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Article

An Intelligent Artificial Neural Network-Adaptive Particle Swarm Optimization Framework for Optimal Energy Management of Grid-Connected Renewable Energy Microgrids

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Abstract: The increasing integration of renewable energy resources into electrical power systems has intensified the need for intelligent energy management strategies capable of addressing the variability of photovoltaic generation and electricity demand. This paper presents a hybrid Artificial Neural Network–Adaptive Particle Swarm Optimization (ANN–APSO) framework for optimal energy management of a grid-connected renewable energy microgrid. Historical household electricity demand data were preprocessed and transformed into temporal and statistical features for short-term load forecasting using an Artificial Neural Network. The forecasted demand profile was subsequently utilized by an Adaptive Particle Swarm Optimization algorithm to optimize battery charging and discharging schedules while satisfying power balance and battery State-of-Charge constraints. The proposed framework was implemented in Python and evaluated using forecasting accuracy, operating cost, renewable energy utilization, and grid energy import. The selected ANN architecture achieved superior forecasting performance compared with the persistence benchmark, while the APSO algorithm outperformed conventional Particle Swarm Optimization and a rule-based energy management strategy by reducing grid energy import, improving renewable energy utilization, and producing the lowest average operating cost under the simulated operating conditions. These results demonstrate that integrating predictive load forecasting with adaptive optimization provides an effective and practical approach for intelligent energy management of grid-connected renewable energy microgrids. The proposed framework offers a scalable solution for future smart-grid applications and distributed renewable energy systems.

Keywords: Artificial Neural Network, Adaptive Particle Swarm Optimization, Renewable Energy, Microgrid, Battery Energy Storage System, Load Forecasting, Energy Management.

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1. Introduction

The increasing deployment of renewable energy resources has accelerated the transition toward cleaner and more sustainable electrical power systems. Among these resources, photovoltaic (PV)-based microgrids have emerged as an effective solution for improving energy security, reducing greenhouse gas emissions, and supporting decentralized electricity generation [1][2].

However, the intermittent nature of renewable energy and the time-varying characteristics of electricity demand introduce significant operational challenges that require intelligent energy management strategies. Efficient coordination of PV generation, battery energy storage systems (BESS), and utility-grid interaction is therefore essential for ensuring reliable and economical microgrid operation[3][4].

Conventional energy management systems commonly employ fixed rule-based strategies or optimization algorithms that react to current operating conditions without considering future electricity demand[5][6] Such approaches may result in inefficient battery scheduling, increased grid-energy import, underutilization of renewable energy, and higher operating costs. Similarly, while Artificial Neural Networks (ANNs) have demonstrated strong capability in short-term load forecasting and Particle Swarm Optimization (PSO) has been widely applied to microgrid optimization[7][8][9][10] many existing studies consider these techniques independently rather than integrating predictive forecasting with adaptive operational decision-making[11] The dissertation identifies limited integration of causal ANN forecasting with constrained battery scheduling, insufficient comparison against benchmark methods, and the need for simultaneous evaluation of technical and economic performance as key research gaps. This paper proposes an intelligent Artificial Neural Network–Adaptive Particle Swarm Optimization (ANN–APSO) framework for optimal energy management of a grid-connected renewable-energy microgrid. Historical household electricity consumption data are preprocessed to generate causal temporal, lagged, and rolling statistical features for ANN-based short-term load forecasting. The forecasted load is then supplied to an Adaptive Particle Swarm Optimization (APSO) algorithm that determines optimal battery charging and discharging schedules while satisfying power-balance and battery State-of-Charge constraints. The complete framework is implemented in Python and integrates forecasting, optimization, and comparative performance evaluation within a single reproducible workflow.

The proposed framework is evaluated by comparing its performance with persistence forecasting, conventional PSO, and a rule-based energy-management strategy. Performance is assessed using forecasting accuracy, operating cost, renewable-energy utilization, grid-energy import, battery constraint compliance, optimization convergence, multi-day validation, and sensitivity analysis. The objective is to demonstrate that combining predictive artificial intelligence with adaptive optimization provides a more effective and practical approach for intelligent renewable-energy microgrid management.

