Energy management in smart grids using internet of things and price-based demand response with a hybrid EVO-PDACNN approach

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Article Info

Article history:

Received Mar 27, 2025
Revised Dec 12, 2025
Accepted Jan 16, 2026

Keywords:

Energy consumption
Energy management
Energy valley optimizer
Internet of things
Peak-to-average ratio
Pyramidal dilation attention convolutional neural network
Smart grids

ABSTRACT

Network control systems for energy distribution play an essential role when renewable energy sources (RES) expand and the smart grid (SG) infrastructure increases. A new approach to energy management (EM) in SGs combines energy valley optimizer (EVO) with pyramidal dilation attention convolutional neural network (PDACNN) to achieve its objectives. Through EVO-PDACNN, the system performs accurate energy consumption forecasting with PDACNN, while the EVO algorithm supports systematic scheduling capabilities. Due to its use, this method reduces the peak-to-average ratio (PAR) by 22% also the cost of electricity (COE) by 12%. This method performs better than the wind-driven bacterial forging algorithm (WBFA), genetic algorithm (GA), particle swarm optimization (PSO), modified elephant herd optimization algorithm (MEHOA), and ant colony optimization (ACO) because it has a new prediction ability and quick response. EVO-PDACNN establishes better performance through lower root mean square error (RMSE), together with mean squared error (MSE) and mean absolute error (MAE), which indicates enhanced cost efficiency and resource management capabilities for SGs. The method strengthens both energy forecasting and operational scheduling operations while effectively dealing with changes in supply and demand, which helps build resilient power systems.

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1. INTRODUCTION

Smart grids (SGs) represent the next generation of power networks, designed to incorporate renewable energy source (RES), storage systems, and advanced communication technologies to increase efficiency, reliability, as well as sustainability [1]. The growing penetration of renewables such as photovoltaics (PV) and wind turbines (WT) introduces significant variability into the system, while the proliferation of internet of things (IoT) devices generates massive streams of operational data [2], [3]. Together, these trends create both opportunities and challenges for energy management (EM) [4]. On one hand, IoT technologies enable advanced demand-side management (DSM), automation, and dynamic monitoring of energy flows [5]. On the other hand, renewable variability, fluctuating peak demand, and the computational burden of processing IoT data streams complicate efficient grid operation [6]. Global projections emphasize the scale of this transformation. The International Energy Agency estimates that renewable electricity generation capacity is expected to reach approximately 4500 MW by 2030, with solar and wind as the dominant contributors [7], [8]. In parallel, the number of IoT-enabled devices is projected to exceed 75 billion by 2025, with many integrated into SGs for monitoring and control [9], [10]. These devices offer enhanced automation, energy savings, and efficiency gains, but they also generate massive datasets that must be analyzed in near real time. This data intensity, combined with renewable intermittency, creates operational challenges including unstable supply-demand balance, peak load stress, and increased vulnerability to inefficiencies [11], [12]. IoT-based EM systems, enabled by smart meters, intelligent controllers, and networked sensors, are vital for balancing supply and demand in SGs [13]. Price-based demand response (DR) has emerged as a promising mechanism, encouraging consumers to adjust consumption in response to dynamic electricity prices [14], [15]. However, the effectiveness of DR depends critically on accurate forecasting and adaptive scheduling to respond to unpredictable variations in generation and demand [16]. At the same time, unresolved issues such as data security risks, high computational requirements, and scalability limitations continue to constrain IoT-driven EM systems [17], [18]. Addressing these challenges requires advanced forecasting and optimization techniques capable of handling renewable fluctuations and large-scale IoT data streams, ensuring cost-effective, reliable, and resilient SG operation [19], [20].

Despite these advancements, the integration of renewable sources and IoT in SGs presents several critical challenges. This is because of the issues relating to variability, fluctuating peak demand, and the complexity of processing data in cases where RES is integrated into SGs. However, neither solar nor wind energy (WE) is steady because while the solar light is highest during the day and is totally off during the night, the wind is similarly not constant due to uncertainty in wind power (WP). Moreover, fluctuations in demand, especially during peak hours, trigger instabilities that can only be controlled after undertaking complex forecasting and scheduling of consumption, supply, and costs of operating the electricity grid. Also, IoT-integrated SGs produce massive data from DERs, smart meters, and sensors that require sound computational models to analyze and manage this data. Nevertheless, IoT technologies bring improvements in terms of automation, distant control, and distributed EM on a large scale; the latter is also accompanied by cybersecurity issues, the limitations of scalability, and decision-making moments. Furthermore, implementing IoT-based SGs is costly since it needs high-speed communication networks, efficient edge computing, also data storage facilities, which remain key barriers. Additionally, decision-making in SGs remains a challenge, as conventional algorithms struggle to process high-frequency IoT data streams efficiently, limiting the system's ability to adapt to fluctuating RES generation as well as consumption patterns. Addressing these challenges has motivated extensive research, leading to various optimizations and scheduling techniques. The following section reviews these approaches.

Numerous studies have attempted to address these challenges using diverse optimization and EM strategies. Some of these studies are reviewed. The methods of wind-driven optimization (WDO) and bacterial foraging optimization (BFO) have been integrated in a wind-driven bacterial forging algorithm (WBFA) introduced by Hafeez *et al.* [21]. To lessen peak-to-average ratio (PAR), reduce electricity bills, also maximize user satisfaction, a schedule for the power usage of IoT-enabled smart appliances in residential complexes was formulated based on the suggested WBFA. The WBFA solution reacts to price-based DR programs automatically, hence solving the core issue with these programs that customers lack the capacity to respond effectively when receiving DR signals.

Along with the integration of RES, *i.e.*, solar energy, thermal energy, controlled heat as well as power, and WE, Rehman *et al.* [22] have focused on energy usage, scheduling, also management in an electric utility's DR program. RES also minimizes the harmful impacts of carbon emissions and electricity prices on the environment. An EM controller and scheduler for smart appliances were introduced. Heuristic algorithms like genetic algorithm (GA), wind-driven optimization, and particle swarm optimization (PSO), then our suggested hybrid algorithms served as their foundation.

The design, location, deployment, and assessment of an IoT-based smart energy management systems (SEMS) encompassing SMs and an IoT middleware module have been illustrated by Saleem *et al.* [23] with the advantages that come along with it. The suggested SEMS was web-based and provides load profiles (LPs) to suppliers and clients at a distance. The incentives can be allocated and regulated by suppliers, who can also motivate customers to modify their energy consumption appreciations to suit their customers' LPs. Also, these LPs were used as a reference for developing some of the DSM techniques. In four of Stylo Pvt. Ltd.'s sites in Pakistan, the suggested system capable of sending directives and tracking the efficiency of the utility's electricity was implemented and assessed.

The hybrid approach, which was presented by Shreenidhi and Ramaiah [24], was an optimal load scheduling technique that manages and shifts the consumer's load, lowering the electricity bill in the process. By accurately predicting the future pricing signal using the DR pricing information, this model's forecaster scheme facilitates the most convenient and economical decision-making. Based on anticipated future prices, the optimization algorithm plans the appliances' power usage habits. This reduces PAR and bill payments through electricity while enhancing user comfort and supporting customers with household load management challenges.

A comfort and user-centric optimization-based DSM scheduler and EM controller for a smart home (SH) has been demonstrated by Ali *et al.* [25]. Based on the DSM, the suggested SEMC develops an operational strategy considering comfort and user-centricity. Customers can save energy expenses, carbon emissions, and PAR, as well as enhance their thermal, lighting, as well as appliance usage preferences by using the created appliance operating plan.

A SH EM system with real-time pricing-based DR for optimal utilization of batteries, EVs, and DG based on RES to mitigate the dependency on the grid has been established by Kanakadhurga and Prabaharan [26]. The SH comprises 18 SH appliances and an electric vehicle (EV). Either V2G or G2V mode can be used with the EV. Thermal and electrical loads were the two categories into which the SH's appliances were divided. The binary PSO (BPSO) method was used to schedule the working time slots and durations of each smart appliance, taking into account the tariff, availability of storage devices, and DGs, all without compromising user preferences. The suggested technique will lower the net COE by minimizing the SH's reliance on the grid in every time slot. The efficiency of the introduced approach was demonstrated by investigating some scenarios, including various configurations of renewable-based DGs, including WT, PV, and battery energy storage systems (BESS) within the SH.

