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Renewable Energy Forecasting and Scheduling with PV Generation and EV Integration

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Abstract

The integration of renewable energy sources such as solar and wind into microgrids remains challenging due to the intermittent and unpredictable nature of generation, which affects reliability, cost efficiency, and operational performance. Conventional energy management systems rely on traditional forecasting and scheduling approaches, resulting in inefficient coordination and increased operating costs, while deep learning models such as LSTM, BiLSTM, and standalone Temporal Convolutional Networks (TCN) struggle to capture complex temporal dependencies and dynamic environmental variations effectively. To address these limitations, this study proposes a two-stage microgrid energy management framework that integrates advanced forecasting with intelligent optimization. In the first stage, a high-accuracy solar photovoltaic (PV) forecasting model is developed using an attention-enhanced Temporal Convolutional Network (TCN- Attention) to improve long-term temporal representation and weather-aware learning. In the second stage, a Mixed-Integer Linear Programming (MILP) optimizer coordinates energy generation, storage, and grid interactions in a cost-effective and reliable manner. The framework is trained and validated using the Kaggle Renewable Energy Microgrid Dataset containing time-series variables such as solar irradiance, temperature, wind speed, humidity, and load demand. Experimental results demonstrate that the proposed TCN-Attention model outperforms classical TCN, BiLSTM, and LSTM models, achieving MAE of 7.2864, MSE of 101.8693, RMSE of 10.093, and an R^2 of 0.923. Furthermore, the MILP-based strategy yields superior economic performance with a net profit of £8.34, cost savings of 131.6%, and a 25% reduction in grid imports, providing a scalable and sustainable solution for future microgrid energy management systems.

Keywords: attention mechanism, battery management, microgrid optimization, mixed-integer linear programming (MILP), temporal convolutional network (TCN)

1. INTRODUCTION

Nowadays, there is a growing need for sustainable energy technologies to replace traditional fossil fuel-based electricity generation, especially in both developed and developing countries [1]. The burning of fossil fuels releases greenhouse gases into the atmosphere, thus making the environment worse, as such, the rate of climate change and thawing of the earth is doubled. Free from pollution, electricity can be produced using numerous renewable energy (RE) sources. This sector includes hydropower, solar power, wind power, biomass, geothermal, and hydrogen [2],[3],[4]. Solar photovoltaic (PV) energy is becoming popular because it is environmentally friendly, cheap, and does not pollute the air very much [5],[6]. RE also contributes to the economy by cutting the electricity bill and allowing people to sell surplus energy to the grid. Nevertheless, the renewable energy sector is still facing challenges, such as the problem of intermittency. A case in point is that solar panels are effective only during the daylight hours, while wind turbines require a certain level of wind to generate power.

The increasing demand for energy worldwide is a consequence of economic development, innovation, and an expanding population. Consequently, it is imperative for every nation to prioritize energy management through efficiency in the consumption of energy [7]. Energy use keeps going up by about 2% a year, and most production

still relies on fossil fuels [8]. Governments and researchers are working on renewable and sustainable energy systems that are supported by strong management and policy measures [9]. By switching to clean energy, we will lessen our dependence on fossil fuels and, in turn, decentralize the emitting of greenhouse gases and, to a large extent, carbon. The International Energy Agency (IEA) predicts that the carbon emissions of the energy sector will be cut by one- third between 2021 and 2030. The major part of this will come from renewable sources, particularly solar and wind power. On the other hand, the generation of reliable energy from renewables like the sun and wind should not be taken for granted all the time. A clear and accurate supposition and planning of the future events in the energy sector are of utmost importance for predicting energy production, balancing supply and demand, and improving system reliability. Through educated guesses, grid operators can make their plans about the amount of renewable energy to be produced. Once properly scheduled, the right moment for energy use, storing, or dispatching is guaranteed. It does this not only with less carbon emissions and lower operating costs, but also by showing the integration of renewables into the grid which, in turn, assists in closing the gap between electricity supply and demand [10], [11].

The solar photovoltaic (PV) energy system that has been in use for many years has become increasingly accepted and is now regarded as one of the foremost methods of producing power with the least possible environmental harm due to its cleanliness, inexhaustibility, and harmony with nature [12]. By utilizing semiconducting materials, PV systems are able to directly convert sunlight into electricity through the photovoltaic effect. Photovoltaic cells absorb light from the sun, which causes electrons to flow and generates an electric current. After that, an inverter converts the DC current to the AC current that houses and companies need. The initial demonstration of solar radiation conversion into electricity was demonstrated in 1954, and its efficiency was found to be 6%. There has been significant improvement in PV technology's performance and affordability since then [13]. In order to address the growing global demand for energy while simultaneously reducing reliance on fossil fuels, photovoltaic (PV) panels are finding widespread use in residential and commercial structures as well as smart city infrastructure. To reach energy targets in the long run, they are essential, and projections show that they will overtake fossil fuels as the leading power source by 2040. The problem with PV systems is that their output varies with the seasons and the time of day. Reason being, they can't produce power without sunlight. In order to provide a steady supply of electricity for modern energy systems, it is crucial to develop effective methods of predicting and planning when to use PV energy [14], Fig. 1 shows a Solar panel diagram.

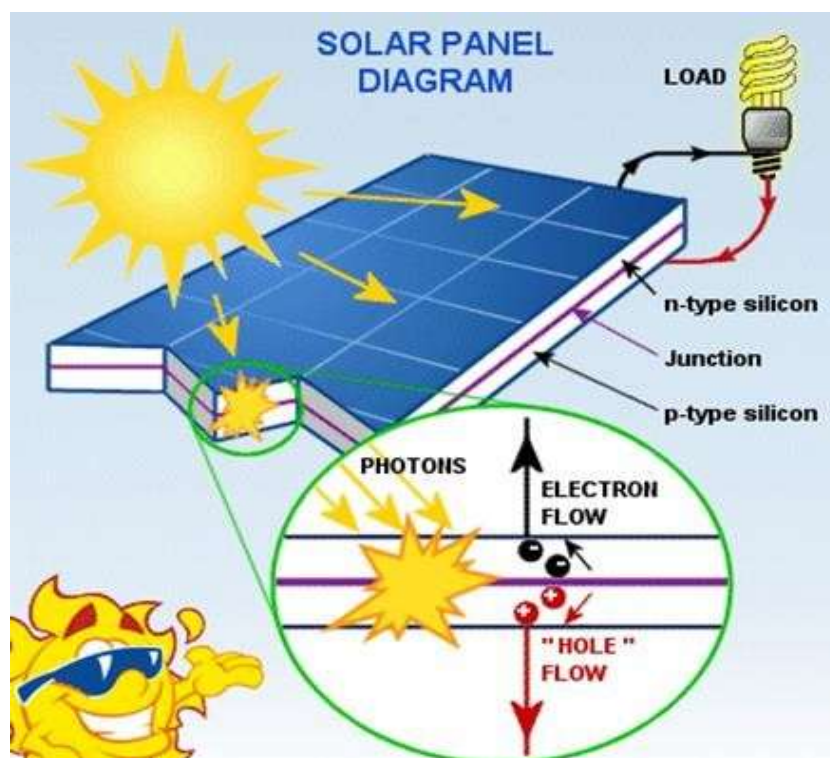


Fig. 1 Solar panel diagram (<https://www.mrsolar.com/what-is-a-solar-panel/>)

In addition to the rapid adoption of solar power, Electric Vehicles (EVs) have emerged as another key component in the transition toward sustainable and intelligent energy networks [15]. Electric vehicles serve two functions: when charging they are energy consumers and at times of peak demand they are the grid power source. Unregulated night charging can considerably increase power usage, therefore, it is beneficial to regulate EV charging patterns. The IEA foresees that by 2030 unregulated EV charging would have the potential to increase the

power requirement in the US by up to four times, while it would be responsible for 6.5% and 9.5% increases respectively in the demand in the EU and China. The consuming of energy from the stored EV batteries is facilitated by the well-organized and proper management of V2G or VGI systems which allow two-way power flow: from the grid to vehicles (discharging) and from vehicles to the grid (charging). This interaction results in the general quality and stability of power being enhanced, the synchronization of demand and supply occurring, and the power grid being less stressed [16]. The coupling of EV charging infrastructure with renewable energy systems (RES), especially solar PV, results in cleaner energy use and more resilient grids. Gridable electric vehicles (GEVs), or vehicles enabling two-way energy exchange, are a result of an ongoing dialogue between the grid, renewable energy sources (RES), and electric vehicles (EVs). V2G telematics facilitate this interaction, thus enabling efficient energy management in smart grid systems of the future. The latest study enhances the overlapping of renewable energy sources and electric cars by proposing a wise energy management system that connects solar photovoltaic (PV) generation, electric vehicle charging infrastructure, and (EV) integration, and bio-inspired optimization techniques to solve major problems in renewable energy management. The central problem is the inconsistency of solar power production resulting from changing weather conditions, which causes uncertainty in energy supply. Besides, the demand patterns might become very erratic because of the unregulated EV charging practices leading to grid instability. More broadly, AI-enabled approaches can support data-driven forecasting, optimization, and operational decision-making in applied resource-management systems [17-18].