1.1 Related Work

A. Microgrid Energy Management

Renewable-energy microgrids have become an important component of modern electrical power systems because they facilitate the integration of distributed energy resources, battery energy storage systems (BESS), and intelligent control technologies[12]. Effective microgrid operation requires an Energy Management System (EMS) capable of coordinating power generation, storage, and load demand while maintaining system reliability and minimizing operating costs. Recent studies have shown that conventional rule-based EMS approaches are simple to implement but often lack the adaptability required to respond efficiently to the variability of renewable-energy generation and dynamic electricity demand. Consequently, intelligent energy-management strategies have become an active area of research for improving operational efficiency and renewable-energy utilization.

B. Artificial Neural Networks for Load Forecasting

Artificial Neural Networks (ANNs) have been widely applied to short-term electrical load forecasting because of their ability to learn complex nonlinear relationships from historical data. ANN-based forecasting has demonstrated improved prediction accuracy compared with conventional statistical methods, making it suitable for microgrid applications where accurate demand prediction supports operational planning. However, many published studies employ ANN solely as a forecasting tool without directly integrating forecast information into the optimization of battery scheduling or energy-management decisions. In the framework proposed in this study, the ANN provides short-term load forecasts using causal temporal, lagged, and rolling statistical features, thereby supplying predictive information for subsequent optimization.

C. Particle Swarm Optimization for Battery Scheduling Particle Swarm Optimization (PSO)

Particle Swarm Optimization for Battery Scheduling Particle Swarm Optimization (PSO) has become one of the most widely used metaheuristic algorithms for solving nonlinear optimization problems in renewable-energy systems [13]. It has been successfully applied to economic dispatch, battery scheduling, and distributed energy-resource coordination because of its relatively simple implementation and effective global search capability. Nevertheless, conventional PSO employs fixed search parameters that may reduce optimization performance by causing premature convergence or slow adaptation under dynamic operating conditions. Adaptive Particle Swarm Optimization (APSO) addresses these limitations by dynamically modifying swarm parameters throughout the optimization process, thereby improving the balance between global exploration and local exploitation and enhancing optimization robustness.

D. Hybrid ANN–APSO Approaches and Research Gap

Recent studies indicate that combining machine-learning techniques with optimization algorithms can improve intelligent microgrid operation by linking prediction with operational decision-making.[14] Hybrid approaches integrate ANN-based forecasting with optimization to support proactive rather than reactive energy management.[15]

However, the literature reviewed in this study identifies several important gaps. These include limited integration of causal ANN load forecasting with constrained battery scheduling in a single reproducible workflow, insufficient comparison of APSO with both conventional PSO and rule-based energy-management systems under identical operating conditions, limited use of persistence forecasting as a transparent benchmark, inadequate reporting of optimization robustness through repeated and multi-day evaluations, and insufficient simultaneous evaluation of technical and economic performance indicators. In addition, relatively few studies investigate the sensitivity of intelligent energy-management frameworks to variations in photovoltaic capacity, battery size, tariff structure, cycling cost, and optimizer configuration.

To address these limitations, this study develops a Python-based ANN–APSO framework that integrates short-term load forecasting with adaptive battery scheduling for a grid-connected photovoltaic microgrid. The framework evaluates forecasting accuracy, optimization performance, operating cost, grid-energy import, renewable-energy utilization, battery constraint compliance, multi-day performance, and sensitivity under a unified computational workflow. This alignment between the literature review, methodology, and experimental evaluation provides the basis for the proposed contribution to intelligent renewable-energy microgrid management.

2. Materials and Methods

2.1 System Architecture

The proposed intelligent energy-management framework was developed for a grid-connected photovoltaic (PV) microgrid comprising a photovoltaic generation unit, Battery Energy Storage System (BESS), utility-grid connection, residential electrical load, and an intelligent Energy Management System (EMS). The EMS coordinates energy exchange among the PV system, battery storage, and the utility grid to ensure reliable electricity supply while minimizing operating cost and maximizing renewable-energy utilization. The overall system architecture used in this study is presented in Figure 1.