An intelligent electromagnetic system for a smart environment was presented by Saleem *et al.* [27]. To ensure effective DSM, it integrated the energy controller with an IoT middleware module. With each appliance, it connected an energy controller—an IoT device comprising a series of sensors and actuators. To maximize the energy use of the air conditioning system based on building operating dynamics and external temperature conditions, it collects data on energy use from all the smart devices across a series of time durations.

EM in SGs has been widely explored using traditional optimization approaches such as GA, PSO, and ACO. While these methods have demonstrated improvements in load scheduling and cost reduction, they remain constrained by single-objective formulations, static scheduling assumptions, and weak adaptability to renewable fluctuations. More recent approaches, such as WBFA and MEHOA, have improved optimization efficiency but still struggle with scalability, forecasting precision, and integration with renewable-rich, IoT-enabled grids. To overcome these challenges, this study introduces a hybrid energy valley optimizer-pyramidal dilation attention convolutional neural network (EVO-PDACNN) framework that integrates PDACNN for accurate forecasting with the energy valley optimizer (EVO) for adaptive multi-objective optimization. This paper shows that combining deep learning (DL)-based forecasting with adaptive optimization provides a scalable as well as effective solution to address the limitations of existing approaches, thereby improving forecasting accuracy, reducing electricity costs, and minimizing PAR in IoT-enabled SGs.

Existing EM approaches in IoT-enabled SGs, such as GA, PSO, ACO, WBFA, and MEHOA, still face critical limitations. They provide only moderate accuracy in forecasting dynamic energy demand, lack adaptability to fluctuations in renewable energy (RE) generation, and often incur high computational costs, making them unsuitable for large-scale deployment. These issues hinder the improvement of cost-efficient, stable, also resilient SG operations. To address this problem, this study suggests a hybrid EVO-PDACNN framework that integrates DL-based forecasting with evolutionary optimization, aiming to enhance prediction accuracy, adaptability, and scheduling efficiency underprice-based DR.

The goal of this study is to advance an intelligent, adaptive, as well as computationally efficient EM framework for IoT-enabled SGs that can address RE variability and dynamic demand underprice-based DR programs. This work argues that combining PDACNN with EVO provides a superior solution compared to conventional optimization methods. By integrating accurate demand prediction with adaptive scheduling, the suggested EVO-PDACNN framework achieves reduced electricity costs, minimized PAR, also enhanced computational efficiency, thereby advancing the state of SG EM.

This study offers several novel contributions that advance EM in IoT-enabled SGs:

a. It introduces a hybrid EVO-PDACNN model combining the ability of DL to make predictions with the ability of evolutionary optimization based on stability in a unified framework, a conceptual change of traditional single-stage or heuristic-only mechanisms.
b. The PDACNN module identifies multi-scale time variations with the help of a pyramidal dilation framework and an attention system, and its forecasting accuracy of load and price prediction is also improved significantly.
c. The EVO algorithm is an adaptive scheduling algorithm that optimizes peak and valley demand, lessens PAR, and minimizes the cost of electricity under different conditions of renewable generation.
d. The framework achieves more scalability, convergence speed, and robustness to renewable variability than GA, PSO, ACO, WBFA, and MEHOA because forecasting and optimization are intimately coupled as interdependent entities.

e. The method exhibits a high performance in the forecast error, cost reduction, PAR reduction, and computational efficiency, which form a significant improvement of the current EM strategies.

To further emphasize the proposed approach, this study introduces a unified methodological framework that integrates PDACNN-based forecasting with EVO-driven optimization. The PDACNN uses a pyramidal dilation architecture and an attention system to extract multi-scale temporal features from the load and price signals, thereby greatly improving prediction accuracy in IoT-based SGs. Simultaneously, the EVO algorithm offers an evolutionary optimization process guided by stability and adjusting the balance between peak and valley demand, minimizing the electricity cost, and minimizing PAR during varying renewable output. The theoretical novelty of this work lies in the interdependence of forecasting and scheduling within a single hybrid architecture, rather than treating them as separate procedures. This combined model enhances scaling, flexibility, and operational performance, which is a significant step forward compared to the traditional methods of heuristic-based or single-stage EM solutions. Moreover, this study has a contribution beyond performance improvement. The presented EVO-PDACNN framework presents a unified forecasting-optimization framework that is essentially distinct from a conventional sequential or heuristically-based EM approach. By combining multi-scale temporal feature extraction with stability-guided evolutionary scheduling, the method advances scientific understanding of how hybrid AI models can enhance resilience, adaptability, and efficiency in SG environments. This integrated perspective contributes to the broader field by offering a replicable and scalable theoretical framework for next-generation EM systems.

The following sections of this work are organized as follows. Section 2 explains the structure of the IoT-enabled EM system in SGs, including the modeling of PV, WT, and BESS. Section 3 outlines the research methodology, dataset, and model training process, while Section 4 explains the working principles of the PDACNN forecaster and EVO scheduler. Section 5 presents and discusses the experimental results, including comparative analyses with GA, PSO, ACO, WBFA, and MEHOA. Section 6 concludes by summarizing outcomes, noting limitations, and suggesting implications and future directions.

2. STRUCTURE OF IOT-BASED ENERGY MANAGEMENT SYSTEM IN SMART GRID

Figure 1 illustrates the IoT-enabled EM system integrated with the EVO-PDACNN approach within an SG framework. IoT sensors monitor and control energy flow among various sources, including PV systems, WT, batteries, and fuel cells (FC) [28]. This connectivity enables DR adjustments based on pricing signals, improving energy efficiency and load balancing across the grid. At the core of the system, IoT technology facilitates seamless energy transmission and distribution. The SG infrastructure ensures efficient energy delivery to SH and buildings, where IoT-connected devices regulate energy consumption in response to price fluctuations.

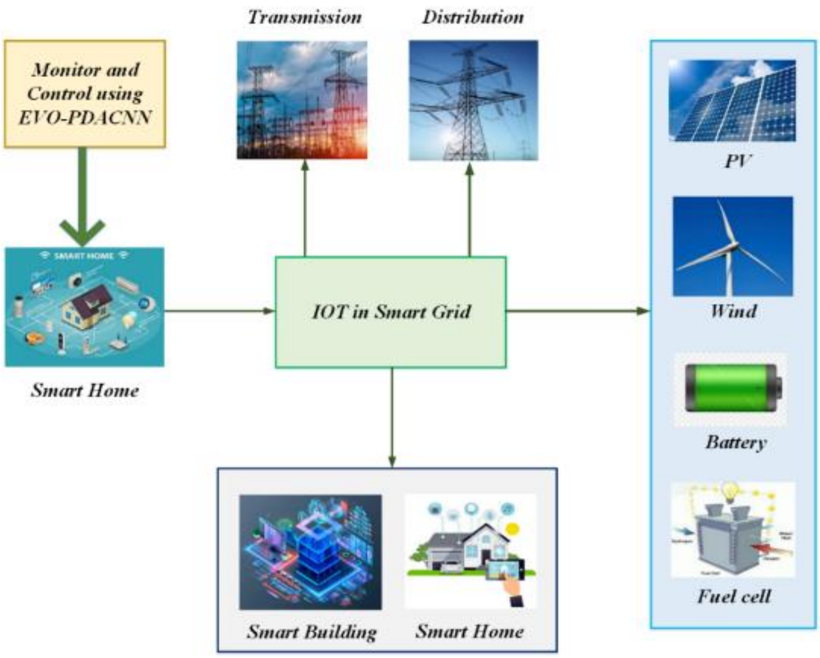

Figure 1. IoT-based EM in an SG integrated with the EVO-PDACNN approach

The EVO-PDACNN approach processes real-time data from IoT devices, employing a hybrid optimization strategy that combines EVO with PDACNN. This method optimizes energy consumption and distribution dynamically, ensuring a balanced DR across both consumer and generation sides of the grid. The integration of IoT with this hybrid approach enhances energy efficiency, particularly in SH and building applications. Using standard physical models (PV/WT/BESS/FC) ensures realistic operational constraints and energy balances; PDACNN reduces forecast error that would otherwise degrade scheduling; EVO offers a robust exploration/exploitation strategy suited for nonconvex, constrained scheduling problems. The combination addresses the three main challenges identified earlier: renewable intermittency, peak variability, and large IoT data volumes.

