Research Article

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Optimized Energy Management in Renewable Energy Integrated Microgrids Using Pyramidal Dilation Attention Convolutional Neural Networks

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ABSTRACT

The use of Diesel Generators (DGs) as a form of backup puts a stress on the operational cost because of the fuel costs and the levels of maintenance. Furthermore, during periods when demand is high, or renewable supplies are low, system efficiency could reduce overall, meaning greater reliance on less efficient supplies and ultimately greater total loss, particularly where battery storage may not be effectively sized to match demand. To overcome these drawbacks, this manuscript proposes an approach for optimizing the Energy Management System (EMS) in Microgrid (MG) integrated with Renewable Energy Sources (RESs). The proposed method is Pyramidal Dilation Attention Convolutional Neural Network (PDACNN). The primary objective of the proposed method is to minimize the total operational costs and improving efficiency of the system. The proposed PDACNN predicts energy generation and consumption patterns, enhancing the efficiency of the MG system incorporating RESs. Then, the proposed method is implemented in MATLAB and compared with various existing approaches like Flying Foxes Optimization-Deep Attention Dilated Residual Convolutional Neural Network (FFO-DADRCNN), Whale Optimization Algorithm and Pattern Search (WOA-PS), Improved Gradient-Based Optimization-Particle Swarm Optimization (IGBO-PSO), African Vultures Optimization Algorithm (AVOA), and Bald Eagle Search Optimizer (BESO). The proposed PDACNN method achieves an operational cost of $1,837 and an impressive efficiency of 98.7%, demonstrating that this approach significantly outperforms existing methods in both cost-effectiveness and operational efficiency, making it an optimal solution for EM in MGs integrated with RESs.

Keywords: Photovoltaic; Wind turbine; Diesel generator; Microgrid; Load; Energy management.

1. INTRODUCTION

Energy management (EM) for a microgrid (MG) incorporating renewable energy sources (RESs) such as Diesel generators (DG), photovoltaic (PV) systems, and battery storage focuses on optimizing the balance between energy generation, storage, and consumption (Sangeetha *et al.* 2018). The objective is to optimize the utilization of natural resources as well as to deliver a reliable and sustainable electrical power capacity to cover fluctuating load requirements (Francesconi *et al.* 2021). Wind and PV systems, as intermittent sources, depend on weather conditions. So, energy storage in batteries plays a crucial role in storing excess energy and supplying it when renewable energy generation is low (De and Mandal, 2022). Efficient control strategies are applied to manage power flow between these sources and the load, ensuring grid stability and reducing the need for conventional generation (Aghdam *et al.* 2025). Additionally, load management techniques are implemented to adjust consumption patterns based on energy availability, further enhancing system efficiency and reliability (Lakshmaiya *et al.* 2023). This integrated energy management approach contributes to minimizing reliance on non-renewable sources, promoting sustainability, and improving the overall performance of the MG system. Multi-source MG-integrated EM modeling and control of DG, PV, and battery storage poses some problems with cost, error, and efficiency (Tao *et al.* 2024). One of the main challenges to large-scale use of renewable energy systems and batteries is that production and installation costs remain relatively high (Zhu *et al.* 2024). Moreover, generation forecast and errors due to unpredictable nature of wind and solar proved a negative impact, where an imbalance between demand and supply results in grid instability (Torkan *et al.* 2022). Another issue is the optimal control of the flow

of energy generated, storage and consumption because renewable power is often generated, stored and distributed in easily changeable intervals (Nagarajan *et al.* 2022). Gradual discharge of battery also decreases the general capacity of storage which is a big challenge of meeting the required energy supply and efficiency in demand (Ali *et al.* 2023).