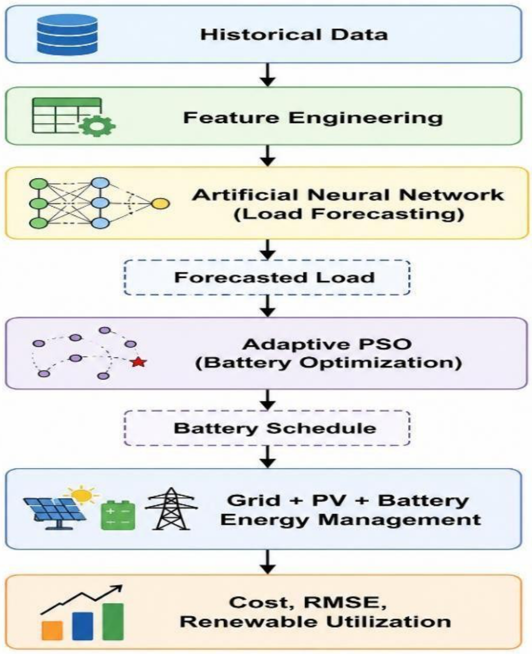

Figure 1. The Overall System Architecture

2.2 Data Acquisition and Pre-processing

Historical household electricity-consumption data were used to develop the forecasting model. Prior to model development, the dataset was cleaned, normalized, and transformed through feature engineering to improve predictive performance. Temporal variables, lagged load values, and rolling statistical features were generated to capture the nonlinear behaviour of electricity demand. The processed dataset was subsequently divided into training, validation, and testing subsets for ANN model development.

2.3 Artificial Neural Network Load Forecasting

A feedforward Artificial Neural Network (ANN) was developed to perform short-term electrical load forecasting. The network receives engineered input features and estimates the corresponding future electrical demand. The architecture consists of an input layer, multiple hidden layers, and a single output neuron representing the forecasted load.

The ANN output is expressed as

$$y^{\wedge} = f(x, \theta)$$

where:

$y^{\wedge}$ represents the predicted electrical load,

x denotes the engineered input feature vector,

θ represents the trained ANN parameters,

$(\cdot)$ denotes the nonlinear mapping learned during training. The predicted load profile serves as the primary input to the optimization stage.

2.4 Adaptive Particle Swarm Optimization

The forecasted electrical demand obtained from the ANN is supplied to the Adaptive Particle Swarm Optimization (APSO) algorithm to determine the optimal battery charging and discharging schedule.

Unlike conventional PSO, APSO dynamically updates its optimization parameters throughout the search process to improve convergence behaviour and avoid premature convergence.

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (pi - x_i^k) + c_2 r_2 (g - x_i^k)$$

while the particle position is updated as

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

where w is the adaptive inertia weight, c_1 and c_2 are adaptive acceleration coefficients, r_1 and r_2 are uniformly distributed random numbers, pi is the particle's best position, and g is the global best position. These equations correspond to the APSO methodology described in your dissertation.

2.5 Battery Energy Storage Model

Battery scheduling was constrained using the State-of-Charge (SOC) model to ensure technically feasible operation. The battery SOC is updated as

$$SOC_{t+1} = SOC_t + \frac{\eta_c P_c - \frac{P_d}{\eta_d}}{E_{bat}} \Delta t$$

where:

SOC_{t+1} is the battery State of Charge at time t,

PC and Pd represent charging and discharging power,

η_c and η_d denote charging and discharging efficiencies,

E_{bat} is the battery capacity.

Battery operation is restricted within predefined minimum and maximum SOC limits.

2.6 Optimization Objective

The objective of the optimization process is to minimize the daily operating cost while satisfying power-balance and battery operational constraints.

The objective function is expressed as

$$\min J = \sum_{t=1}^{T} C_t P_{grid,t} \Delta t$$

where:

C_t is the electricity tariff,

P_{grid}, is the grid-import power,

T represents the scheduling horizon.

2.7 Performance Evaluation

The forecasting model was evaluated using:

i. Mean Absolute Error (MAE),
ii. Root Mean Square Error (RMSE),
iii. Mean Absolute Percentage Error (MAPE),
iv. Symmetric Mean Absolute Percentage Error (sMAPE),
v. Coefficient of Determination $R2$.

The optimization framework was assessed using:

i. Daily operating cost,
ii. Grid-energy import,
iii. Renewable-energy utilization,
iv. Battery constraint compliance,
v. Optimization convergence,
vi. Multi-day validation,

vii. Sensitivity analysis.

3. Results

3.1 ANN Load Forecasting Performance

The proposed Artificial Neural Network (ANN) model was evaluated using a chronological train–validation–test split after preprocessing 2,075,259 minute-level household electricity records into 34,022 hourly observations through resampling and causal feature engineering. The selected ANN architecture consisted of three hidden layers with 64, 32, and 16 neurons, respectively. This configuration provided the best balance between forecasting accuracy and model complexity among the evaluated architectures.