2.1. Modelling of photovoltaics

PV system modeling is fundamental for predicting energy output and optimizing SG performance. Modeling determines the optimal solar PV cell design, improving the overall performance of the PV system. However, modeling PV cells can be challenging due to the intrinsic nonlinearity of the cell [29]. Equation (1) gives the total current produced by the single-diode PV model:

$$i = i_{PV} - i_d - i_P \tag{1}$$

where, i_{PV} denotes the current produced by the PV, i_d denotes the current passing through the diode, and i_P indicates the current through the shunt resistance. The existing equation can be rewritten as (2) by changing the expressions for i_d and i_P.

$$i = i_{PV} - i_0\left(exp\left(\frac{V_d}{q_1 V_t} - 1\right)\right) - \left(\frac{V + iR_S}{R_P}\right) \tag{2}$$

where, V_t indicates the thermal voltage, q_1 represents the ideality factor, i_0 represents the diode, d denotes diode leakage current, and R_S represents the number of cells linked in series. The relationship between short-circuit current (SCC) and irradiance is given by (3):

$$i_{PV} = \left(\frac{g}{g_0}\right)\left[i_{SC} + K_j(T - T_0)\right] \tag{3}$$

The SCC under conventional test conditions is indicated by i_{SC}. K_j stands for the current coefficient factors, while g and T, respectively, reflect the actual temperature and irradiation values. The cell temperature in Kelvin is denoted by T, and the Boltzmann constant is signified by K.

2.2. Modeling of wind

WT modeling is crucial for assessing RE contribution, as output depends on wind speed (WS) characteristics and turbine parameters. The speed of the wind and the area it blows across affect how much power a WT can produce [30]. Equation (4) is used to calculate a WT's power output:

$$P_{WT}(t) = \begin{cases} 0 V(t) \leq V_{cin} or V(t) \geq V_{coff} \\ P_R^W \frac{V(t) - V_{cin}}{V_R - V_{cin}} V_{cin} < V(t) < V_R \\ P_R^W V_R \leq V(t) < V_{coff} \end{cases} \tag{4}$$

where, $V(t)$, P_R^W, V_{cin}, and V_R stand for the WS at the necessary height, the cut-in and cut-off speeds, the rated WS, and the rated power of WT, respectively. Equation (5) represents WS's probability density function (PDF):

$$P(v_1 \leq v \leq v_2) = \int_{v1}^{v2} F_v dv \tag{5}$$

where, F_v represent the WS PDF, v_1 and v_2 indicates any 2 WS. The Weibull distribution used for WS modeling is given in (6):

$$F_v = \frac{K}{C}\left(\frac{v}{C}\right)^{K-1} exp\left(\left(\frac{v}{C}\right)^K\right) \tag{6}$$

where K, C also v are the shape parameter, scale parameter, as well as WS, respectively. The WS at a specific height is calculated using (7):

$$V = V_0 \left(\frac{E_{WT}}{E_0}\right)^{\alpha} \tag{7}$$

where, the WS at the necessary height is shown by V, V_0, and α. The friction coefficient is denoted by E_0, and the WS at reference height by E_{WT}. The total WP generated $P_{WT}(t)$ by WT is given by (8):

$$P_{WT}(t) = M_{WT}P_{WT}(t) \tag{8}$$

where, M_{WT} represents the number of WT.

2.3. Modeling of battery

Battery storage (BS) modeling plays a vital role in balancing RE variability, also ensuring an uninterrupted power supply in SGs. Because WS and irregular solar radiation can affect power generation, backup ESs such as lithium-based and lead-acid batteries have been deployed. Large-scale Energy storage system (ESS) employs these batteries due to their affordability, robustness, and ease of use. The number of days without interference from power sources is shown by the BS, which is modified to meet load requirements. The required battery capacity for a given load demand is calculated using (9):

$$B_c = \frac{(L_d{}^{*}ad)}{(dod^{*}\eta_B{}^{*}\eta_I)} \tag{9}$$

where, B_c stands for battery capacity, L_d for load demand, dod for depth of discharge, η_B and η_I for battery and inverter efficiency. The BESS formulation is employed. The goal of developing hybrid PV/WT and BESS is to improve both economic and technological performance at the same time.

3. METHODS

3.1. Standard and novel approaches

This study integrates both standard and novel approaches to ensure methodological soundness and demonstrate the originality of the suggested framework. On the standard side, well-established models were used for PV, WT, and BESS, as these formulations are widely validated in RE research and accurately capture system dynamics under varying conditions. A benchmark dataset of electricity prices and load demand from September 2006 to August 2007 was employed, as it is frequently used in SG studies and captures daily, weekly, and seasonal variations relevant to DR evaluation. Conventional approaches such as GA, PSO, ACO, MEHOA, and WBFA were implemented as baseline methods, providing a strong reference point for comparison. The novel contribution of this work is the hybrid EVO-PDACNN framework, where the PDACNN enhances forecasting accuracy by capturing long-term temporal dependencies and prioritizing critical consumption-price features, while the EVO adaptively balances peak and valley demand to minimize cost and PAR. Together, these components overcome the scalability, adaptability, and accuracy limitations of conventional methods in IoT-enabled SGs. Validity of the suggested approach is supported by three aspects: i) reliance on widely accepted system models and a benchmark dataset ensures reliability and comparability, ii) benchmarking against established optimization algorithms provides fair performance evaluation, and iii) assessment through robust metrics (root mean square error (RMSE), mean absolute error (MAE), mean squared error (MSE), PAR reduction, cost reduction, computational time) and statistical validation confirms that the improvements achieved by the EVO-PDACNN framework are both significant and reliable.

3.2. Dataset description

The dataset used in this study provides historical load and price data, enabling accurate training, validation, and testing of the suggested EVO-PDACNN model. For training, validating, and testing the suggested EVO-PDACNN model to solve the suggested specific optimization problem of IoT-based EM underprice-based DR, this work employs a dataset containing power prices and load data from September 2006 to August 2007. While the training data set is from September 2006 to May 2007, which is used to train the model and extract patterns between energy consumption and pricing, the validate dataset is from June 2007 to July 2007 to check for model generalization and prevent overfitting; the test data set is for August 2007 to measure the model's performance on data that it has not seen before and ensure that the model does, in fact, work for real-world forecasts. Thus, the considered dataset distinguishes changes in energy demand for different hours of the day, weekdays/weekends, and seasons, which is good for evaluating DR in SGs. Thus, the study shows that the suggested EVO-PDACNN approach brings less error in energy consumption forecasting and price prediction than the existing approaches and, therefore, could be considered more accurate.

3.3. Model training

The training process integrates PDACNN forecasting with EVO optimization, ensuring accurate predictions and efficient scheduling under dynamic conditions. The input time-series data undergoes Min-Max normalization to scale values within [0, 1], ensuring stable training. The dataset is divided into subgroups for training (70%) and testing (15%), and validation (15%). The PDACNN model is trained using the Adam optimizer with a batch size of 64 and a learning rate of 0.001 for processing efficiency, with MSE serving as the loss function. Simultaneously, the EVO runs in parallel, optimizing hyperparameters by evaluating the MAPE after each training iteration. Once optimization is complete, the best EVO-tuned PDACNN model is tested on unseen data, with performance assessed using RMSE, MAE, and MAPE, ensuring robust generalization.

3.4. Experimental procedure

The research was conducted through a structured five-step procedure. First, a benchmark dataset of electricity price and load (September 2006-August 2007) was collected, preprocessed to handle missing values, normalized, and divided into training, validation, also testing sets. Second, standard models for PV, wind, and battery systems were implemented to simulate renewable generation and storage dynamics. Third, the forecasting stage employed PDACNN, which was trained and validated to capture consumption-price patterns with high accuracy. Fourth, the scheduling stage applied the EVO, which iteratively refined scheduling strategies to balance peak and valley demand and minimize electricity costs. Finally, performance was evaluated on the test set using widely accepted error metrics and economic indicators, and experiments were repeated multiple times with statistical testing to confirm the significance and reliability of the results.