Several research studies have concentrated on optimizing EM in MGs incorporating RESs, employing a variety of techniques and methodologies. (Kumar *et al.* 2024) have suggested enhancement of EMS in a smart MG by integrating RESs like PV systems and Wind Turbines (WTs) with an Energy Storage System (ESS). The hybrid technique FFO-DADRCNN is used for predictive modelling. (Hai *et al.* 2023) developed an optimal scheduling of energy resources in a microgrid that incorporates RESs, specifically a solar PV unit, while addressing the uncertainties associated with their output. The study focused on a day-ahead scheduling paradigm that accounts for various climatic conditions affecting power generation. The method used was the WOA-PS. (Alghamdi, 2024) reported the enhancement of EM and scheduling in a microgrid by utilizing an IGBO algorithm. The approach focused on maximizing renewable energy generation while minimizing operating costs, with evaluations that include scenarios both with and without battery storage, considering energy exchange with the grid. The analysis used a representative MG that integrates both renewable and non-renewable resources. The IGBO algorithm was validated against conventional methods, including GBO-PSO. Elkholy *et al.* (2024) designed an adaptive artificial intelligence-based home EMS to enhance customer comfort and reduce operational costs within home MGs. The developed techno-economic smart HEMS utilized a Field-Programmable Gate Array (FPGA) for high-speed processing and incorporated AVOA to optimize performance and coordinate backup sources. Fathy (2023a) developed an EMS for MGs incorporating Plug-in Hybrid Electric Vehicles (PHEVs) and RESs to enhance the flexibility of the distribution network and address energy crises and environmental issues. The strategy utilized the BESO to regulate the generation of various units, including WT, PV systems, micro turbines (MT), fuel cells (FC), storage batteries, PHEVs, and grid connections. Research in EMS for MGs incorporating RESs reveals notable gaps, particularly in optimizing the integration of diverse energy generation and storage technologies. Existing methodologies, such as the FFO-DADRCNN, HWOA-PS, and IGBO algorithm, have made advancements in predictive modelling and scheduling. Additionally, the BES optimizer and AVOA have been suggested for regulating the generation of various units, including WT, PV systems, MT, FC, and storage batteries. Nevertheless, some issues in the existing renewable energy policies remain crucial to solve, in particular the fluctuations in production, and the optimization between the usage of energy sources and operation cost. Although some approaches rely on fine optimization algorithms, they seem lacking in systematically modeling the phenomena of energy exchange with the grid as well as the impact of energy storage systems. Thus, there is an urgent call for advanced approaches, which may promote higher operational performance and decrease prediction inaccuracy and operating expenses for MGs and integrate adaptable resources management successfully. The increasing demand for sustainable energy solutions highlights the critical need for efficient algorithms capable of managing all aspects of microgrids (MGs) to address energy challenges and environmental concerns. In this context, a novel approach integrating the Predictive Dual-Attention Convolutional Neural Network (PDACNN) is proposed to optimize the energy management system (EMS) in MGs with renewable energy sources (RESs). This methodology enhances energy management by accurately forecasting energy generation and consumption, thereby reducing total operational costs and improving system efficiency. By leveraging advanced modeling techniques, the PDACNN effectively captures fluctuations in renewable energy generation and user demand, ensuring better alignment between supply and demand. Extensive simulations conducted in MATLAB validate the effectiveness of the PDACNN, demonstrating significant improvements in operational costs, energy utilization, and overall system performance in managing MGs integrated with RESs.

