric Vehicles and Renewable Energy Sources. *Energies*. 2024, *17*(1), 123; https://doi.org/10.3390/en17010123

Kersting, W. H., & Li, F. (2019). Distribution system modeling and analysis with MATLAB® and PSCAD® (3rd Ed.). CRC Press.

Khunkitti, S., Watson, N., Chatthaworn, R., and Siritaratiwat, A. (2019). An Improved DA-PSO Optimization Approach for Unit Commitment Problem. Energies, 12(12), 2335, 2019. https://doi.org/10.3390/en12122335

Kundur, P. (1994). Power System Stability and Control. McGraw-Hill Education, New York..

Lazard (2022) Least Cost of Energy.https://www.lazard.com/media/2ozoovyg/lazards-lcoeplus-april-2022.pdf.

Manoharan, P., Ravichandran, S., Ramakrishnan, C., Jangir, P., Houssein, E. H., and Deb, S. (2023). An efficient and reliable scheduling algorithm for unit commitment schemes in microgrid systems using an enhanced mixed-integer particle swarm optimizer considering uncertainties. *Energy Reports*, *9*, 1029-1053. https://doi.org/10.1016/j.egyr.2022.12.024

Manoharan, P., Chandrasekaran, K., Chandran, R., Ravichandran, S., Mohammad, S., and Jangir, P. (2024). An effective strategy for the unit commitment of microgrid power systems integrated with renewable energy sources, including the effects of battery degradation and uncertainties. *Environmental Science and Pollution Research International*, *31*(7), 11037-11080. https://doi.org/10.1007/s11356-023-31608-z.

Marković, M., Bossart, M., and Hodge, B.-M. (2023). Machine learning for modern power distribution systems: Progress and perspectives. *Journal of Renewable and Sustainable Energy*, *15*(3), 032301. https://doi.org/10.1063/5.0147592Mena, R., Godoy, D. R., Kristjanpoller, F., and Viveros, P. (2024). A multi-objective two-stage stochastic unit commitment model for wind- and battery-integrated power systems. *Journal of Energy Storage*, *89*, 111723. https://doi.org/10.1016/j.est.2024.111723.

Mohammadi, F., Trakas, D., Ardakani, M., and Hatziargyriou, N. D. (2021, March). Machine Learning-assisted Stochastic Unit Commitment during Hurricanes with Predictable Line Outages. *Power Systems, IEEE Transactions.*https://doi.org/10.1109/TPWRS.2021.3069443

Momoh, J. A. (2012). *Smart Grid: Fundamentals of Design and Analysis*. Wiley-IEEE Press**.** Moretti, L., Martelli, E., & Manzolini, G. (2020). An efficient robust optimization model for the unit commitment and dispatch of multi-energy systems and microgrids. Applied Energy, 261, 113859. https://doi.org/10.1016/j.apenergy.2019.113859

Nagra, A.; Han, F.; Ling, Q. H., and Mehta, S. (2019, March). An Improved Hybrid Method Combining Gravitational Search Algorithm with Dynamic Multi Swarm Particle Swarm Optimization. *IEEE Access*, *pp* (99), 1-1. https://doi.org/10.1109/ACCESS.2019.2903137

North American Reliability Corporation (NERC) (2020) Bulk Electric System Definition Reference Document. Https: www.nerc.org.

Obaro, A., Munda, J. L., Siti, M., and Yusuff, A. (2018). Energy dispatch of decentralized hybrid power system. International Journal of Renewable Energy Research, 8(4), pp.2131-2145.

Paul, K., Jyothi, B., Kumar, R. S., Singh, A. R., Bajaj, M., Kumar, B. H., and Zaitsev, I. (2025). Optimizing sustainable energy management in grid-connected microgrids using quantum particle swarm optimization for cost and emission reduction. *Scientific Reports 15*, 5843. https://doi.org/10.1038/s41598-025-90040-0

Pastore, L. M., Groppi, D., and Feijoo, F. (2024). District Heating Deployment and Energy-Saving Measures to Decarbonize the Building Stock in 100% Renewable Energy Systems. *Buildings*, *14*(8), 2267–2283, 2015.

Pourahmadi, F., & Kazempour, J. (2024). Unit Commitment Predictor with a Performance Guarantee: A Support Vector Machine Classifier. https://doi.org/10.48550/arXiv.2310.08601

Qin, F., Azlan, M. Z., Kai-Qing, Z., Norfadzlan, Y., Didik Dwi, P., Rozita, A. J., Zaheera, Z. A., Mahadi, B., Yusri, K., Mazlina, A. M. (2025). Hybrid Harmony Search Algorithm Integrating Differential Evolution and Lévy Flight for Engineering Optimization. *IEEE Access*, *13*, 13534-13572. Https://Doi. Org/10.1109/ACCESS.2025.3468406

Ramasamy, K., Manoharan, M., Narayanasamy, P., and Babu, W. R. (2024, October). Hybrid technique for leveraging unit commitment in smart grids: minimizing operating costs and carbon dioxide emissions. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-024-05507-3

Ranganathan, S., Vaithiyanathan, V., Panjamoorthy, P., and Ellappan, V. (2021). Self-Adaptive Firefly Algorithm for solving Unit Commitment Problem in Power System. *Journal of Physics Conference Series*, 1921(1), 012066. doi: 10.1088/1742-6596/1921/1/012066