4. PROPOSED HYBRID EVO-PDACNN APPROACH

The enhancement of EM in SG with the suggested Hybrid EVO-PDACNN approach integrates IoT technologies with advanced forecasting as well as optimization methods. This method involves the use of the PDACNN for an accurate forecast on energy demand with the help of monitors and IoT sensors to capture complex consumption patterns. Once the demand is derived, the EVO optimally times the scheduling of energy distribution with the intent of cutting the PAR cost as well. The explanation of the suggested method, step by step, is provided.

4.1. Pyramidal dilation attention convolutional neural network

The PDACNN is employed as a forecasting model to capture complex temporal dependencies in energy demand and price signals. Data processing of PDACNN takes advantage of three mechanisms of neural network, including structural pyramid and dilation, and lastly the attention components. The same feature of the pyramidal structure enables the network to process data of any size for the purpose of discovering fine-grained and also more abstract features [31]. The multi-scale technique is capable of providing an efficient analysis for multiple applications, such as signal processing and other time series analysis applications. By dilation, the network gets enlarged context awareness, but without adding extra parameters to the model. PDACNN can effectively adjust the dilation rates within pyramid levels to handle data having various input sizes, which makes this model ideal for several problems that have intricate patterns. Due to its high scalability and processing capacity, PDACNN succeeds at handling big IoT data streams to maximize energy distribution efficiency as well as minimize expenses stemming from variable pricing. Additionally, its versatility allows PDACNN to be adapted to various SG scenarios, improving both operational efficiency and consumer satisfaction by aligning energy demand with price signals.

$$E_w = e_1^1 \wedge e_2^2 \wedge e_3^3 \wedge \ldots\ldots \wedge e_w^q \tag{10}$$

where, $w = 2_{q1}$ indicates dilated factor for the stacking of sub dilated convolutional layer (SDCL) and denotes the q^{th} PDC layer, e_w^q represents q^{th} SDCL, as well as E_w denotes w^{th} PDC coating. The expression for spectral attention is shown in (11).

$$b'_w = R_{scale}(b_w, k_w) = k_w, w = 1, \ldots, a \tag{11}$$

where, k_w denotes the sum of all possible pools, average pooling $Acti^{sav}$, and $R_{scale}(b_w, k_w)$ signifies spectral-wise multiplication between the feature map b_w also the scalar k_w. In terms of spatial attention, the sigmoid activation function utilized for the global average pooling and maximum pooling of the input data is represented by (12).

$$Acti = Sig([Acti^{sav}, Acti^{sma}] * Q) \tag{12}$$

where, Q denotes learnable built-in parameter that represents the convolution process. For every sample (xi), a predicted one-hot label $\hat{b}_u$ can be obtained by using the PDAC network's prediction of unlabeled data. SPL uses (13) to give each sample a_u a weight s_u:

$$\underset{o,s}{AvgD}(o, s; \delta) = \sum_{u=1}^{v} s_u \partial\left(\hat{b}_u, h(a_u, o)\right) - \eta \sum_{u=1}^{v} s_u \; 0 \leq s_u \leq 1, u = 1, \ldots\ldots, m \tag{13}$$

In the model, m indicates a parameter. Weight s_u represents simple to obtain, as shown in (14).

$$s_u = \begin{Bmatrix} 1, & if\partial\left(\hat{b}_u, h(a_u, o)\right) < \beta \\ 0, & otherwise \end{Bmatrix} \tag{14}$$

The output component is created by combining the results as well as then feeding them into the convolution layer. Hyperparameter of PDACNN is presented in Table 1.

Table 1. PDACNN hyperparameter

Hyperparameter	Value
Kernel size	3×3
Dilation rates	[1, 2, 4, 8]
Learning rate	10^{-3}
Batch size	64
Number of epochs	100

4.2. Energy valley optimizer

The EVO serves as an adaptive optimization algorithm that balances supply and demand by minimizing cost, PAR, and system instability. The EVO is a sophisticated optimization framework that manages energy consumption, storage, and distribution in energy systems, particularly SG and hybrid RES [32]. It addresses the challenge of uneven energy demand, commonly known as "valleys" during low demand and "peaks" during high demand, by utilizing advanced algorithms, predictive analytics, and ML models. EVO also co-optimizes an ESS together with several distributed RE, such as wind or solar energy. It can be highlighted that the EVO has a range of benefits, for example, it helps to decrease volatility in the grid and improve the management of ESS. EVO also enables the integration of intermittent RE in many cases and, as a result, strengthens and makes the energy system more secure. Finally, its forecasting capabilities help the company to predict energy requirements and thus help in cutting expenses over the longer term, as well as enhancing the stability also efficiency of the energy supply. The following step-by-step process shows the functioning of the above-mentioned architecture:

Step 1: initialization

Set the input parameters, such as the PV wind also the battery's voltage, and current.

Step 2: random generation

The EVO initializes decision variables as represented in (15):

$$Y_n^k = Y_{n,MIN}^k + Rand.\left(Y_{n,MAX}^k - Y_{n,MIN}^k\right), \begin{cases} n = 1,2, \ldots, m. \\ k = 1,2, \ldots, h \end{cases} \tag{15}$$

where, m is the universe's total particle count, h is the dimension of the problem, Y_n^k is the j^{th} decision variable that determines the starting position of the i^{th} candidate, $Y_{n,MAX}^k$, $Y_{n,MIN}^k$ are the lower and upper bounds of the j^{th} variable, and $Rand$ denotes a random number in the range [0, 1] with a uniform distribution.

Step 3: fitness function

Equation (16) illustrates how the EVO algorithm minimizes the objective function through iterative optimization.

$$F = Min(ObjectiveFunction) \tag{16}$$

where, F represents the fitness function.

Step 4: exploration phase

The position update mechanism guides particles toward the center and the most consistent particle, replicating their tendency to converge to the stability band. During the exploration phase, the updated position is calculated using (17):

$$Y_n^{new1} = Y_n + \frac{(R_1 \times Y_{bs} - R_2 \times Y_{cp})}{sl_n}, n = 1,2,\ldots,m \tag{17}$$

where, Y_{bs} is the particle's position vector with the highest stability level, Y_{cp} is the particle center's position vector, and sl_n is the i^{th} particle's stability level.

Step 5: exploitation phase

To improve algorithmic exploitation, an additional location update procedure is used for the particles utilizing beta decay. In the exploitation phase, the position update (18):

$$Y_n^{new2} = Y_n + \left(R_3 \times Y_{bs} - R_4 \times Y_{ng}\right), n = 1,2,\ldots.,m \tag{18}$$

where, Y_{bs} indicates the particle's position vector with the highest level of stability, and Y_{ng} denotes the particle's neighboring position vector around the i^{th} particle. The new solution is refined using (19):

$$Y_n^{new} = Y_n + R, n = 1,2,\ldots.,m \tag{19}$$

where, Y_n^{new} and Y_n are the future and present location vectors. Figure 2 depicts the EVO algorithm's workflow, optimizing energy scheduling by balancing peak and valley demand for cost-effective distribution. The EVO hyperparameter is illustrated in Table 2.