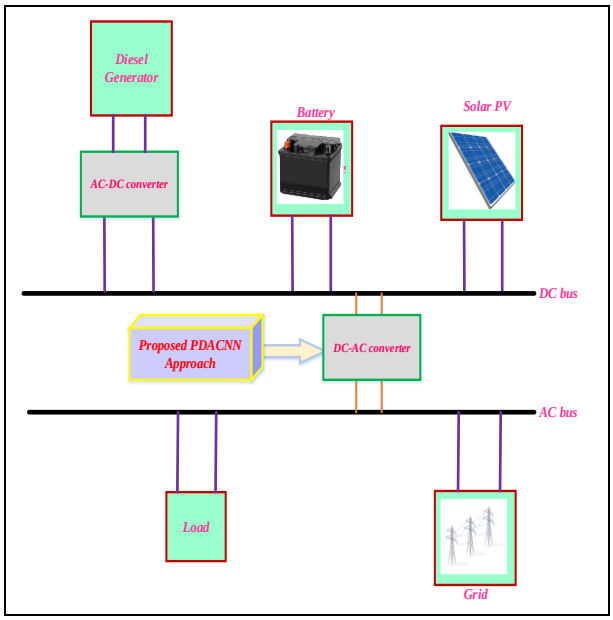


Fig. 1: Structure of EM in microgrid integrating RESs

2. CONFIGURATION OF RENEWABLE ENERGY SOURCES-INTEGRATED MICROGRID SYSTEM

The structure of EM in microgrid integrating RESs is shown in Fig. 1. It features a Diesel generator connected through an AC-DC converter, a solar PV

providing DC power directly, and a battery for energy storage. These components feed into a DC bus, managed by a proposed PDACNN control approach, which likely optimizes energy distribution. The power from the DC bus is converted to AC using a DC-AC converter for use by local loads or for feeding into the grid, ensuring efficient integration of both renewable and conventional energy sources.

2.1 Modelling of PV

A PV equivalent circuit is used to account for losses associated with load current and a shunt resistor represents leakage current (Josphineleela *et al.* 2023). Eqn (1) is the mathematical formula for the output current.

$$i_l = i_{Ph} - i_D - i_{Sh} \quad \ldots (1)$$

where, i_{Ph} indicates photo-generated current, i_D refers to diode current, i_{Sh} is shunt resistor current.

$$i_D = i_{SD}.\exp\left[\frac{Q.(v_l + r_S.i_l)}{N \cdot k \cdot T} - 1\right] \quad \ldots (2)$$

where, i_{SD} denotes reverse saturation current of diode, Q refers to electron charge, v_l refers to cell output voltage, r_S refers to series resistance, N refers to diode ideality factor, k refers to Boltzmann constant, and T denotes cell temperature in Kelvin.

$$i_{Sh} = \frac{v_l + r_S \cdot i_l}{r_{Sh}} \quad \ldots (3)$$

where, r_{Sh} refers to shunt resistance. Based on Eqns (2) and (3), Eqn (1) can transform as

$$i_l = i_{Ph} - i_{SD} \cdot \exp\left[\frac{Q.(v_l + r_S.i_l)}{N \cdot k \cdot T} - 1\right] - \frac{v_l + r_S \cdot i_l}{r_{Sh}} \quad \ldots (4)$$

2.2 AC Grid Modelling

The AC grid converter system's mathematical modelling can then be expressed as follows (Ramesh *et al.* 2022),

$$\frac{Dv_G}{DT} = \frac{i_G}{c_G} - \frac{i_{l_G}}{c_G} \quad \ldots (5)$$

$$\frac{v_G}{l_G} = \frac{Di_G}{DT} + (1-u)\frac{v_{DC}}{l_G} - d_1 \quad \ldots (6)$$

$$\frac{Dv_{DC}}{DT} = (1-u)\frac{i_{l_G}}{c_{DC}} - \frac{i_{o_G}}{c_{DC}} + d_2 \quad \ldots (7)$$

where, i_G indicates grid rectified current, v_G indicates voltage input rectified of the grid, u indicates controller signal, d_1 and d_2 indicates dynamics uncertainty in the energy stage parameters, i_{l_G} indicates current of the inductor, c_{DC} indicates DC-link capacitor.

Equation (5) represents the rate of change of voltage v_G over time and is governed by the capacitance c_G. The voltage v_G increases when the supplied current i_G is greater and decreases when the load current i_{l_G} increases. The presence of capacitance in the denominator indicates that the rate of change of voltage is inversely proportional to the capacitance meaning a higher capacitance leads to a slower voltage variation. This equation essentially describes the charging and discharging dynamics of a capacitor within the system.