The latest study enhances the overlapping of renewable energy sources and electric cars by proposing a wise energy management system that connects solar photovoltaic (PV) generation, electric vehicle charging infrastructure, and (EV) integration, and bio-inspired optimization techniques to solve major problems in renewable energy management. The central problem is the inconsistency of solar power production resulting from changing weather conditions, which causes uncertainty in energy supply. Besides, the demand patterns might become very erratic because of the unregulated EV charging practices leading to grid instability and higher operational costs. It is a great challenge technologically and economically to deal with these variations and at the same time, let the generation, storage, and consumption be in perfect equilibrium.

The study tackled the challenges and successfully implemented the Attention-enhanced Temporal Convolutional Network (TCN) which accurately predicts solar power generation and EV charging requirements. The forecasts serve as the basis for the application of a Mixed Integer Linear Programming (MILP) model which optimizes energy usage and lessens the pressure on the grid. Besides, biologically inspired optimization methods not only support human decision-making but also increase the robustness of the systems under stress. This project, therefore, aims to develop an intelligent, dependable, and sustainable energy management system capable of dealing with scheduling and forecasting problems that will facilitate the integration of solar photovoltaic power generation and electric vehicles in the future smart grid infrastructures.

2. BACKGROUND

2.1 Temporal convolutional neural network

To excel at sequence modeling, a brand new convolutional neural network known as TCN was developed. To grasp distant patterns, TCN models employ a series of temporal convolutional filters arranged in a hierarchical fashion. By using residual block structure and dilated casual convolutions, TCN enhances the receptive field and net depth. To increase the receptive field in dilated casual convolutions, one can use dilated convolution to convolve an output at time t entirely with items from time t and earlier in the previous layer. In contrast to standard convolutions, dilated convolutions maintain a constant distance between adjacent filter taps. A 1-D sequence input $x \in R^n$ and a filter $f: \{0, \dots, k-1\} \rightarrow R$ were defined as follows, for any sequence of items, the convolution operation F .

$$F(s) = (x *_{(d)} f)(s) = \sum_{i=0}^{k-1} f(i) \cdot x_{s-di} \quad (20)$$

In this case, d is the dilation factor, k is the filter size, and the amount $s-di$ represents the previous direction. A larger filter size k and a larger dilation factor d can expand the TCN's receptive field. With three separate dilation factors and a filter size of three, the expanded causal convolution structure is shown in Figure 6. The residual block is utilized by TCN in a manner similar to that of dense networks. You need the 1×1 Conv layer when a residual block's input and output attributes aren't equal. To facilitate their merging, residual blocks shrink the input to correspond to the feature count of the output. Skip connection is another name for the total of inputs and outputs from a transformation. By distributing it throughout a vast network, residual blocks circumvent the vanishing gradient issue.

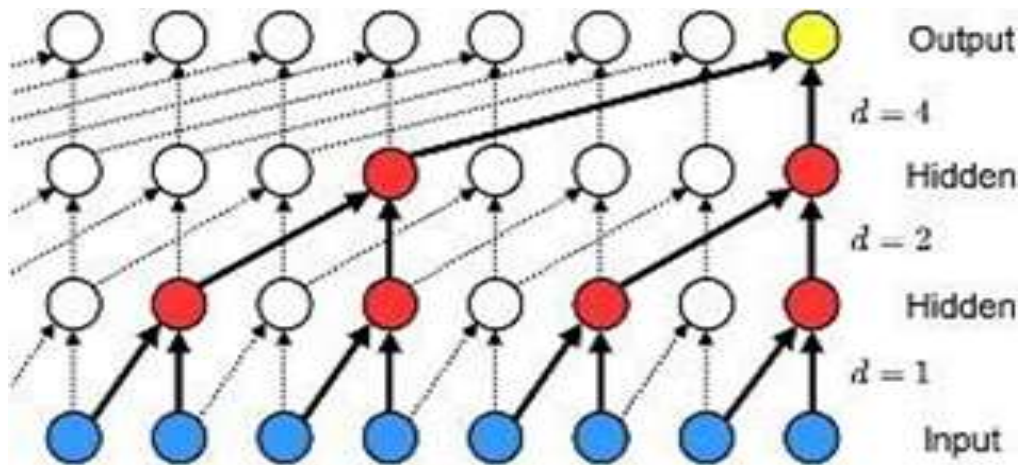


Fig. 2: TCN model architecture

From the figure-2 Temporal Convolutional Network (TCN) processes sequential data using stacked dilated causal convolutions, where each layer raises the dilation rate ($d = 1, 2, 3, 4$) to enlarge the receptive field without loss of resolution. The design assures temporal causality (no more data leaking) by padding inputs asymmetrically. Lower layers (e.g. $d = 1$) capture fine-grained patterns, whereas higher layers (e.g., $d = 4$) aggregate larger contexts. When combined with residual connections and weight normalization, TCNs effectively simulate long-range relationships in sequences, making them useful for applications such as time-series forecasting and voice processing. The dilation hierarchy ($d \in \{1, 2, 4\}$) balances local detail with global context.

2.2 Attention mechanism

The attention mechanism processes information by simulating the human brain and eyesight, much as other neural network-based techniques. Human eyesight only concentrates on the particular areas of the picture, processing the rest of it gradually. This causes the environment to be observed in "low-resolution" and the targeted areas of the human vision space to be experienced "high-resolution." To put it another way, it minimizes the unnecessary bits and assigns lower weights to the important ones. This saves the brain from processing the full visual space and enables it to accurately and effectively concentrate on the most critical aspects.

The attention mechanism was developed by researchers in response to this feature of human eyesight. It was created in 2014 originally for applications involving natural language processing [19]. Since then, it has been extensively used for a variety of purposes, including computer vision tasks [20]. It has been stated that it can improve approaches that are mostly CNN-based [21]. Furthermore, it has been used in combination with graph neural networks [22] and recurrent neural network models [23]. Assigning varying weights to distinct pieces of information is the fundamental concept behind the attention process. As a result, the DL model is drawn to meaningful information when it is given a greater weight [24]. Four characteristics may be used to categorize attention mechanism methods:

In the Attention's structure shown in, $\{x_1, x_2, x_3, \dots, x_t\}$ denotes the input sequence, $\{h_1, h_2, h_3, \dots, h_t\}$ denotes the hidden layer state, $\{a_1, a_2, a_3, \dots, a_t\}$ denotes the attention weight of the hidden layer state, s_t denotes the product sum of the hidden state and the weight, and y_t is the output at time slot t . The specific calculation formula is as follows:

$$a_i = \frac{\exp(e_i)}{\sum_{k=1}^T \exp(e_k)}$$

$$s_t = \sum_{i=1}^T a_i h_i$$

$$e_i = v^T \tanh(W h_i + b)$$

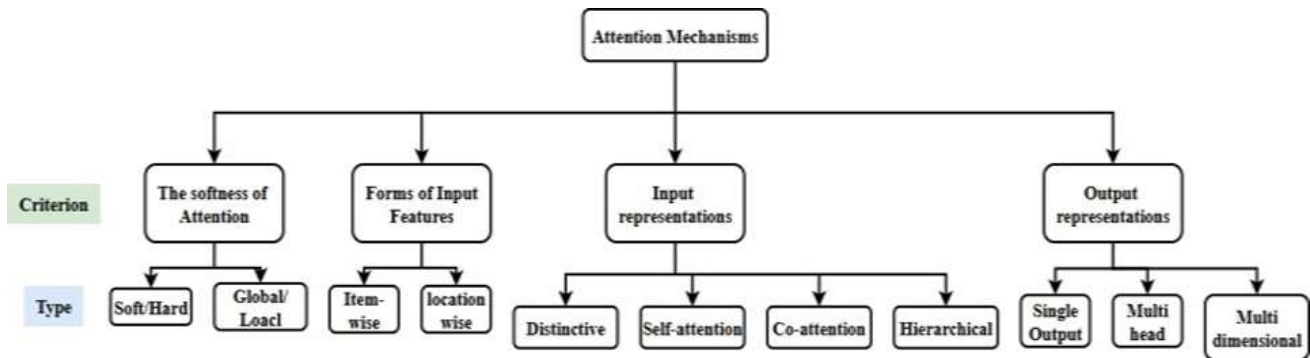


Fig. 3: An overview of attention mechanism

- **The softness of attention:** Deterministic or soft attention is hypothesized [19]. With each weight averaged, this network creates the context vector. The attention mechanism calculates the context vector, a high-dimensional vector representation of input items or sequences, using contextual information. Hard attention, or stochastic attention, randomly selects context vector sample elements [25]. Reduces computation time. In computer vision and RS image processing, global and local attentions are prevalent [26] [27]. Global attention handles all inputs like soft attention. Global attention uses the present time step output instead of the previous one to simplify soft attention, whereas local attention mixes soft and hard attentions. This technique avoids hard attention's no differentiability by examining a subset of input components and is less computationally intensive.
- **Forms of input features:** Required inputs separate attention systems according to items and locations. A model requires either explicit or preprocessed inputs to perform item-wise attention [25]. In this case, the model needs to identify faulty inputs, while location-wise attention does not require known inputs. RS image processing often uses location-wise attention because to the pictures' properties and focused activities [28].
- **Input representations:** Single- and multi-input attention models exist [29][30]. The input processing methodology varies per model. Most attention networks analyze single-input in two steps. Co-attention, a multi-input attention network, mixes two sources simultaneously. This enables RS image change detection [31]. Self-attention networks compute attentions from model inputs alone. Co-attention, a multi- input attention network, mixes two sources simultaneously. This enables RS image change detection. Self-attention networks calculate attentions from model inputs, eliminating external information dependencies [32]. Focusing on areas improves model performance in complex backdrops [33]. Original input, put, and input levels/scales determine hierarchical attention weights [34]. Pictures are classified with fine-grained attention [35].
- **Output representations:** One output is used by the majority of attention processes. Weight scores for a single feature are computed. Two more multi-head attention systems that are multi-dimensional. Attention weights are generated by the multi-head attention mechanism by linearly examining subsets of inputs and combining them [36]. With CNN algorithms, it's very useful. In contrast to the majority of NLP methods that use vectors to calculate weights, multidimensional attention uses feature matrices. Methods. The majority of NLP algorithms use multidimensional attention, which calculates weights using feature matrices rather than vectors.