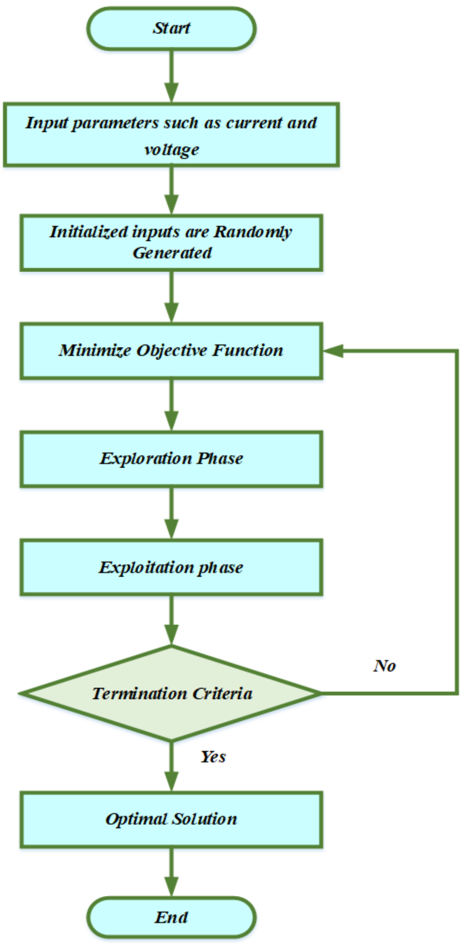

Figure 2. Flowchart of EVO

Table 2. EVO hyperparameter

Hyperparameter	Value
Population size	50
Maximum iterations	100
Mutation rate	0.2
Convergence threshold	10^{-5}
Crossover rate	0.8

Step 6: Termination

The process ends if the optimal solution is found; if not, move on to step 3. Check the requirements for termination.

5. RESULTS AND DISCUSSION

The simulation outcomes establish that the suggested EVO-PDACNN approach significantly outperforms existing methods in forecasting accuracy and optimization efficiency. Based on simulation results, the performance of the suggested EVO-PDACNN approach is examined in this section. The hybrid approach EVO and PDACNN for EM in the SG system. Implemented on MATLAB, the method is evaluated with existing approaches such as WBFA, GA, PSO, MEHOA, and ACO to evaluate its effectiveness and improvements.

Figure 3 illustrates the evaluation of FC power output over 24 hours in an IoT-based SG system operating under a price-based DR strategy. The power output starts at 1.1 kW at 1 hour and decreases to 0.8 kW at 2 hours. Following this dip, the output experiences a deviation, rising to 2.2 kW at 9 hours and peaking at 5.7 kW at 15 hours. The output concludes at 0.3 kW after 24 hours. These fluctuations indicate that the lowest levels occur during early morning and late evening, while notable peaks are observed in the mid-afternoon. These peaks likely correspond to periods of higher demand, demonstrating the FC's adaptive response to dynamic energy requirements. The figure highlights the system's capability to optimize energy generation in response to pricing signals.

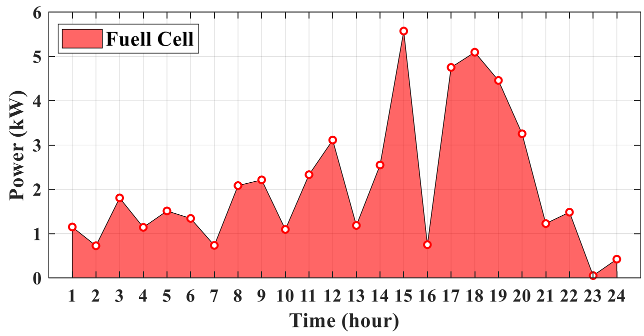

Figure 3. One-day evaluation of FC power

Figure 4 illustrates the evaluation of WP output over the same 24-hour period, represented in red. The power generation from the WP shows a more variable pattern compared to the PV output. There is a significant spike around hour 15, indicating a period of higher WS and energy generation. Throughout the day, the WP output fluctuates more dramatically, with periods of low and moderate generation interspersed. This variability highlights the challenge of managing WE as it is less predictable than solar energy, necessitating robust EM strategies in the SG to accommodate these fluctuations and ensure a balanced supply and demand.

Figure 5 presents the evaluation of PV power output over 24 hours within the context of an SG system. The graph, marked in blue, indicates that PV power production exhibits a distinct diurnal pattern, peaking around hours 12 to 15, which corresponds to midday when sunlight intensity is at its highest. The output starts low in the early hours, gradually increasing as the sun rises, and then tapering off in the late afternoon and evening. This behavior underscores the dependence of solar power generation on sunlight availability, reflecting how EM systems can leverage this intermittent source during peak solar hours to optimize overall grid performance.

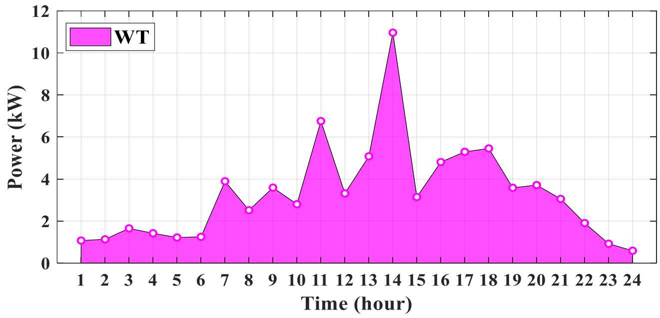

Figure 4. Evaluation of WP over a single day

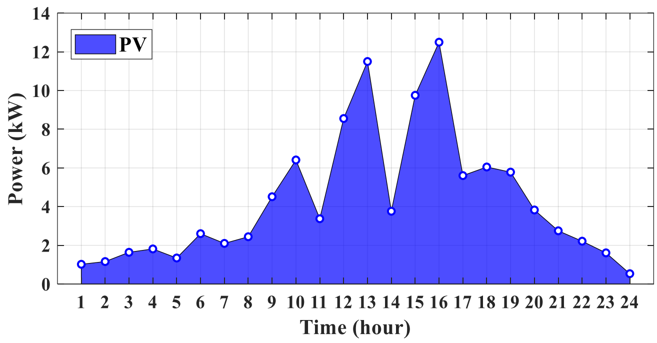

Figure 5. Single-day evaluation of PV power

Figure 6 compares the power outputs from PV, wind, and FC sources over 24 hours, revealing distinct patterns in their contributions. The PV output peaks at approximately 12 kW around hours 12 to 15, coinciding with peak sunlight availability, while the wind output reaches a maximum of 10 kW around hour 15, and showcases significant variability with multiple fluctuations throughout the day. The FC output remains more consistent, peaking at around 5 kW but generally staying below the peaks of both PV and WE. This data illustrates how the PV and WE sources can provide higher outputs during specific times, while the FC acts as a reliable backup, ensuring a balanced energy supply in the SG despite the intermittent nature of RE generation.

Figure 7 presents an evaluation of demand power variations over the duration of one year, illustrating key fluctuations in energy consumption. Starting at 27.5 kW at 0 hours, the demand initially rises, reaching 29 kW by 1000 hours and further increasing to 31 kW at 2,500 hours, indicating higher energy consumption during this phase. Following this peak, the demand gradually decreases to 28.2 kW at 5000 hours, reflecting a period of reduced energy use. However, as the year progresses, there is a notable increase in demand, culminating in a significant peak of 37 kW at 8700 hours. The figure highlights the dynamic nature of annual power demand as well as underscores the need for adaptive management in SG to handle such variations effectively.

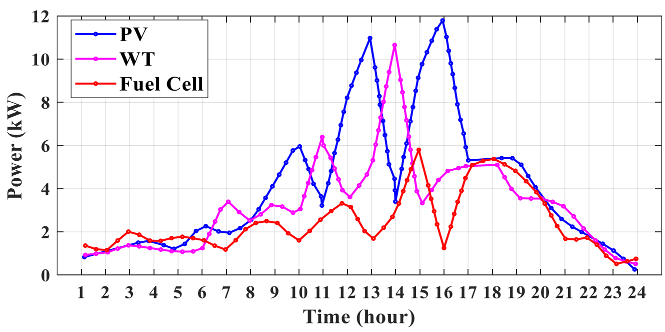

Figure 6. Single-day comparison of individual power sources

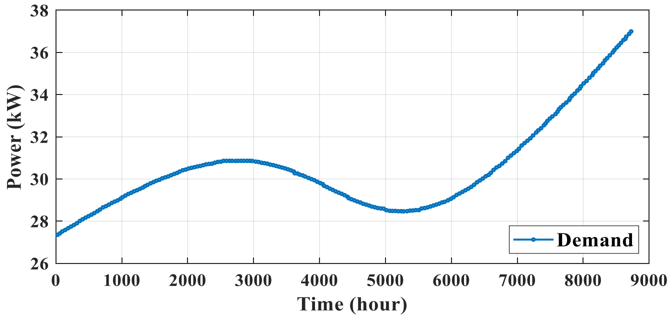

Figure 7. Evaluation of demand power in one year

Figure 8 provides an evaluation of FC power output over one year, showing fluctuations in performance and contribution to the energy grid. At the beginning (0 hours), the power output varies widely, ranging from 1.9 to 9.9 kW, suggesting the FC's role in responding to varying energy demands, supplementing other sources during peak periods. As time progresses, the output continues to fluctuate, but by 8900 hours, the range narrows to between 1.9 kW and 9.8 kW, indicating more consistent operation resulting from optimized performance and stable energy demands. This figure highlights the FC's flexibility in adjusting its output to meet the grid's needs, playing a crucial role in ensuring a reliable energy supply throughout the year, particularly in balancing supply and demand during periods of RE variability.