Equation (6) links the generator-side voltage v_G with the rate of change of current $\frac{Di_G}{DT}$ and the applied DC voltage v_{DC}. The parameter l_G, likely an inductance, suggests that this equation captures inductive dynamics, which naturally involve the time derivative of current. The term $(1-u)\frac{v_{DC}}{l_G}$ introduces a control parameter u, which may represent a duty cycle in a switching power converter. This implies that the DC voltage contribution to v_G is modulated based on the control input u. The presence of d_1 indicates an external disturbance or loss factor that affects the system, which could stem from resistive losses, electromagnetic interference, or other environmental factors.

The equation (7) describes how the DC-side voltage v_{DC} changes over time based on input and output currents, as well as capacitance c_{DC}. The term $(1-u)\frac{i_{l_G}}{c_{DC}}$ suggests that the input current from the generator-side inductor is regulated by the control parameter u, affecting how much current contributes to charging or discharging the DC capacitor. The term $\frac{i_{l_G}}{c_{DC}}$ accounts for the output current, which drains charge from the capacitor and thereby decreases v_{DC}. Finally, the disturbance term d_2 represents additional effects such as losses, external loads, and fluctuations in supply conditions.

2.3 DG Modelling

Diesel generator is operated to serve the peak demand of the area. Fuel required (q) in order to operate DG depends upon rated power of DG and can be modelled as follows (Muthu *et al.* 2021),

q_T (T) = $\alpha_{Diesel\ Genrator}\ p_{Diesel\ Genrator}$ (T) + $\beta_{Diesel\ Genrator}\ p_{Diesel\ Genrator,\ rated}$ … (8)

Where, $p_{Diesel\ Genrator}$ denotes power yield of DG at a particular time, $p_{Diesel\ Genrator,\ rated}$ denotes rated power of DG, $\alpha_{Diesel\ Genrator}$ and $\beta_{Diesel\ Genrator}$ denotes constants of DGs.

2.4 Modeling of Battery

The majority of batteries are represented from an EM standpoint using an equivalent circuit, such as the Thevenin model, resistance-capacitance model, and internal resistance model (R_{int}). The R_{int} model can accurately represent the battery's energy consumption even though it does not adequately capture the battery's dynamic responsiveness (Wang *et al.* 2018). The model features a respectable accuracy range and a straightforward design.

The SoC_{BAT} and v_{BAT} can be calculated as follows,

$$SoC_{BAT} = SoC_0 - \frac{\int_{T_0}^{T} i_{BAT} DT}{Q_T} \quad \ldots (9)$$

where, SoC_0 is the initial State of Charge (SoC), i_{BAT} denotes internal current, Q_T is the battery capacity.

$$v_{BAT} = N_B - \left[v_0(SoC) - Ir_{BAT}(SoC)\right] \quad \ldots (10)$$

where, N_B denotes number of battery cells in series, r_{BAT} denotes equivalent internal resistance, v_{BAT} is the voltage of battery.

Based on the open circuit voltage, the battery efficiency in the discharge state is calculated as follows:

$$\eta_{BAT} = \frac{v_{BAT}}{N_B v_0(SoC)} \quad \ldots (11)$$

3. OPTIMIZING ENERGY MANAGEMENT IN MICROGRID INTEGRATED WITH RES BASED ON PDACNN TECHNIQUE

The optimization of EMS in MGs integrated with RESs is addressed in this study using the PDACNN method. The PDACNN method effectively minimizes total operational costs while optimizing energy distribution and resource utilization from PV systems, DG, and battery storage, leading to more efficient system operations and better alignment of energy supply with demand.

3.1 Pyramidal Dilation Attention Convolutional Neural Network (PDACNN)

It is an advanced neural network model used to predict energy generation and consumption patterns, enhancing the efficiency of MGs. By employing pyramidal dilation, PDACNN effectively extracts multi-scale contextual information from diverse energy data, enabling the model to handle complex patterns in energy utilization (Raj *et al.* 2020). The attention mechanism enhances the accuracy in the prediction model by directing the network towards the relevant features in energy generation and consumption greatly reducing the impact of irrelevant features (Long *et al.* 2021). This makes PDACNN applicable for delivering reliable solutions to varying energy demands in MGs, enhancing the stability and functionality of presented models while offering the possibilities to handle vast date arrays in the shortest amount of time (Chukka *et al.* 2021). The use of the forecasting model in determining energy generation and consumption is useful in efficient resource utilization and stability of MGs. For energy prediction, PDACNN becomes a strong technology guarantor for improved MG energy management and optimal energy allocation as highlighted in eqn (12).