2.3 Mixed integer liner programmer

MILP has been extensively used to solve optimization challenges, including but not limited to networks and communication. For example, it has been used in the communication industry for resource allocation in offloading for fog computing [37], multi-access edge computing (MEC) [38], and wavelength division multiple access (WDMA). Additionally, it is crucial to network research for tasks like supply chain network improvement [19], virtual network reconfiguration scheduling, and network latency reduction [20]. Recent studies have also integrated MILP with bio-inspired algorithms to improve computational efficiency and achieve adaptive scheduling under uncertain renewable generation scenarios [21]. These studies demonstrate that MILP remains a powerful framework for tackling both conventional energy optimization problems and emerging challenges in renewable energy forecasting, PV scheduling, and EV- integrated smart grid management. Think of a MILP model like this:

$$\begin{aligned} \min_{x,y} \quad & c^T x + h^T y \\ \text{s.t.} \quad & Ax + Gy \leq b, \\ & x \in X, x \in \{0,1\}^n, y \in \mathbb{R}^p \end{aligned}$$

Here x is a vector with binary variables and A is its corresponding coefficient matrix in constraints. y is a vector with non-negative continuous variables and G is its corresponding coefficient matrix in constraints. c^T is the coefficient vector of variable x in the objective function and h^T is the coefficient vector of variable y in the objective function.

3. LITERATURE REVIEW

In recent years, renewable energy forecasting and scheduling have gained immense importance due to the increasing dependency on solar photovoltaic (PV) generation and the rapid integration of electric vehicles (EVs) in power systems. Various researchers have pointed out that the non-predictability of solar irradiance and the time-varying charging pattern of EVs pose enormous challenges to stable and efficient energy management. Precise solar power forecasts are critical to ensure grid stability and maximum energy dispatching. Deep learning models have made significant strides in enhancing the accuracy of solar energy forecasting by discovering complex patterns between environmental factors like irradiance, temperature, and humidity. Atiea et al. [20] delivered a Bayesian optimization stacked ensemble learning method for improving photovoltaic power generation forecasts, which significantly enhanced the accuracy of predictions over conventional models. Likewise, Li et al. [21] proposed a deep learning model for solar and wind energy forecasting in Northwest China, demonstrating that the hybrid approach yielded superior generalization and reliability amid fluctuating weather conditions.

Zhen et al. [24] proposed an ultra-short-term power forecasting model founded on an enhanced bi-directional long short-term memory (Bi-LSTM) network optimized by genetic learning, which successfully predicted PV output without access to meteorological data. The model exhibited low RMSE for 5-minute, 15-minute, and 30-minute intervals, validating its applicability for real-time microgrid operations. Liu et al. [25] combined the Normal Cloud Parrot Optimization algorithm with an extreme learning machine to perform solar PV forecasting and obtained enhanced efficiency in various climatic conditions. Likewise, Alqahtani and Shaheen. [26] enhanced photovoltaic integration in distribution feeders through an adaptive algorithm that improved voltage profiles and minimized energy loss. These investigations demonstrate that hybrid deep learning and optimization-driven forecasting algorithms improve energy prediction accuracy substantially, thus enabling enhanced scheduling decisions for renewable energy systems. Recent work in AI-enabled resource management similarly emphasizes the value of data-driven monitoring, predictive analytics, and intelligent decision support for improving resource-use efficiency [17-18] [39].

Concurrently, incorporation of electric vehicles (EVs) into power grids based on renewables has attracted significant attention because it also serves as both a load and a distributed storage unit. Nonetheless, untimely charging during peak hours can cause serious grid imbalances and loss of energy. Kabir et al. [27] proposed an integer linear programming model for optimal EV charging from PV- powered charging stations with energy storage facilities, allowing variable rates of charging and optimal reduction of electricity cost within deadline constraints. Likewise, Bouhours et al. [28] employed an optimized model for EV charging to enhance the voltage profile and minimize energy losses in a low-voltage distribution network. Most recently, Ruoso et al. [29] investigated the effects of high- penetration EVs at the national level on energy balances and concluded that incorporating renewable-based charging of EVs largely mitigates fossil fuel reliance and emissions while enhancing system flexibility.

Yang et al. [30] proposed a multi-objective stochastic optimization model that considered uncertainty associated with renewable resources, demand response, and storage capacity, and illustrated that such models could minimize the cost for retailers while maximizing the utilization of clean energy. Alzahrani et al. [31] then expanded this idea with a model which co-optimized load scheduling and management of distributed energy resources in smart power grids, where it reduced operational costs by 11.9% and pollutant emissions by 6.12%. Likewise, İnci et al. [32] wrote that co-ordinated operation of EVs and PV systems enhances grid stability, alleviates peak stress, and supports sustainable grid expansion. These results corroborate Tavakoli et al. [33], who underscored the fact that integrated PV-EV operation cancels out the negative impacts of intermittency and uncertainty when coordinated effectively.

Emerging trends in bio-inspired optimization have yielded effective means of coping with the nonlinear and multi-objective nature of renewable energy systems. Research has shown that bio-inspired and hybrid intelligent systems can optimize forecasting, scheduling, and energy dispatch in a simultaneous manner. Krishna and

Hemamalini [34] applied a better energy management algorithm in hybrid microgrids and demonstrated more optimal handling of uncertain parameters than conventional control methods. Afzal [35] introduced bio-inspired hybrid optimization for electric vehicle performance improvement and recorded 20% less energy usage and 30% increased battery life through adaptive and smart scheduling. Karim et al. [37] proposed a bio-inspired time-series forecasting model for wind power and proved its efficacy in enhancing forecasting accuracy and stability, indicating good prospects for solar and hybrid systems also.

4. Methodology

This study uses a dual-stage microgrid energy forecasting and optimization method. To assure quality and temporal integrity, a real-world renewable energy dataset is extensively collected and preprocessed. Next, a novel hybrid forecasting model that combines a Temporal Convolutional Network (TCN) with an attention mechanism predicts solar PV generation. Finally, a Mixed-Integer Linear Programming (MILP) optimizer determines the microgrid's most cost-effective operational schedule using the projections.

4.1 Data Collection

The study was carried out using the comprehensive Renewable Energy Microgrid Dataset sourced from Kaggle, that presents exact time-series data from a hybrid renewable energy system in operation. The dataset is a good example of the intricate relationship between weather and energy output, as it continuously tracks and captures the various specified parameters at regular intervals. The data's multiple dimensions and temporal granularity render it a perfect candidate for the development and evaluation of sophisticated forecasting models as well as microgrid management optimization procedures. It is the latter characteristic of the dataset that provides the former advantage in the dynamics of renewable energy investigation and the assessment of the proposed hybrid model through the inclusion of real-world operational scenarios in different seasons that persist the difficulties of actual microgrid operations.

Dataset Link: <https://www.kaggle.com/datasets/programmer3/renewable-energy-microgrid-dataset>

4.2 Data Description

The dataset consists of a variety of metrics meant to capture the microgrid's environment in terms of the operation: timestamps, hour of day, day of the week, and monthly patterns that identify cyclical energy usage. The generation of renewable energy is influenced by solar irradiance, wind speed, temperature, humidity, and air pressure. The main source of operational data is represented by energy system variables such as solar PV output and load patterns that indicate grid consumption. In order to represent more precisely the inherent periodicity of microgrid energy generation and consumption dynamics and the impact of external variables, daylight indicators and seasonal pattern identifiers were incorporated into the model.

4.3 Load and Battery Profile Modelling

The battery subsystem is responsible for the simulation of the microgrid lithium-ion storage unit charge-discharge dynamics. The operational parameters include state of charge (SOC), round-trip efficiency, charge/discharge rate limitations, and capacity thresholds. The efficiency-adjusted balancing equations that maintain the SOC dynamics to conserve energy and also depict the storage utilization restrictions are applied here. The model applies degradation-aware logic to prevent over-cycling of the battery, thus protecting its health.

The load profile is a representation of the daily and seasonal residential or community energy consumption. It is influenced by human activity cycles, which lead to higher demand in the morning and evening. The load values are simulated as a stochastic time-series with base and peak demand characteristics, thus reflecting the consumption diversity. These profiles are required for the training of the forecasting model and the definition of the real-world constraints for the MILP optimizer.