Figure 9 presents the evaluation of the PAR over the one year, illustrating how the ratio fluctuates throughout the period. At the beginning (0 hours), the PAR value ranges between 0.3 and 0.62, indicating variability in the load distribution and peak demand management within the energy grid. As the year progresses, the PAR value decreases, with the range narrowing to between 0.29 and 0.6 by the 8900th hour. This reduction in PAR suggests an improvement in load balancing and a more efficient distribution of energy over time. The declining trend reflects efforts to manage peak loads and optimize grid performance, ensuring more stable and efficient energy consumption patterns across the year.

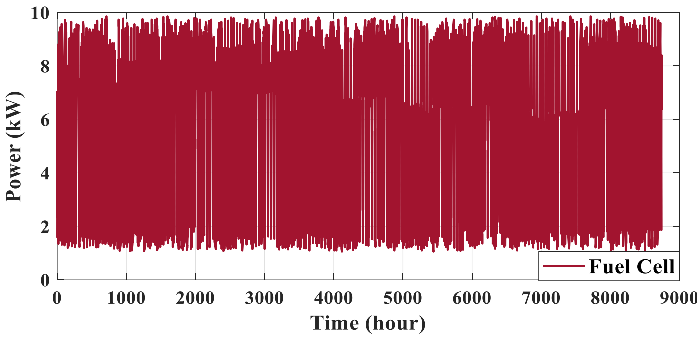

Figure 8. Evaluation of FC for one year

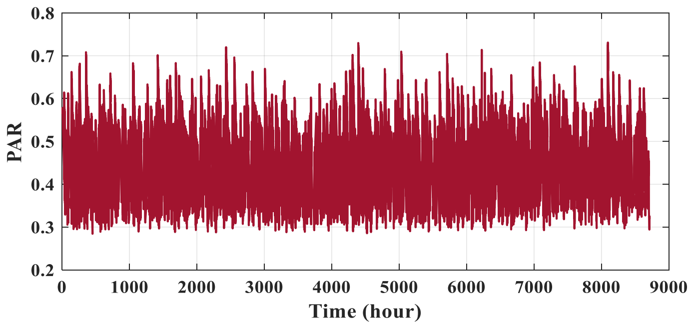

Figure 9. Yearly evaluation of PAR

Figure 10 provides an evaluation of PV power output over the course of one year, showcasing the variability in energy generation from solar sources. At the beginning (0 hours), the power output ranges between 1 kW and 22 kW, reflecting the initial presentation of the PV system under fluctuating sunlight circumstances and potential influences from environmental factors. As the year progresses, the power output remains relatively consistent, ending with a range of 1 to 23 kW by the 8900th hour. This slight increase in the upper limit of the output indicates improvements in solar energy capture or efficiency throughout the year. The figure highlights the capacity of the PV system to generate energy consistently, emphasizing its role in contributing to the overall energy supply in the SG.

Figure 11 illustrates an evaluation of WP output over the one year, highlighting the variations in energy generation from wind sources. At the beginning (0 hours), the power output ranges between 2 kW and 16 kW, indicating the initial performance of the WT under varying wind conditions and environmental influences. As the year progresses, the power output shows a notable increase, with the range expanding to between 2 kW and 23 kW by the 8900th hour. This increase suggests enhancements in turbine efficiency over time, allowing for greater energy capture. The figure emphasizes the WT's ability to contribute a significant and variable portion of energy to the grid, reflecting its importance in the overall energy mix within the SG system.

The graphical evidence shows dynamic behavior. To further substantiate these findings, Tables 3 to 6 provide quantitative comparisons across forecasting accuracy, cost reduction, computation time, and statistical reliability. Table 3 presents a comparison of statistical performance metrics: MAE, MSE, and RMSE across various solution techniques, including both existing methods and the suggested approach. In this comparison, the GA shows relatively high error metrics with an MAE of 3.45, MSE of 6.94, and RMSE of 4.1, indicating less accurate predictions. The WBFA improves upon GA with lower values of 3.19 (MAE), 6.21 (MSE), and 3.5 (RMSE). PSO further reduces error metrics to 2.81 (MAE), 5.38 (MSE), and 3.2 (RMSE), indicating better performance. The MEHOA continues this trend with values of 2.34 (MAE), 4.03 (MSE), and 2.9 (RMSE), showing significant improvements. ACO performs even better with lower error margins of an MAE of 1.82, MSE of 3.87, and RMSE of 2.4, showing improved predictive precision. The MASE values are 0.0133 for the suggested method, which is less than that of the other methods, thus indicating the best performance in terms of MAE, MSE, and RMSE of 1.19, 3.21, and 1.7, respectively. This explains why there are a number of potential benefits of utilizing the suggested approach as a part of solving the analyzed problem, as it demonstrates enhanced accuracy and reliability as compared with existing methods.

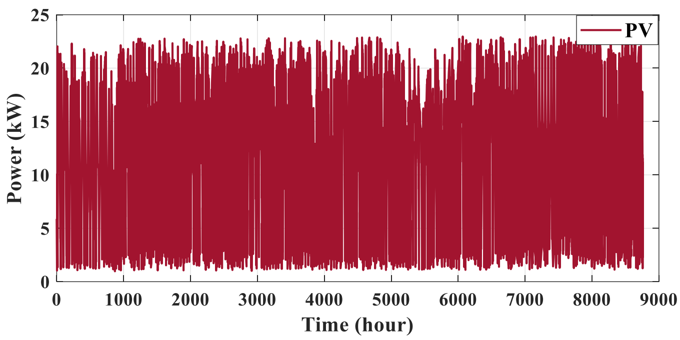

Figure 10. Yearly evaluation of PV power

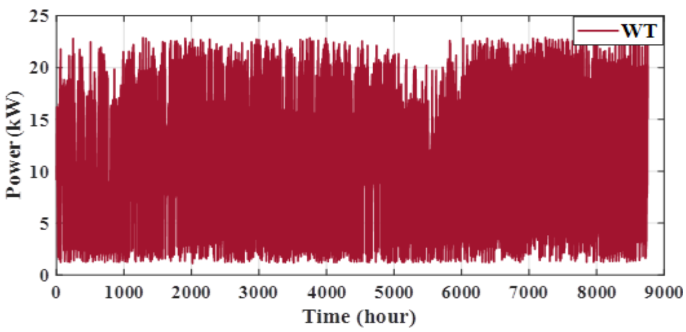

Figure 11. Yearly evaluation of WP

Table 3. Statistical evaluation comparison of suggested and existing techniques

Solution techniques	MAE	MSE	RMSE
GA	3.45	6.94	4.1
WBFA	3.19	6.21	3.5
PSO	2.81	5.38	3.2
MEHOA	2.34	4.03	2.9
ACO	1.82	3.87	2.4
EVO-PDACNN	1.19	3.21	1.7

Table 4. Comparison of power bill reduction and PAR reduction for various solution techniques

Solution techniques	Power bill reduction (%)	PAR reduction (%)
GA	2	6
WBFA	4	9
PSO	5	14
MEHOA	7	18
ACO	10	20
EVO-PDACNN	12	22