On the test dataset, the ANN achieved a Mean Absolute Error (MAE) of 0.3283 kW, a Root Mean Square Error (RMSE) of 0.4747 kW, and a coefficient of determination (R^2) of 0.5520. Although the Mean Absolute Percentage Error (MAPE) remained relatively high because of small household-load values, the combined MAE, RMSE, R^2, and sMAPE metrics demonstrate that the proposed model provides a reliable basis for short-term microgrid load forecasting.

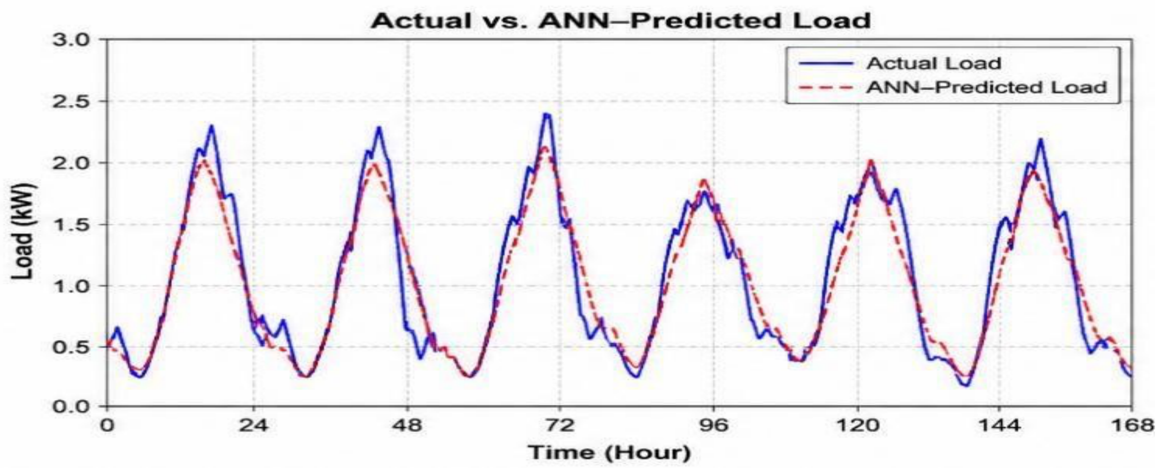

Figure 2. Actual versus ANN-predicted load

Table 1. ANN Forecasting Performance

Metric	Value
MAE (kW)	0.3283
RMSE (kW)	0.4747
MAPE (%)	41.88
R^2	0.5520

3.2 Comparison with Persistence Forecasting

To assess the effectiveness of the forecasting model, the ANN was compared with a persistence forecasting benchmark. The persistence model produced an RMSE of 0.5846 kW and an R^2 of 0.3206, whereas the proposed ANN reduced RMSE by approximately 18.8% while providing a substantially higher coefficient of determination. These results indicate that the ANN successfully extracted useful nonlinear relationships from historical load patterns and engineered temporal features, thereby improving forecasting accuracy over a simple baseline approach.

3.3 APSO Optimization Performance

The forecasted load profile generated by the ANN was subsequently used as input to the Adaptive Particle Swarm Optimization (APSO) algorithm for battery scheduling. The initial 24-hour optimization experiment verified the effectiveness of the integrated ANN–APSO framework. Compared with the rule-based Energy Management System (EMS), the proposed approach reduced the adjusted daily operating cost from ₦1,487.66/day to ₦1,479.90/day, representing an improvement of approximately 0.52%. In addition, renewable-energy utilization increased from 93.79% to 99.41%, indicating more effective coordination between photovoltaic generation, battery storage, and grid interaction.

3.4 Multi-Day Comparative Evaluation

A multi-day validation study was performed to compare APSO, conventional PSO, and a rule-based EMS. The results demonstrated that APSO achieved the lowest mean operating cost, lowest grid-energy import, and highest renewable-energy utilization among the evaluated methods.

Table 2. Multi-Day Optimization Performance

Method	Mean Cost (₦/day)	Grid Import (kWh/day)	Renewable Utilization (%)
Rule-Based EMS	1260.99	10.27	77.43
Conventional PSO	1267.63	10.03	79.36
Adaptive PSO	1256.63	9.85	82.44

Relative to the rule-based EMS, APSO reduced average grid-energy import by approximately 4.1% and increased renewable-energy utilization by 5.01 percentage points. The economic improvement in operating cost was modest but consistent with the optimization objective and operating assumptions adopted in the study.