4.4 Data Preprocessing

The complete data pretreatment pipeline was developed to ensure the quality of data, to augment the importance of features, and to compose the dataset for model training in an efficient way. The temporal processing phase consisted of the conversion of the raw timestamp strings into structured date time objects, and then the extraction of cyclical time features with trigonometric transformations to depict the energy patterns' periodicity accurately, as well as the creation of logical daylight indicators based on the standard solar hours. The feature engineering included the production of additional temporal indicators, for instance, the day-of-year measurements and the seasonal markers, while all the features were standardized using Standard Scaler for providing the same scaling across the variables. The quality assurance process for data involved a detailed analysis of missing values followed by proper imputations, removal of duplicate records in a systematic manner to avoid data leaking, and rigorous checking of data distributions along with the application of outlier detection methods. The temporal ratio of 80-20 was applied to the dataset in a systematic manner which preserved the chronological order, thus keeping the time series intact and avoiding any future information leakage during the model training and evaluation phases.

4.5 Model Building

To draw conclusions, the study combines mathematical optimization with cutting-edge deep learning for the purpose of predicting the future. The two-phase analytical model is characterized by a very close and mutually dependent relationship. The hybrid TCN-Attention forecasting model not only takes the best features of the attention-based models and Temporal Convolutional Networks but is also the best among these designs. The model uses causal convolutions to minimize the chance of losing future information and to maintain the highest temporal integrity, a range of temporal blocks with progressively increasing dilation rates to capture both short-term and long-term dependencies, and residual connections to carry out training with a stable gradient flow. The attention mechanism comprises self-attention layers that are aimed at winning the race of spotting long-range dependencies in time-series data, attention weights that are flexible enough to be adjusted dynamically to highlight important time steps, and context vector generation which is supportive of getting the most relevant temporal information for the prediction. The Mixed-Integer Linear Programming optimizer, which plays a vital role in the decision-making process of energy scheduling, provides a strong basis with an objective function that not just minimizes total operational costs but also achieves an optimal distribution of grid purchases, energy sales, and battery operations, thereby maintaining a balancing act among the three. It includes a wide range of decision variables such as the amounts of grid power transactions, the rates of battery charge and discharge, the levels of state of charge and the binary indicators of the operational states. All these are controlled by a set of realistic constraints which include power balance equations, battery capacity and rate limitations, logic for preventing simultaneous operation, and state of charge dynamics that take efficiency factors into account.

Algorithm 1 Hybrid TCN-Attention Solar Forecasting

```

1: Input: Historical sequence  $X = \{x_1, x_2, \dots, x_T\}$ , where  $x_i \in \mathbb{R}^d$ 
2: Output: Prediction  $\hat{y}_{T+1}$ , attention weights  $A$ 
3: Parameters: Num channels  $[c_1, c_2, c_3]$ , kernel size  $k$ , dropout rate  $\delta$ 
4: procedure TCN-ATTENTION( $X$ )
5:   Initialize temporal blocks with dilations  $\{1, 2, 4\}$ 
6:    $X \leftarrow \text{Transpose}(X)$  ▷ Convert to (batch, channels, seq)
7:   for  $i \leftarrow 1$  to 3 do ▷ Temporal Convolutional Layers
8:      $d_i \leftarrow 2^{i-1}$  ▷ Dilation rate
9:      $X \leftarrow \text{TemporalBlock}(X, c_i, k, d_i, \delta)$ 
10:  end for
11:   $X \leftarrow \text{Transpose}(X)$  ▷ Convert back to (batch, seq, channels)
12:  Attention Mechanism:
13:   $E \leftarrow \tanh(W \cdot X + b)$  ▷ Energy calculation
14:   $A \leftarrow \text{softmax}(V \cdot E)$  ▷ Attention weights
15:   $C \leftarrow \sum_{i=1}^T A_i \cdot X_i$  ▷ Context vector
16:   $\hat{y}_{T+1} \leftarrow W_a \cdot C + b_a$  ▷ Final prediction
17:  return  $\hat{y}_{T+1}, A$ 
18: end procedure
19: procedure TEMPORALBLOCK( $X, c_{out}, k, d, \delta$ )
20:   $p \leftarrow (k - 1) \times d$  ▷ Padding calculation
21:   $X_{conv} \leftarrow \text{Conv1D}(X, c_{out}, k, \text{dilation} = d, \text{padding} = p)$ 
22:   $X_{conv} \leftarrow \text{Chomp1D}(X_{conv}, p)$  ▷ Remove excess padding
23:   $X_{conv} \leftarrow \text{ReLU}(\text{Dropout}(X_{conv}, \delta))$ 
24:  if  $\dim(X) \neq c_{out}$  then
25:     $X_{res} \leftarrow \text{Conv1D}(X, c_{out}, 1)$ 
26:  else
27:     $X_{res} \leftarrow X$ 
28:  end if
29:  return  $\text{ReLU}(X_{conv} + X_{res})$  ▷ Residual connection
30: end procedure

```

Algorithm 2 MILP Energy Scheduling Optimization

```

1: Input: Solar forecast  $S = [s_1, \dots, s_H]$ , load demand  $L = [l_1, \dots, l_H]$ 
2: Parameters: Battery capacity  $B_{max}$ , charge/discharge rates  $P_{ch}^{max}, P_{dis}^{max}$ 
3: Prices: Grid purchase  $p_g$ , grid sell  $p_s$ , battery cost  $p_b$ 
4: procedure OPTIMIZESCHEDULE( $S, L$ )
5:   Initialize MILP problem:  $\min \sum_{t=1}^H Cost_t$ 
6:   Define decision variables:
7:      $G_t^{buy}, G_t^{sell} \geq 0$  ▷ Grid purchase/sell at time  $t$ 
8:      $B_t^{ch}, B_t^{dis} \in [0, P_{max}]$  ▷ Battery charge/discharge
9:      $SOC_t \in [0, B_{max}]$  ▷ Battery state of charge
10:     $u_t^{ch}, u_t^{dis} \in \{0, 1\}$  ▷ Charging/discharging binary
11:   Objective function:
12:     $\min \sum_{t=1}^H [p_g G_t^{buy} - p_s G_t^{sell} + p_b (B_t^{ch} + B_t^{dis})]$ 
13:   Subject to constraints:
14:   for  $t \leftarrow 1$  to  $H$  do
15:     Power balance:
16:      $s_t + B_t^{dis} + G_t^{buy} = l_t + B_t^{ch} + G_t^{sell}$ 
17:     Battery dynamics:
18:     if  $t < H$  then
19:        $SOC_{t+1} = SOC_t + 0.95 B_t^{ch} - B_t^{dis} / 0.95$ 
20:     end if
21:     Operational constraints:
22:      $u_t^{ch} + u_t^{dis} \leq 1$  ▷ No simultaneous charge/discharge
23:      $B_t^{ch} \leq u_t^{ch} P_{ch}^{max}$ 
24:      $B_t^{dis} \leq u_t^{dis} P_{dis}^{max}$ 
25:      $G_t^{sell} \leq s_t + B_t^{dis}$  ▷ Sell limit
26:   end for
27:   Initial condition:
28:    $SOC_1 = 0.5 \times B_{max}$  ▷ Start at 50% SOC
29:   Solve MILP using branch-and-cut
30:   return Optimal schedule  $\{G^{buy}, G^{sell}, B^{ch}, B^{dis}, SOC\}$ 
31: end procedure

```

4.6 Performance Metrics

Root Mean Squared Error (RMSE): The mathematical formula is the square of the Mean Square Error (MSE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_i - y_i)^2}{N}}$$

Mean Squared Error (MSE): Find the average difference between the expected and observed values in a dataset by taking the square root of that difference.

$$MSE = \frac{\sum_{i=1}^N (x_i - y_i)^2}{N}$$

R- Squared: The performance evaluation can be derived from the statistical metric R^2 (R- squared) if the independent variables explain a considerable amount of the variation in the dependent variable. In mathematical terms, it looks like:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

Mean Absolute Error (MAE): By averaging the actual differences between the projected and actual values, the Mean Absolute Error (MAE) is determined. The statistic measures the average absolute amount of errors in a set of predictions, independent of their direction [30].