Table 5. Comparison of computational time

Solution methods	Computational time (s)
GA	19.5
WBFA	17.4
PSO	16.9
MEHOA	13.2
ACO	10.7
EVO-PDACNN	9.8

Table 6. Statistical evaluation of suggested and existing methods

Statistical measure	Proposed (EVO)	WBFA	GA	PSO	MEHOA	ACO
Mean	0.0021	0.0148	0.0108	0.0152	0.0089	0.0123
Standard deviation (SD)	0.0005	0.0029	0.0027	0.0032	0.0018	0.0024
95% confidence interval	[0.0018, 0.0024]	[0.0121, 0.0175]	[0.0085, 0.0131]	[0.0125, 0.0179]	[0.0074, 0.0104]	[0.0102, 0.0144]
Kolmogorov-Smirnov (KS) p-value	0.071	0.043	0.035	0.048	0.056	0.041
Wilcoxon rank sum test (W) p-value	0.009	0.017	0.021	0.015	0.012	0.019
Kruskal-Wallis (KW) p-value	0.012	0.031	0.034	0.028	0.025	0.029

Table 4 evaluates PAR and electricity cost reduction. EVO-PDACNN reduces PAR by 22% and electricity cost by 12%, outperforming ACO (20% PAR, 10% cost) and MEHOA (18% PAR, 7% cost). GA achieves only modest improvements (6% PAR, 2% cost). This evidence demonstrates that EVO-PDACNN is the most effective solution for mitigating peak loads while lowering consumer expenses.

Table 5 compares computational efficiency. EVO-PDACNN achieves the fastest runtime (9.8 s) versus ACO (10.7 s) and MEHOA (13.2 s), while GA requires the longest time (19.5 s). Faster computation is essential because IoT-enabled SGs generate massive streams of high-frequency data. If optimization takes too long, the system cannot adapt to rapid demand or generation changes. Therefore, the reduced runtime proves that EVO-PDACNN is not only accurate but also practically deployable in large-scale, data-intensive grid environments.

A statistical comparison between the suggested EVO method and the WBFA, GA, PSO, MEHOA, and ACO procedures is displayed in Table 6. It could also be noted that the obtained results reflect the fact that EVO has the lowest mean of the objective value of 0.0021, which reflects its better performance in terms of optimization. It is evident that EVO shows lower values of SD, where SD is the smallest, and at 0.0005, this means that the solution is more reliable and consistent than any other algorithm when run at different times. Specifically, EVO has the lowest level of confidence interval [0.0018, 0.0024], which attests to the method's accuracy. The KS test p-value (0.071) suggests that EVO maintains a statistically stable distribution. The Wilcoxon Rank Sum and KW test p-values (0.009 and 0.012, respectively) confirm the significant difference in performance favoring EVO over the other methods. Overall, these statistical measures establish EVO as a more reliable and effective approach compared to traditional optimization algorithms.

5.1. Discussion

The results demonstrate that the suggested EVO-PDACNN framework significantly enhances SG EM compared to existing optimization methods. By combining DL-based forecasting with adaptive scheduling, the approach delivers both accuracy and efficiency. Specifically, the model achieves lower error metrics (MAE=1.19, RMSE=1.7), faster computational performance (9.8 s), and substantial improvements in system outcomes, including a 22% reduction in PAR and a 12% reduction in electricity costs. These outcomes highlight the framework's capability to address the challenges of fluctuating demand, RE intermittency, and large-scale IoT data processing. In relation to prior work, earlier approaches such as GA, PSO, ACO, WBFA, and MEHOA focused primarily on single-objective optimization or static scheduling strategies. While these methods offered incremental improvements in DR and load scheduling, they were constrained by limited adaptability, slower convergence, and less precise forecasting under dynamic conditions. For example, WBFA improved residential DR but exhibited weaker scalability, whereas GA and PSO showed relatively high computational costs and reduced accuracy on large datasets. Our findings reshape existing knowledge by demonstrating that a hybrid approach integrating PDACNN forecasting with EVO optimization outperforms these conventional methods. PDACNN effectively captures complex temporal dependencies in energy consumption and price signals, enabling more accurate forecasting, while EVO adapts scheduling in response to variations in renewable output and consumer demand. This dual mechanism ensures not only cost savings and reduced peak loads but also improved system stability and resilience. Overall, this study advances the field by showing that hybrid AI-driven frameworks can overcome the limitations of heuristic-only methods, providing scalable and multi-objective solutions for IoT-enabled SGs. The implications extend beyond improved performance metrics: reduced PAR alleviates stress on distribution infrastructure, cost savings benefit both utilities and consumers, and enhanced forecasting accuracy facilitates greater integration of RES. Collectively, these contributions position EVO-PDACNN as a robust and future-ready framework for sustainable SG operation.

6. CONCLUSION

This paper addresses the shortcomings of current EM strategies that are inefficient in predicting, adjusting to renewable fluctuation, and timely scheduling in IoT-powered SGs. It is a unified structure that combines forecasting and scheduling as a dependent component, which allows for more precise load forecasting and adapting resource distribution. The main results prove that the proposed EVO-PDACNN approach can enhance the functioning of the system significantly. It decreases PAR by 22% and decreases the cost of electricity by 12% and is also faster to compute as compared to GA, PSO, ACO, WBFA, and MEHOA. The method also provides reduced forecasting errors, which depict greater accuracy and strength in the dynamic setting with renewable variability. These findings confirm that the hybrid EVO-PDACNN architecture is a more efficient, scalable, and resilient system for using EM in SGs. The implications extend to practical deployment in large-scale grids, microgrids (MGs), and IoT-based energy networks, where improved cost efficiency, peak load reduction, and operational reliability are critical. As reliance on renewable generation continues to grow, the suggested framework offers a feasible and robust pathway toward sustainable and intelligent energy system operation.

Limitations: i) EVO-PDACNN relies on historical energy consumption and pricing data, so incomplete or inaccurate information can reduce prediction and scheduling performance; ii) Hybridization increases computational demand, potentially limiting real-time applicability, minor modifications may be needed for large-scale SG systems with numerous distributed energy resources; and iii) Performance depends on reliable IoT communication networks, and user behavior or policy measures can make responses to pricing-based demand response unpredictable.

The findings of this study have several important implications for next-generation SG operation. In EVO-PDACNN, the framework allows making more precise predictions, more flexible scheduling, and better demand balancing, which makes it appropriate to apply to the large-scale SGs, MGs, and IoT-based energy networks. Its ability to reduce PAR and electricity cost supports utilities in enhancing grid stability and meeting evolving regulatory and sustainability requirements. The hybrid structure also offers a promising pathway for integrating high-penetration renewable resources, EV charging coordination, and distributed energy resources. Future development can focus on incorporating stochastic modeling to better capture uncertainties in renewable generation, extending the framework to distributed or edge-computing environments for faster response, and strengthening cybersecurity layers to protect IoT-enabled operations. The applicability and resilience of the EVO-PDACNN architecture will be expanded further by exploring the multi-MG coordination, adaptive pricing schemes, and real-time responsiveness. These improvements will lead to smarter, autonomous, and greener EM systems.

ACKNOWLEDGEMENT

The authors would like to thank REVA University for continuous support, infrastructure, and encouragement in carrying out the research, fostering a collaborative academic environment.

FUNDING INFORMATION

Authors state no funding involved.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] B. Singh, R. Ray, J. S. Bhadoriya, A. Kumar, and A. R. Gupta, "Techno-economic feasibility analysis with energy storage and demand response program for the smart home energy management," *Electrical Engineering*, vol. 106, no. 4, pp. 5133–5152, Aug. 2024, doi: 10.1007/s00202-024-02274-2.

[2] A. Khodadadi, S. Adinehpour, R. Sepehrzad, A. Al-Durra, and A. Anvari-Moghaddam, "Data-driven hierarchical energy management in multi-integrated energy systems considering integrated demand response programs and energy storage system participation based on MADRL approach," *Sustainable Cities and Society*, vol. 103, p. 105264, Apr. 2024, doi: 10.1016/j.scs.2024.105264.