$$M_i = m_1^1 \wedge m_2^2 \wedge m_3^4 \wedge \ldots \wedge m_i^d \quad \ldots (12)$$

where, M_i denotes the i^{th} PDC layer, $\wedge$ denotes the stacking of sub-dilated convolutional layers, and m_i^d denotes the i^{th} sub-dilated convolutional layer with dilated factor $d = 2^{i-1}$ in the i^{th} PDC layer. In such a scenario, Eqn (12) takes on a new form given by:

$$H'_i = E_{scale}(H_i, a_i) = a_i \cdot H_i \quad \ldots (13)$$

where, a_i denotes average pooling a_i^{avg} and maximum pooling $a_i^{\max}$, $E_{scale}(H_i, a_i)$ denotes the spectral wise multiplication of the scalar and the feature map H_i.

Initially, global average pooling and maximum pooling were applied to the input features to provide spatial attention (Anand *et al.* 2024). The results were then integrated, and the convolutional layer forecasts energy generation and consumption patterns, as demonstrated in Eqn (14).

$$ab = sigm\left(\left[ab^{avg}, ab^{\max}\right] * V\right) \quad \ldots (14)$$

where, W denotes adjustable built-in parameter, * denotes convolution operation of the data.

The performance of energy generation and consumption pattern prediction is enhanced using Equation (15), which defines a composite loss function incorporating the general cross-entropy function c_{ce} and an auxiliary term c_{rce}. The parameter β regulates the contribution of each term, where c_{rce} plays a crucial role in alleviating data imbalance and enhancing classification robustness.

$$c_{sce} = \beta c_{ce} + (1-\beta) c_{rce} \quad \ldots (15)$$

To further refine the classification confidence, we introduce the forward affiliation factor (FωAF), represented in Equation (16). This metric quantifies the difference between the highest and second-highest class membership probabilities of a labeled sample, ensuring better class separation. By integrating FωAF (Y_k), we complement the loss function in Equation (15), reinforcing the model's ability to distinguish between closely related classes.

$$F\omega AF\ (Y_k) = P_F\ (Y_k) - P_{AF}\ (Y_k) \quad \ldots (16)$$

where $P_F\ (Y_k)$ and $P_{AF}\ (Y_k)$ denote the highest and second-highest class membership probabilities, respectively. A lower FωAF (Y_k) indicates that the probabilities of the best and second-most likely classes are close, potentially leading to misclassification. Therefore, optimizing the loss function alongside FωAF (Y_k) ensures improved prediction reliability and robustness in classification tasks.

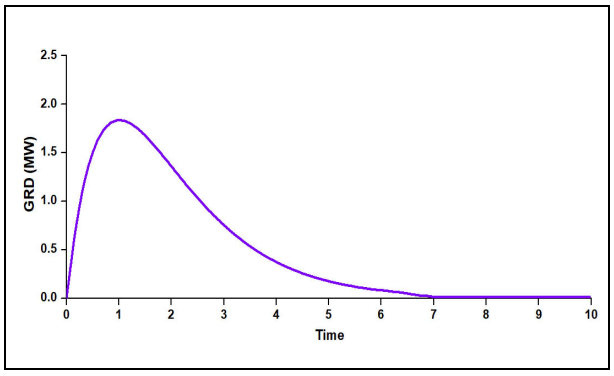


Fig. 2: Analysis of grid power

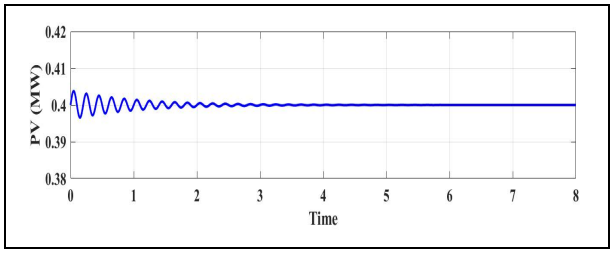


Fig. 3: Analysis of PV power

4. RESULT AND DISCUSSION

The effectiveness of the proposed PDACNN method is illustrated through simulation results in this section. This approach optimizes energy distribution and resource utilization for MGs integrated with RESs (Sun *et al.* 2024). Implemented using MATLAB, the method demonstrates significant improvements in operational efficiency and overall cost-effectiveness.