$$MAE = \frac{\sum_{i=1}^N |\hat{y}_i - y_i|}{N}$$

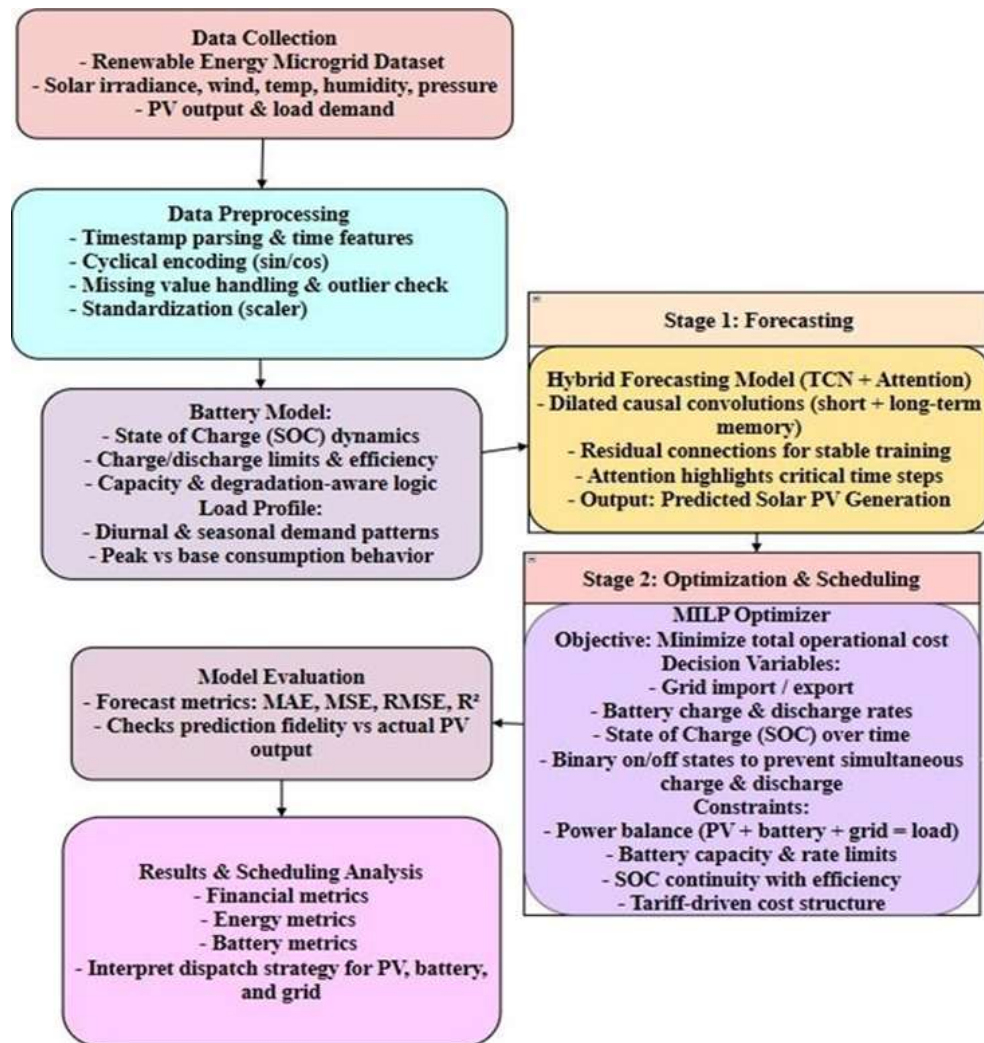


Fig. 4: Flow chart of Proposed Approach

5. Results and Discussions

The experiment's results reveal the significant improvement in predictive effectiveness of the suggested hybrid TCN- Attention model. The following part presents a comparison of different benchmark models using standard metrics as well as visual representations of the actual and predicted values.

5.1 Performance Metrics

Table 1. Performance Metrics

Model	MAE	MSE	RMSE	R ²
Proposed Model	7.28 64	101.869 3	10.0 93	0.923
TCN Model	10.235 8	201.501 6	14.195 1	0.874 8
BiLSTM Model	10.048 6	204.557 7	14.302 4	0.840 1
LSTM Model	13.686 7	371.968 4	19.286 5	0.775 2

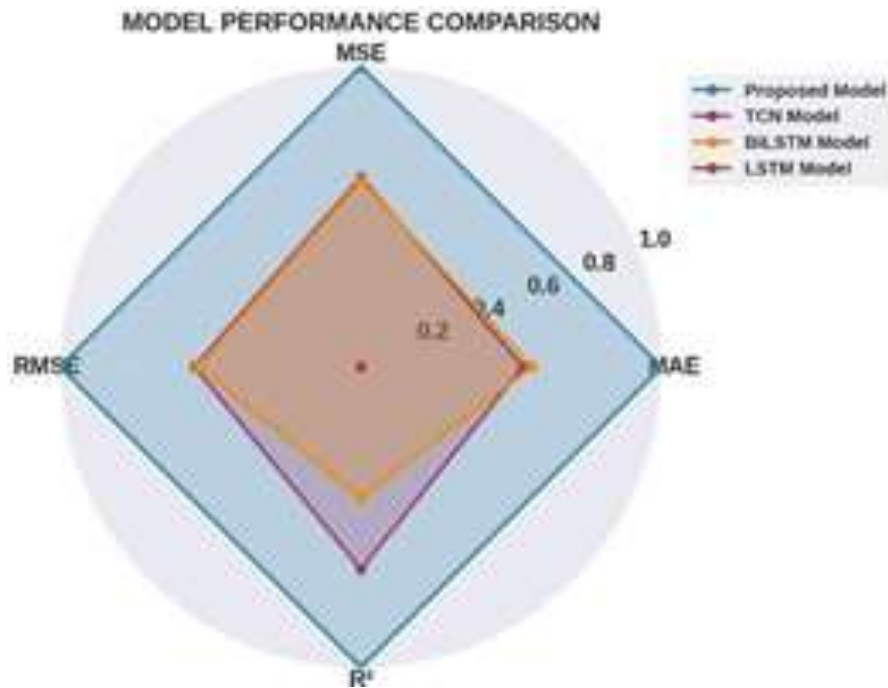
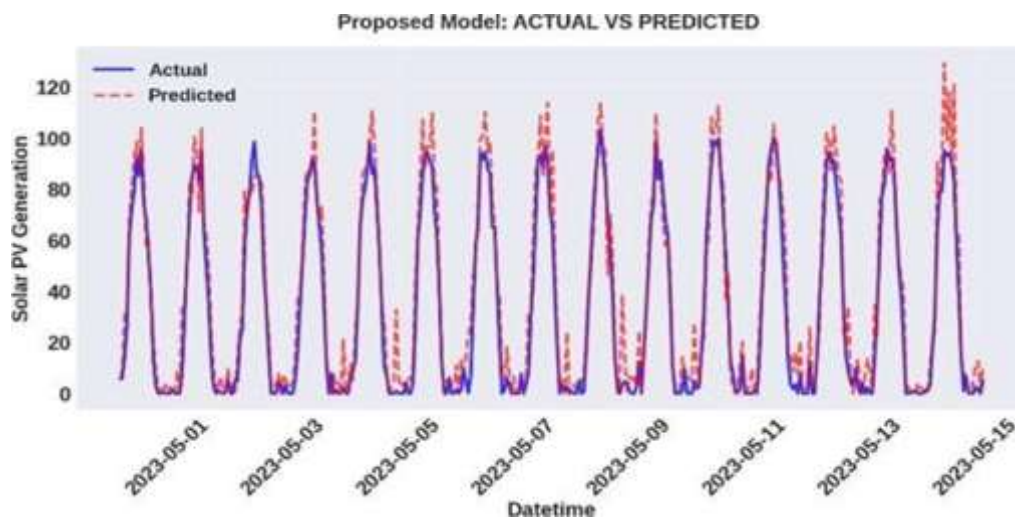


Fig.5: Performance Metrics

The comparison of four prediction models—the Proposed Model, TCN Model, BiLSTM Model, and conventional LSTM Model—is presented in the table and figure. The assessment which incorporates major metrics such as R-squared (R^2) score, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE), reveals the Proposed Model as the most powerful one. The model has the highest R^2 (0.923, meaning almost 92% of the data variation is explained) and the lowest error rates (MAE: 7.2864, MSE: 101.8693, RMSE: 10.093)

demonstrating its superiority over the other models in all the parameters. Meanwhile, the other models have their error values increase and R^2 scores decrease progressively, with the basic LSTM model being the least effective. This extensive analysis is illustrated in Figure 2 where the Proposed Model is evidently pointed out as the most accurate and trusted model for the task in question.