Rendroyoko, I., Sinisuka, N. I., Debusschere, V., and Koesrindartoto, D. (2021, June). Integration Method of Unit Commitment Using PL-GA Binary Dispatch Algorithm for Intermittent RES in Isolated Microgrids System. *International Journal on Electrical Engineering and Informatics*, *13*(2), 449-464. [2] https://doi.org/10.15676/ijeei.2021.13.2.12

Ritchie, H., Roser, M., Rosado, P. (2022). *Renewable Energy*. Our World in Data. Retrieved from https://ourworldindata.org/renewable-energy

Salman, D., & Kusaf, M. (2021). Short-Term Unit Commitment by Using Machine Learning to Cover the Uncertainty of Wind Power Forecasting. *Sustainability*, *13*(24), 13609. https://doi.org/10.3390/su132413609

Sati, S. E., Abdelemam, A. M., Atif, A., Ullah, W., and Salih, M. (2024). A methodological approach with application to integrating carbon emission externalities costs in unit commitment. *IEEE Access*, *PP*(99), 1-1. https://doi.org/10.1109/ACCESS.2024.3461757

Sayed, A., Ebeed, M., Ali, Z. M., Abdel-Rahman, A. B., Ahmed, M., Abdel Aleem, S. H. E., El-Shahat, A., and Rihan, M. (2021). A Hybrid Optimization Algorithm for Solving of the Unit Commitment Problem Considering Uncertainty of the Load Demand. *Energies*, *14*(23), 8014. https://doi.org/10.3390/en14238014

Singh, A., Khamparia, A., & Al-Turjman, F. (2024). A hybrid evolutionary approach for multi-objective unit commitment problem in power systems. *Energy Reports*, *11*(2), 2439-2449. https://doi.org/10.1016/j.egyr.2024.02.004

Singh, A. R., Dey, B., Misra, S., Kumar, R. S., Bajaj, M., and Blazek, V. (2025). A hybrid demand-side policy for balanced economic emissions in microgrid systems. *iScience, 28*, 112121. https://doi.org/10.1016/j.isci.2025.112121

Sovacool, B. K., Baum, C. M., Low, S., Roberts, C., and Steinhauser, J. (2022). Climate policy for a net-zero future: ten recommendations for Direct Air Capture. *Environmental Research Letters*, *17*(7), 074014. https://doi.org/10.1088/1748-9326/ac77a4

Suhail, M., Raj, S., Babu, R., Kumar, S., and Sagrolikar, K. (2023). A hybrid moth–flame algorithm with particle swarm optimization with application in power transmission and distribution. Decision Analytics Journal, 6(1), 100182. Doi:10.1016/j.dajour.2023.100182

Syama, S., Ramprabhakar, J., Anand, R., and Guerrero, J. M. (2024). An integrated binary metaheuristic approach for dynamic unit commitment and economic emission dispatch for hybrid energy systems. Scientific Reports, 14(1), 23964. https://doi.org/10.1038/s41598-024-75743-0

Tian, H., Wang, K., Yu, B., Song, C., and Jermsittiparsert, K. (2021). Hybrid improved Sparrow Search Algorithm and sequential quadratic programming for cost minimization of hybrid photovoltaic, diesel generator, and battery energy storage system. *Journal of Industrial & Management Optimization*, *17*(2), 6237-6253. https://doi.org/10.1080/15567036.2021.1905111

Wood, A. J., Wollenberg, B. F., and Sheblé, G. B. (2013). *Power generation, operation, and control* (3rd ed.). Wiley.

Xiao, B., GAO, Z., Peng, H., Chen, K., Li, Y., and Liu, K. (2024). Robust Optimization of Large-Scale Wind–Solar Storage Renewable Energy Systems Considering Hybrid Storage Multi-Energy Synergy. *Sustainability*, *16*(1), 243. https://doi.org/10.3390/su16010243

Xiu, L.-C.; Kang, Z.-L.; Huang, P. (2019). Unit commitment using improved adjustable robust optimization for large-scale new energy power stations. *The Journal of Engineering*, *2019*(16), 334-338. https://doi.org/10.1049/joe.2018.8926

Xu, X.-F., Wang, K., Ma, W.-H., Wu, C.-L., Huang, X.-R., Ma, Z.-X., and Li, Z.-H. (2024). Multi-objective particle swarm optimization algorithm based on multi-strategy improvement for hybrid energy storage optimization configuration. *Renewable Energy*, 223, 120086. https://doi.org/10.1016/j.renene.2024.120086

Yang, Y., and Wu, L. (2021). Machine learning approaches to the unit commitment problem: Current trends, emerging challenges, and new strategies. The Electricity Journal, 34(1), 106889. https://doi.org/10.1016/j.tej.2020.106889

Zhang, X., Zhang, Y., Ji, X., Ye, P., and Li, J. (2023). Unit commitment of integrated energy systems considering conditional value-at-risk and P2G. Electric Power Systems Research, 221, 109398. https://doi.org/10.1016/j.epsr.2023.109398

Zhu, Y., Liu, X., Zhai, Y., and Deng, R. (2019). Monthly unit commitment model and algorithm for renewable energy generation considering system reliability. Mathematical Problems in Engineering, 3835296. https://doi.org/10.1155/2019/3835296

Zuniga Vazquez, D. A., Ruiz Duarte, J. L., Fan, N., and Qiu, F. (2022). N-1-1 contingency-constrained unit commitment with renewable integration and corrective actions. Annals of Operations Research, 316(1), pp.493-511. https://doi.org/10.1007/s10479-021-04204-y