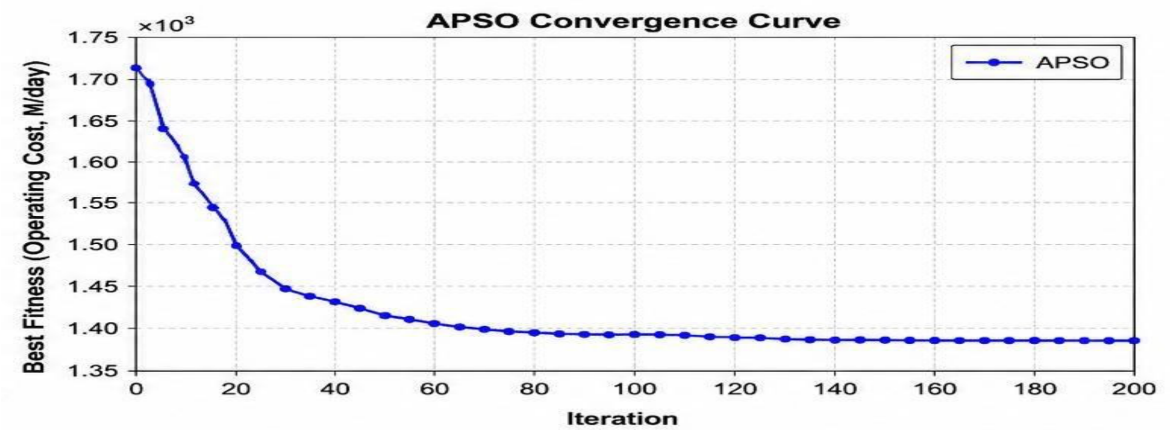

Figure 3. APSO Convergence Curve

4. Discussion

The results demonstrate that integrating predictive load forecasting with adaptive optimization provides measurable improvements in renewable-energy microgrid operation. The ANN produced more accurate short-term demand estimates than the persistence benchmark, enabling the optimization algorithm to make better battery scheduling decisions. APSO further improved optimization performance by dynamically adjusting swarm parameters during the search process, resulting in better convergence behaviour and reduced dependence on utility-grid electricity.

An important observation from the sensitivity analysis is that the economic benefit of intelligent battery scheduling depends strongly on system design and operating conditions. Battery capacity, photovoltaic capacity, electricity tariff assumptions, and battery cycling cost all influenced the magnitude of the optimization benefit. Consequently, the principal contribution of the proposed framework is not only the reduction in operating cost but also its ability to improve renewable-energy utilization and reduce grid dependency while maintaining battery operational constraints. These findings support the application of predictive artificial intelligence and adaptive optimization for intelligent renewable-energy microgrid management.

5. Conclusion

This paper presented an intelligent Artificial Neural Network–Adaptive Particle Swarm Optimization (ANN–APSO) framework for optimal energy management of a grid-connected renewable-energy microgrid. The proposed framework integrated ANN-based short-term load forecasting with APSO-based battery scheduling to improve the coordination of photovoltaic generation, battery energy storage, and utility-grid interaction. Historical household electricity-consumption data were preprocessed and transformed into causal temporal and statistical features for load forecasting, while the forecasted demand profile was used by the APSO algorithm to optimize battery charging and discharging under operational constraints.The results demonstrated that the selected ANN architecture achieved improved forecasting performance compared with the persistence benchmark, providing more reliable predictive information for energy-management decisions. Furthermore, APSO outperformed both conventional Particle Swarm Optimization and the rule-based energy-management strategy by achieving the best overall multi-day performance in terms of operating cost, grid-energy import, and renewable-energy utilization. Although the economic improvement varied under different operating assumptions, the most consistent benefits of the proposed framework were enhanced renewable-energy utilization and reduced dependence on utility-grid electricity. Sensitivity analysis further showed that the effectiveness of intelligent battery scheduling is strongly influenced by photovoltaic capacity, battery size, electricity tariff structure, and battery cycling cost.Overall, the proposed ANN–APSO framework provides a practical computational approach for predictive energy management in renewable-energy microgrids by combining machine-learning-based forecasting with adaptive optimization. The framework offers a reproducible foundation for future intelligent microgrid applications. Future work should focus on real-time implementation, hardware validation, and the integration of additional distributed energy resources and advanced forecasting techniques to further improve operational performance.

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