5.2 Actual Vs Prediction graphs



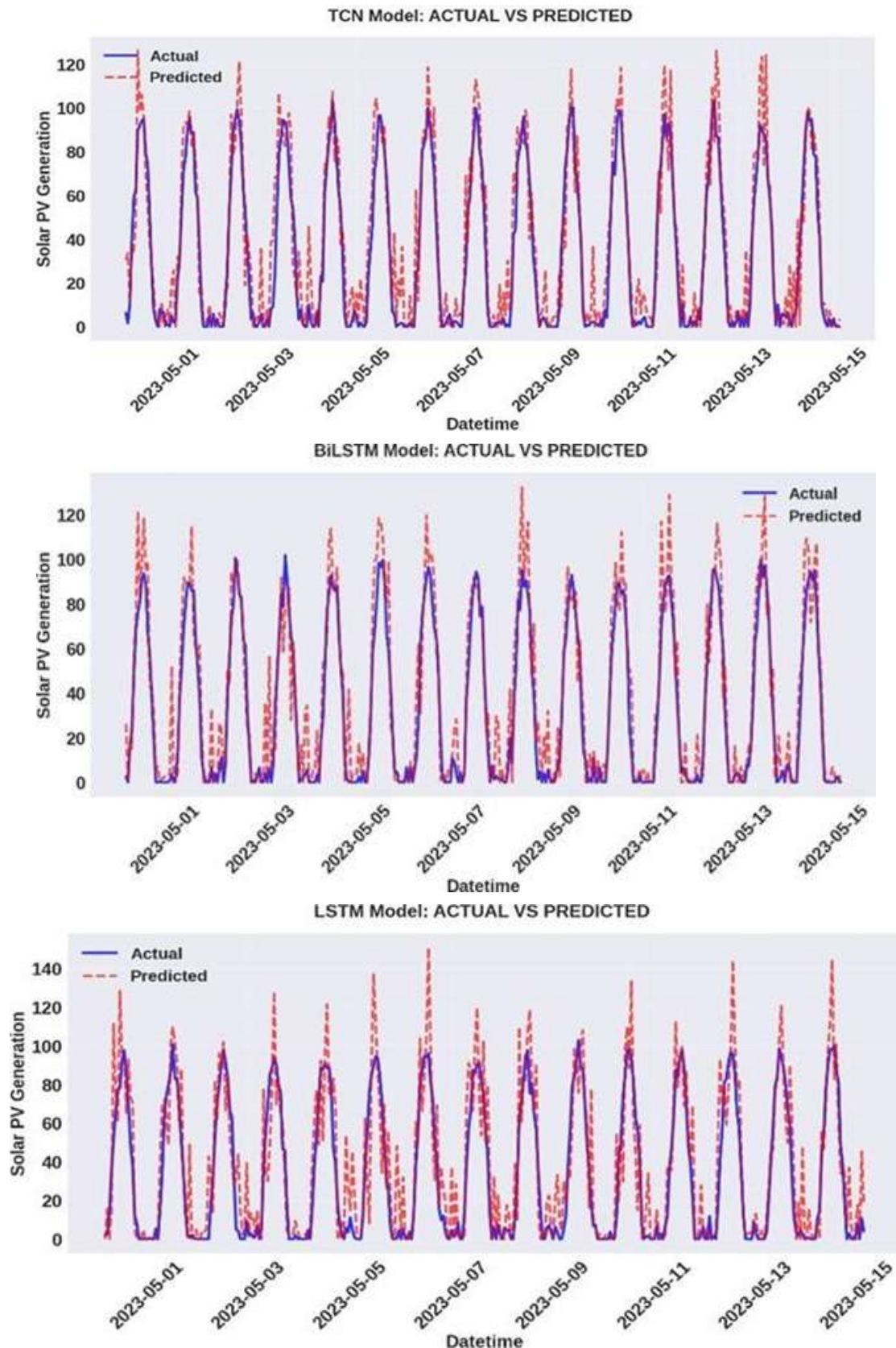


Fig. 6: Actual Vs Prediction graphs for different Models

The image presents the comparison of real and expected solar PV generation for four models— the Proposed Model, TCN Model, BiLSTM Model, and LSTM Model— throughout the same period. In each subplot, predicted values (the red dashed line) and actual solar PV generation values (the blue line) are shown over time and expressed in kilowatts. The prediction of the proposed model represents a very high level of accuracy since there is practically no deviation from the actual trend. The model's excellent temporal learning and flexibility are

evident in its precise capturing of the peaks and troughs of solar production. The TCN Model has very small deviations at some of the peak points which indicate slight forecast lags; however, it still is a good overall performer since it is very close to the actual data. The BiLSTM Model has very small errors in the case of fast fluctuations which implies that it is somewhat sensitive to sudden changes in the generation patterns, but it still produces smooth forecasts that are well aligned. Finally, the LSTM Model shows more noticeable shifts during the periods of peak generation indicating a less accurate fit than the suggested model but still keeping an overall similar trend. In general, the comparison states that although all models successfully portray the total cyclical pattern of solar PV generation, the suggested model is the best one in terms of prediction accuracy and correlation to actual values.

5.3 Microgrid Scheduling Strategy Analysis

Utilizing the high-fidelity forecasts from the suggested TCN-Attention model, three optimization techniques—Mixed-Integer Linear Programming (MILP), Dynamic Programming (DP), and Constraint Programming (CP) were employed to ascertain the most efficient operational schedule.

5.4 Experimental Setup

The experimentation is carried out in a setting that is very similar to a real residential microgrid comprising solar photovoltaic systems, a lithium-ion battery, and the national grid, all operated on a time-of-use pricing basis. The simulation goes on for a week with a 10-minute resolution (1,008 time slices) to carefully represent the slight changes in generation and consumption. The electricity consumed by the household is artificially created in a manner that is very much like the actual consumption patterns—very minimal at night, rapidly increasing in the morning and evening, and with occasional fluctuations and small peaks introduced to replicate appliance usage. The solar PV profile is extracted from a genuine renewable energy dataset by selecting solar-specific entries, resampling them to 10-minute intervals, interpolating them, and creating an average daily generation pattern which is then scaled to a 5 kW capacity with a 0.95 derating factor. A UK-style time-of-use tariff sets out four import pricing periods (night, day, peak, evening) and a fixed export rate, which create realistic cost incentives. The described battery system (10 kWh, 5 kW power limit, 95% efficiency, SOC 10–90%) follows the physical and

operational restrictions completely which means that it cannot charge and discharge at the same time, it cannot import or export power, and it cannot be charged from the grid. The Mixed-Integer Linear Programming (MILP) model is constructed to minimize the total operational cost, which is calculated by taking the costs of import away from the revenues of export and complying with the power balance, state of charge dynamics, and capacity limits constraints. The optimization is performed with PuLP, then there is a post-processing step to compute the financial and technical metrics such as total cost, energy import/export, battery efficiency, and cost savings compared to baseline scenarios (without solar and solar-only). Visualization panels display two-day energy flows, battery state-of-charge patterns, tariff curves, cost comparisons, and average daily trends, which give the user a thorough understanding of system performance with the proposed MILP-based control technique.

5.4.1 Financial Metrics

Table 2. Financial Metrics of Optimization Strategies

Metric	MILP	Dynamic Programming	Constraint Programming
Total Net Cost [£]	-8.34	-7	-5.51
Total Import Cost [£]	5.82	8.82	10.66
Total Export Revenue [£]	14.16	15.83	16.17
Cost Savings vs. Base [£]	34.7	33.36	31.87
Savings Percentage [%]	131.60%	126.60%	120.90%

Table 2 clearly indicates the profitability levels of the three optimizers. The Mixed-Integer Linear Programming (MILP) technique got the best money-related outcome, with a Total Net Cost of -£8.34, which means a net gain. This was mainly due to its extremely low Total Import Cost of £5.82, which was the lowest among all methods. Its Total Export Revenue of £14.16 was lower than those of others, but the intelligent cutting down of costs forced the largest Cost Savings relative to the base scenario of £34.70, implying a remarkable Savings Percentage of 131.6%. On the contrary, Dynamic Programming (DP) made a gain with a net cost of -£7.00; however, it had a high import cost of £8.82 and export income of £15.83 which made the total savings less (£33.36, 126.6%). Constraint Programming (CP) earned the least profit, with a net cost of -£5.51, because it had the highest import cost (£10.66) despite getting the highest export revenue (£16.17), eventually saving £31.87 or 120.9%.

5.4.2 Energy Metrics

Table 3. Energy Metrics of Optimization Strategies

Metric	MILP	Dynamic Programming	Constraint Programming
Grid Import [kWh]	35.9	48.4	48.5
Grid Export [kWh]	94.4	105.5	107.8
Self- Consumption Ratio [%]	19.2	19.2	19.2

The energy flow metrics detailed in Table 3 made clear the different grid interactions each optimization model implemented. The three models had the same Self- Consumption Ratio of 19.2%, which indicates that the basic conditions of load and solar generation were the same for the three. However, the grid transactions were the main difference among the models. The MILP optimizer demonstrated a careful import strategy by taking only 35.9 kWh from the grid, which was a reduction of 25% compared to the other two models. At the same time, the MILP model was able to sell 94.4 kWh of surplus energy. On the other hand, both Dynamic Programming and Constraint Programming took more significant import and export actions, with the former drawing 48.4 kWh and the latter 48.5 kWh from the grid, at the same time selling larger amounts of 105.5 kWh and 107.8 kWh, respectively. This clearly states that the MILP method was focused on internal resource utilization to minimize grid dependency.

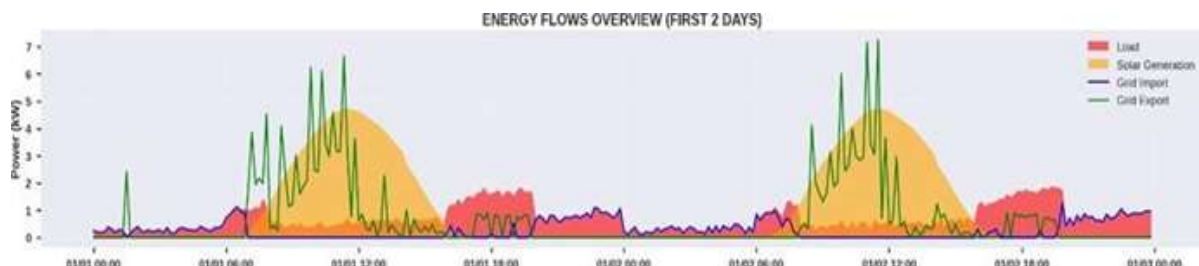
5.4.3 Battery Metrics

Table 4. Battery Metrics of Optimization Strategies

Metric	MILP	Dynamic Programming	Constraint Programming
Energy to Battery [kWh]	55.3	70	46.5
Energy from Battery [kWh]	49.9	63.2	42
Battery Efficiency [%]	90.2	90.4	90.2

Table 4 presents the operational data of the battery, which reflects the three different approaches to storage management. Among the three, Dynamic Programming (DP) was the most aggressive, using the battery for active energy arbitrage with 70.0 kWh of energy supplied to the battery and 63.2 kWh of energy taken out from the battery. The throughput activity thus generated made the Battery Efficiency slightly higher at 90.4%. The MILP optimizer followed a more balanced and tactical approach charging the battery at 55.3 kWh and discharging at 49.9 kWh, which meant that the focus was on using the storage to reduce peak imports rather than doing continuous cycling. Constraint Programming (CP) showed to be the most conservative in its use of the battery, the least charging and discharging values being 46.5 kWh and 42.0 kWh, respectively, and reaching an efficiency of 90.2%, the same as MILP. This suggests that CP's strategy was more about direct energy export than internal storage and later utilization of the energy.