Figure 2 depicts the analysis of grid power, measured in megawatts (MW). Initially peaking at approximately 2 MW at 1sec, the grid power gradually declines close to zero by the end of the period. This trend indicates an effective EMS sources or stored energy rather than relying on grid electricity (Kaliappan and Natrayan, 2023). The smooth reduction in grid power highlights the MG's ability to operate sustainably and efficiently, showcasing the advantages of integrating RES. Fig. 3 presents the analysis of PV power. Starting at approximately 0.39 MW, the power output fluctuates with small oscillations, reaching a peak of about 0.41 MW around 2 s before settling at approximately 0.40 MW. These oscillations suggest variations in solar irradiance, potentially caused by changing weather conditions or shading on the PV panels (Mehta *et al.* 2024). By the end of 8 s, the power output stabilizes around 0.40 MW, indicating a consistent and reliable generation of solar energy (Guven, 2024). Fig. 4 presents the analysis of battery power. Initially, the battery output is approximately 0 MW, but it rapidly drops to around -5 MW between 1 and 2 s, indicating a discharge phase where the battery supplies power to the grid. After this discharge, the output stabilizes close to 0 MW, reflecting minimal battery activity (Natrayan and Kaliappan, 2023). This behaviour demonstrates the battery's critical role in balancing energy supply and demand within the MG, allowing for effective integration of RESs while enhancing the overall operational reliability of the EMS. Fig. 5 illustrates the analysis of DG power (Li *et al.* 2024). The DG shows an initial oscillation, peaking at approximately 0.05 M and reaching a minimum of about -0.05 M between 10 and 20 s (Promthaisong and Eiamsa, 2019). These oscillations diminish gradually, with the waveform stabilizing around 0 M after 20 s. For the remainder of the observation period, from 20 to 60 s, the DG value remains consistently close to zero, indicating a stable state after the transient oscillations subside (Fathy *et al.* 2022b).

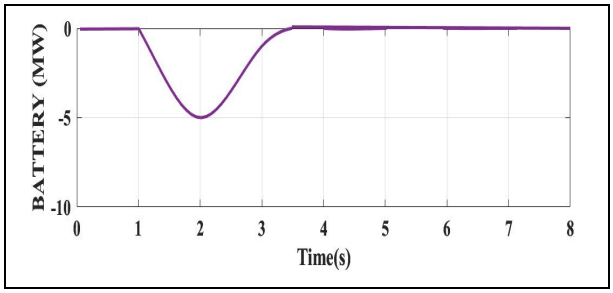


Fig. 4: Analysis of battery power

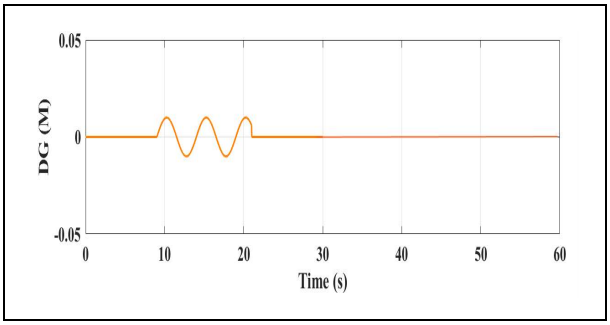


Fig. 5: Analysis of DG power

Table 1. Comparison of cost and efficiency for proposed and existing approaches

Methods	Operational cost ($)	Efficiency (%)
Proposed PDACNN	1837	98.7
FFO-DADRCNN	1840	98
HWOA-PS	1855	96
IGBO	1863	97.6
BES	1879	98.2
AVOA	1845	96.9