[3] C. K. Rao, S. K. Sahoo, and F. F. Yanine, "Demand side energy management algorithms integrated with the IoT framework in the PV smart grid system," in *Advanced frequency regulation strategies in renewable-dominated power systems*, Elsevier, 2024, pp. 255–277.

[4] B. K. Jha, A. Tiwari, R. B. Kuhada, and N. M. Pindoriya, "IoT-enabled smart energy management device for optimal scheduling of distributed energy resources," *Electric Power Systems Research*, vol. 229, p. 110121, Apr. 2024, doi: 10.1016/j.epsr.2024.110121.

[5] L. Wen, K. Zhou, W. Feng, and S. Yang, "Demand side management in smart grid: a dynamic-price-based demand response model," *IEEE Transactions on Engineering Management*, vol. 71, pp. 1–30, 2022, doi: 10.1109/TEM.2022.3158390.

[6] E. J. Salazar, M. Jurado, and M. E. Samper, "Reinforcement learning-based pricing and incentive strategy for demand response in smart grids," *Energies*, vol. 16, no. 3, p. 1466, Feb. 2023, doi: 10.3390/en16031466.

[7] P. R. Krishnan and J. Jacob, "An IoT based efficient energy management in smart grid using DHOCSA technique," *Sustainable Cities and Society*, vol. 79, p. 103727, Apr. 2022, doi: 10.1016/j.scs.2022.103727.

[8] Y. Wan, J. Qin, X. Yu, T. Yang, and Y. Kang, "Price-based residential demand response management in smart grids: a reinforcement learning-based approach," *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 1, pp. 123–134, Jan. 2021, doi: 10.1109/JAS.2021.1004287.

[9] S. A. Hashmi, C. F. Ali, and S. Zafar, "Internet of Things and cloud computing-based energy management system for demand side management in smart grid," *International Journal of Energy Research*, vol. 45, no. 1, pp. 1007–1022, Jan. 2021, doi: 10.1002/er.6141.

[10] B. N. Alhasnawi, B. H. Jasim, Z.-A. S. A. Rahman, and P. Siano, "A novel robust smart energy management and demand reduction for smart homes based on internet of energy," *Sensors*, vol. 21, no. 14, p. 4756, Jul. 2021, doi: 10.3390/s21144756.

[11] A. Fraija, N. Henao, K. Agbossou, S. Kelouwani, M. Fournier, and S. H. Nagarsheth, "Deep reinforcement learning based dynamic pricing for demand response considering market and supply constraints," Smart Energy, vol. 14, p. 100139, May 2024, doi: 10.1016/j.segy.2024.100139.

[12] L.-G. Hua *et al.*, "Smart home load scheduling system with solar photovoltaic generation and demand response in the smart grid," *Frontiers in Energy Research*, vol. 12, Aug. 2024, doi: 10.3389/fenrg.2024.1322047.

[13] A. H. Alghtani, V. Tirth, and A. Algahtani, "Lens-oppositional duck pack algorithm based smart home energy management system for demand response in smart grids," *Sustainable Energy Technologies and Assessments*, vol. 56, p. 103112, Mar. 2023, doi: 10.1016/j.seta.2023.103112.

[14] A. Alzahrani *et al.*, "Demand response for optimal power usage scheduling considering time and power flexibility of load in smart grid," *IEEe Access*, vol. 11, pp. 33640–33651, 2023.

[15] F. R. Albogamy *et al.*, "Optimal demand-side management using flat pricing scheme in smart grid," *Processes*, vol. 10, no. 6, p. 1214, Jun. 2022, doi: 10.3390/pr10061214.

[16] P. Pawar, M. TarunKumar, and P. Vittal K., "An IoT based intelligent smart energy management system with accurate forecasting and load strategy for renewable generation," *Measurement*, vol. 152, p. 107187, Feb. 2020, doi: 10.1016/j.measurement.2019.107187.

[17] P. Bouquet, I. Jackson, M. Nick, and A. Kaboli, "AI-based forecasting for optimised solar energy management and smart grid efficiency," *International Journal of Production Research*, vol. 62, no. 13, pp. 4623–4644, Jul. 2024, doi: 10.1080/00207543.2023.2269565.

[18] R. Manivannan, "Research on IoT-based hybrid electrical vehicles energy management systems using machine learning-based algorithm," *Sustainable Computing: Informatics and Systems*, vol. 41, p. 100943, Jan. 2024, doi: 10.1016/j.suscom.2023.100943.

[19] S. Balavignesh, C. Kumar, R. Sripriya, and T. Senjyu, "An enhanced coati optimization algorithm for optimizing energy management in smart grids for home appliances," *Energy Reports*, vol. 11, pp. 3695–3720, Jun. 2024, doi: 10.1016/j.egyr.2024.03.031.

[20] J. A. A. Silva, J. C. López, C. P. Guzman, N. B. Arias, M. J. Rider, and L. C. P. da Silva, "An IoT-based energy management system for AC microgrids with grid and security constraints," *Applied Energy*, vol. 337, p. 120904, May 2023, doi: 10.1016/j.apenergy.2023.120904.

[21] G. Hafeez *et al.*, "Efficient energy management of IoT-enabled smart homes under price-based demand response program in smart grid," *Sensors*, vol. 20, no. 11, p. 3155, Jun. 2020, doi: 10.3390/s20113155.

[22] A. U. Rehman *et al.*, "An efficient energy management in smart grid considering demand response program and renewable energy sources," *IEEE Access*, vol. 9, pp. 148821–148844, 2021.

[23] M. U. Saleem, M. R. Usman, M. A. Usman, and C. Politis, "Design, deployment and performance evaluation of an IoT based smart energy management system for demand side management in smart grid," *IEEE Access*, vol. 10, pp. 15261–15278, 2022.
[24] S. H. S. and N. S. Ramaiah, "A two-stage deep convolutional model for demand response energy management system in IoT-enabled smart grid," *Sustainable Energy, Grids and Networks*, vol. 30, p. 100630, Jun. 2022, doi: 10.1016/j.segan.2022.100630.
[25] S. Ali *et al.*, "Demand response program for efficient demand-side management in smart grid considering renewable energy sources," *IEEE Access*, vol. 10, pp. 53832–53853, 2022.
[26] D. Kanakadhurga and N. Prabaharan, "Smart home energy management using demand response with uncertainty analysis of electric vehicle in the presence of renewable energy sources," *Applied Energy*, vol. 364, p. 123062, Jun. 2024, doi: 10.1016/j.apenergy.2024.123062.
[27] M. Saleem *et al.*, "Integrating smart energy management system with Internet of Things and cloud computing for efficient demand side management in smart grids," *Energies*, vol. 16, no. 12, p. 4835, Jun. 2023, doi: 10.3390/en16124835.
[28] G. Hafeez *et al.*, "An innovative optimization strategy for efficient energy management with day-ahead demand response signal and energy consumption forecasting in smart grid using artificial neural network," *IEEe Access*, vol. 8, pp. 84415–84433, 2020.
[29] D. Yousri, T. S. Babu, E. Beshr, M. B. Eteiba, and D. Allam, "A robust strategy based on marine predators algorithm for large scale photovoltaic array reconfiguration to mitigate the partial shading effect on the performance of PV system," *IEEE Access*, vol. 8, pp. 112407–112426, 2020.
[30] H. Armghan, M. Yang, A. Armghan, N. Ali, M. Q. Wang, and I. Ahmad, "Design of integral terminal sliding mode controller for the hybrid AC/DC microgrids involving renewables and energy storage systems," *International Journal of Electrical Power & Energy Systems*, vol. 119, p. 105857, Jul. 2020, doi: 10.1016/j.ijepes.2020.105857.
[31] M. Azizi, U. Aickelin, H. A. Khorshidi, and M. Baghalzadeh Shishehgarkhaneh, "Energy valley optimizer: a novel metaheuristic algorithm for global and engineering optimization," *Scientific Reports*, vol. 13, no. 1, p. 226, Jan. 2023, doi: 10.1038/s41598-022-27344-y.
[32] W. Hou, N. Chen, J. Peng, W. Sun, and Q. Du, "Pyramidal dilation attention convolutional network with active and self-paced learning for hyperspectral image classification," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 16, pp. 1503–1518, 2023.

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