5.4.4 Mixed integer linear programming



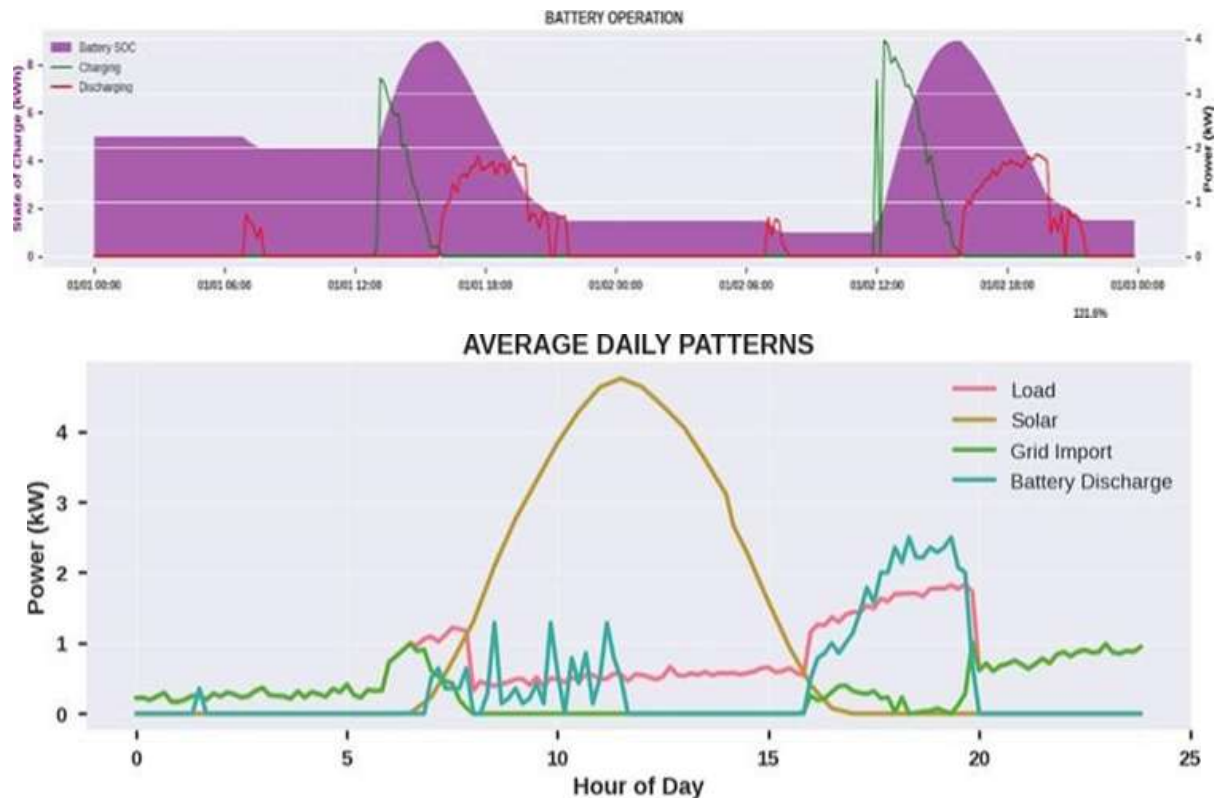
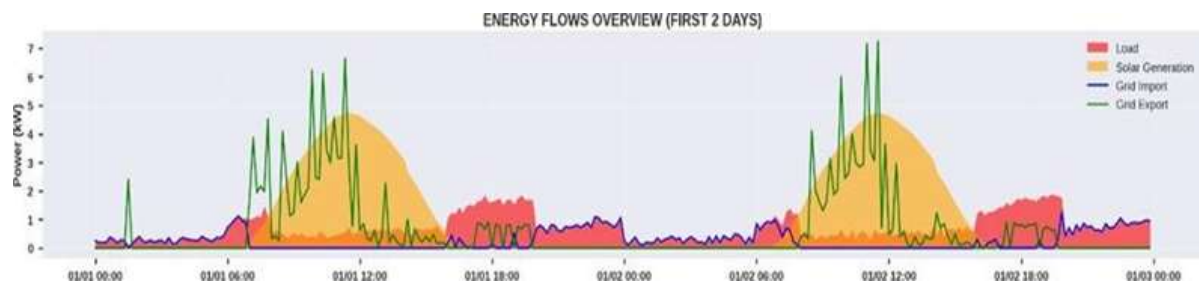
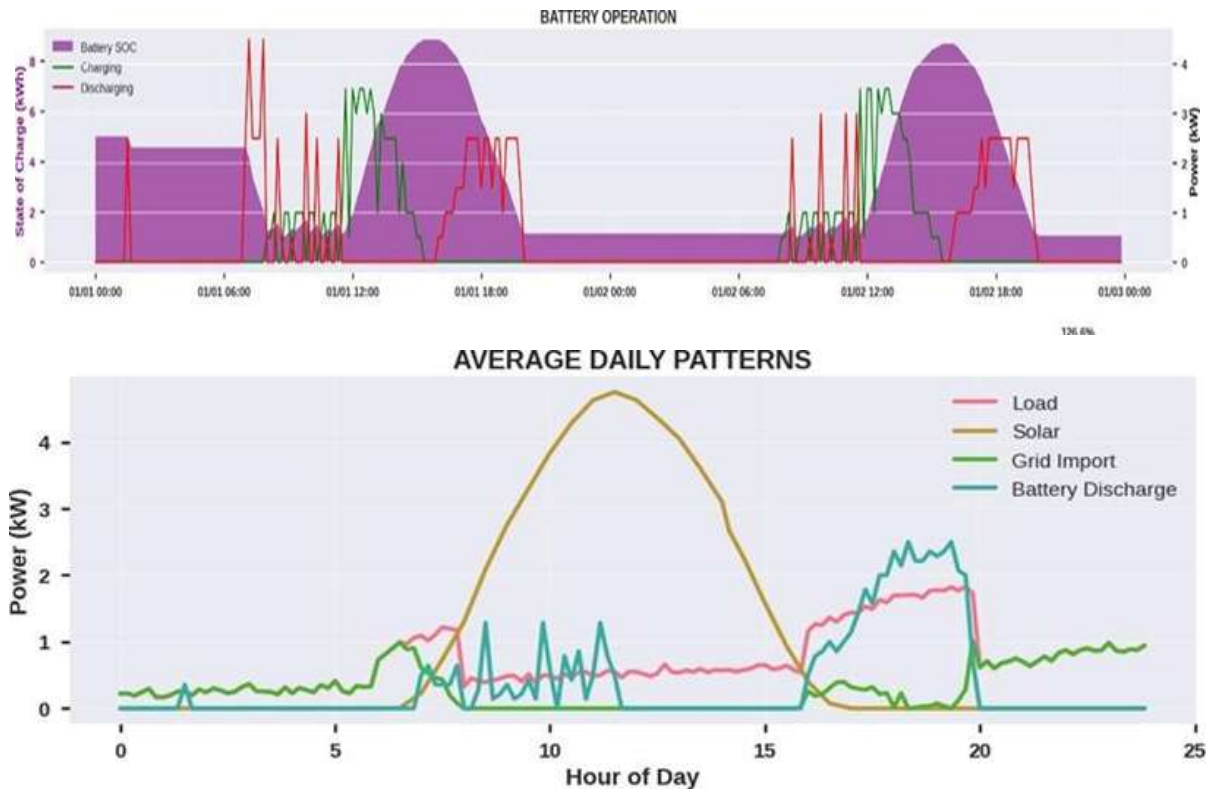


Fig.7 MILP-optimized energy system (PV + battery + grid)

The diagram shows the outcomes of Mixed Integer Linear Programming (MILP) optimization applied to a solar photovoltaic (PV)-battery-grid energy system. It has three visual panels that together summarize the energy production, storage and consumption processes over time. The first panel, titled Energy Flows Overview, shows power generation and consumption variation during two days. At the solar power curve's peak, midday, a large amount of photovoltaics generation is indicated, while the households' consumption remains relatively constant but slightly higher in the late hours. The most grid import occurs in the early morning and the evening, coinciding with the hours of solar generation, whereas the grid export shows up around noon when solar power is more than the total battery charging and load demand. The second panel, Battery Operation, gives the battery state of charge (SOC) along with its charging and discharging cycles. The purple section indicates the State of Charge (SOC), which quickly rises during the solar peak hours as the battery takes in energy (red line) and then decreases in the evening as the battery gets drained to meet the household demands (green line). The cycle represents the smart energy time-shifting process by which solar energy not directly consumed during daylight hours is stored for later use, thereby reducing the dependence on the grid. The last panel, Average Daily Patterns, gives a summary of the system's usual 24-hour operation. The demand for solar power is at its peak from 7:00 AM to 4:00 PM when it fulfills a major part of the daytime load, while during the night battery discharge mainly takes place to alleviate grid imports at the peak tariff periods. This optimal scheme shows how MILP assures both cost savings and efficient energy usage by coordinating throughout the day solar production, battery operation, and grid interaction.