Table 1 summarizes the costs and efficiencies of various EM approaches in MGs integrated with RESs. The proposed PDACNN method leads the comparison with the lowest operational cost of $1,837 and the highest efficiency at 98.7%. The next is the FFO-DADRCNN method that costs operation at $1,840 and boasts 98% efficiency. The HWOA-PS method is $1,855 higher in terms of operational cost efficiency than the other approaches with 96 percent (Khimsuriya *et al.* 2022). The amount of money used for the IGBO method's operation is $1,863 while the efficiency rate stands at 97.6%. The BES method has an operational cost of $ 1879 and an efficiency of 98.2%. Finally, the AVOA method costs $1,845 to operate while achieving 96.9 percent efficiency (Albdoor *et al.* 2024). This data shows that the PDACNN is more cost efficient and effective than other methods because it can be implemented within the sample timeframe (Jayachandra *et al.* 2016).

In the scenario of MGs integrated with RES, the proposed PDACNN method has been proven to be successful in terms of improving the distribution of energy and utilizing the resources efficiently. The progressive reduction of grid power confirms the ability of MG to count on stored energy and renewable sources, increasing the level of ecology (Chhaparwal *et al.* 2024). The trends in the performance of the PV system show that the system exhibits steady generation of power from renewable solar power source, though there are slight changes due to influence from factors such as weather conditions (Aguila *et al.* 2022). The discharge phase of the battery claims a significant importance in energy control and balancing with the high reliability of the operation (Yang *et al.* 2025). Additionally, the dynamics of the DG power demonstrate stabilization after transient oscillations, emphasizing the integration of diverse energy sources. The findings further corroborate the superiority of the PDACNN method, achieving the lowest operational cost of $1,837 and the highest efficiency at 98.7%, surpassing other existing methods (Mohseni and Pishvaee, 2023). Collectively, these results illustrate that the proposed PDACNN method not only enhances operational efficiency but also contributes to cost-effectiveness in the management of MGs with integrated RESs.

5. CONCLUSION

This study presents an optimized energy management approach for renewable energy-integrated microgrids using the Pyramidal Dilation Attention Convolutional Neural Network (PDACNN), effectively enhancing system efficiency, stability, and cost-effectiveness. The PDACNN leverages deep learning-driven predictive modeling to improve energy forecasting accuracy and optimize energy distribution among photovoltaic systems, diesel generators, and battery storage. Simulation results validate its superior performance, achieving the lowest operational cost of $1,837 and the highest efficiency of 98.7%, outperforming conventional approaches such as FFO-DADRCNN ($1,840, 98%), WOA-PS ($1,855, 96%), IGBO ($1,863, 97.6%), BES ($1,879, 98.2%), and AVOA ($1,845, 96.9%). The method effectively mitigates fluctuations in renewable energy generation, ensures optimal resource utilization, and reduces grid dependency, highlighting its sustainability advantages. The analysis of energy components, including grid power, PV power, battery power, and diesel generator power, further confirms the robustness of PDACNN in managing energy transitions and maintaining system stability. The method's ability to dynamically adapt to load variations enhances microgrid resilience while reducing operational costs and improving energy efficiency. By ensuring smooth battery discharge cycles and coordinated energy distribution, PDACNN establishes itself as a scalable and intelligent solution for sustainable microgrid operations. The findings emphasize the potential of deep learning-based optimization in advancing microgrid energy management, reducing reliance on fossil fuels, and promoting cost-effective renewable energy utilization.

Future Work

Future work will consist of expressing more robust parameters to incorporate more types of RESs and different load variations. Further, the incorporation of improved Objective Rating Method (ORM) and the usage of machine learning algorithms will strengthen the prediction aspect of EMSs. Subsequent studies will also relate to the possibility of integrating demand response

management techniques applicable to energy consumption to enhance system efficiency.

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CONFLICT OF INTEREST

The authors declared no conflict of interest in this manuscript regarding publication.

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