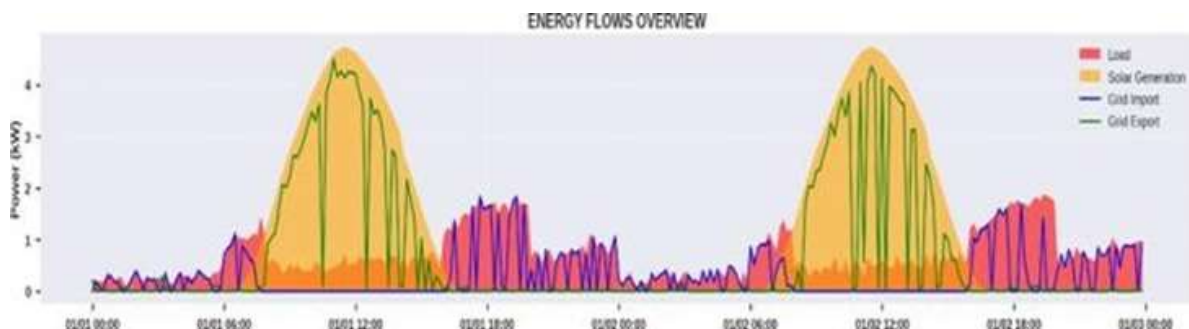
5.4.5 Dynamic programming

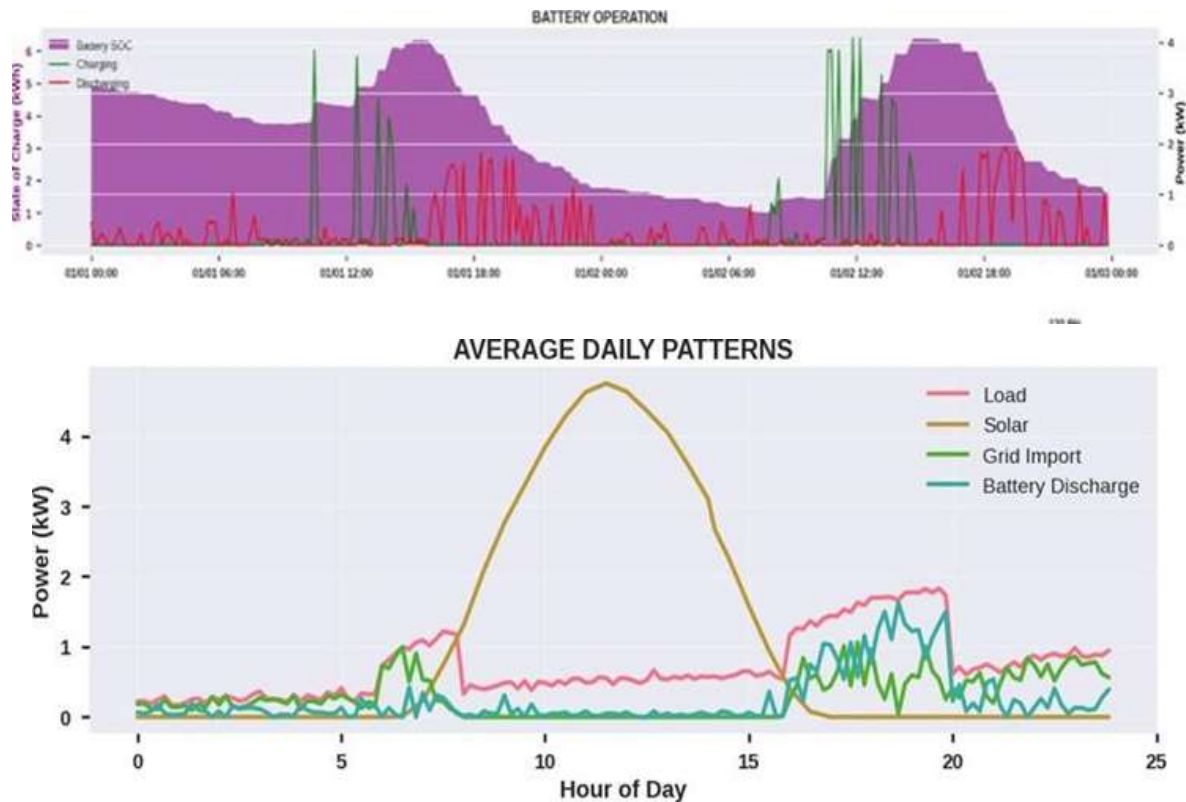




The image shows the results of optimization performed using Dynamic Programming (DP) for a combined energy system consisting of solar photovoltaic (PV), battery, and grid elements. It contains three graphic panels that together depict energy flow, battery operation, and average daily performance within a dynamic optimization scenario. The upper panel named Energy Flows Overview (First 2 Days) shows the time interaction between different energy components over a period of two days. The solar generation (orange curve) reaches its peak at noon, while the household load (red curve) has a relatively stable profile over the day. The grid imports (green spikes) happens irregularly, especially in the early morning and during the evening, while grid export (blue line) is seen briefly when the battery is full and the consumption is less than the solar generation. This changing nature of a model behavior points out the scheduling of the model which is aimed at reducing grid dependence. The middle panel, Battery Operation depicts the changes in state of charge (SOC) and the charging/discharging cycles. The purple zone indicates State of Charge (SOC), which grows rapidly when the sun shines and falls in the evening when the demand exceeds the generation. The red (charging) and green (discharging) lines show that under dynamic programming the battery behaves more actively and smoothly, with many charge–discharge transactions occurring every day. This signifies better timing control and a quick responsive adjustment to fast fluctuations in load and generation conditions. The lower section, Average Daily Patterns, shows the typical 24- hour energy changes. The solar power production is at its highest between 10:00 AM and 2:00 PM, while the load demand remains constant throughout the day, with just a slight increase in the evening. Grid import mainly supports the system during the early morning and evening hours, whereas battery discharge is concentrated on the late afternoon to early night period, thus covering peak demand and reducing grid dependence. The picture conveys that Dynamic Programming enables the system to adopt the best time-sensitive energy management strategy, thus allowing to the system to continuously adjust the PV generation, battery operation, and grid pulling or pushing according to the real- time changes in demand and solar power availability.

5.4.6 Constraint Programming (CP)





In the image, the outcomes of the hybrid solar photovoltaic (PV)–battery–grid energy system optimization using Constraint Programming (CP) are presented along with the method of constraint-based scheduling coordinating the energy flows, battery operation and the average daily power patterns. The performance of the system for a two-day period is displayed in the first panel, Energy Flows Overview. The load (red) remains more or less constant throughout the day with very mild rises in the evening, while solar generation (orange curve) is characterized by very clear peaks during midday. Grid export (blue) coincides with peak solar output when the system produces excess energy, while grid import (green spikes) occurs rather sporadically, mainly in the early morning and evening when solar energy is not enough. This pattern implies that the CP model that imposes operational limits rather than merely optimizing for cost or energy has effectively controlled the generation and demand. The third panel, Battery Operation, illustrates the shifts in the battery's state of charge (SOC) and, as a result, the charge-discharge activities. SOC is the purple fill that slowly diminishes during the night when keeping the load going after having gone up quite a lot during the day when the battery receives power from the sun and thus charges. The battery activity has been controlled and made periodic as shown by the red and green lines, respectively representing charging and discharging rates. Through the whole day, the CP method keeps the SOC transitions quite constant and inhibits the frequent changing by relying on more stringent logical and operational boundaries than the dynamic or MILP approaches. The average relationships of the important factors are shown daily in the third panel, Average Daily Patterns. The period from 10:00 AM to 2:00 PM sees an increase in solar output and a decrease in load consumption at the same time. The discharge of the battery is mainly active during peak hours in the evening, whereas, grid import rises significantly in the evening when solar generation stops and the battery is almost empty. In other words, the figure shows how Constraint Programming ensures methodical, rule-based energy flow regulation, maintaining logical viability, and seamless system transitions. It also effectively synchronizes battery operation, grid usage, and solar generation while taking into account operational constraints like charge/discharge restrictions and system stability conditions.

5.5 DISCUSSION

The system for managing the microgrid in two stages, which combines a complex prediction model with a mathematical optimization engine, has been approved by this study. The hybrid TCN-Attention model is the best for prediction accuracy, as it has extremely low error rates (MAE: 7.2864, RMSE: 10.093) and very good explaining power (R^2 : 0.923), which means that it will be useful for the further development of optimization methods. The visual comparison of the actual and predicted values demonstrates the model's superb ability to simultaneously capture the overall trends and very small scale temporal dynamics, where the benchmark LSTM and BiLSTM models fell behind, especially during peak generation times. The precise estimations of renewable generation are a source of more probable and cost-effective operational schedules, thus creating a necessity for high-fidelity forecasting. The optimization stage, based on these accurate estimates, showed that Mixed-Integer Linear

Programming (MILP) defeated Dynamic Programming (DP) and Constraint Programming (CP) in a very strategic way. The MILP optimizer gave the highest financial result of £8.34 net profit and a cost saving of 131.6% over the basic scenario. MILP's grid interaction strategy is the reason behind its strong financial outcome. All optimizers had the same ratio for self-consumption, however, MILP imported 25% less energy from the grid (35.9 kWh) than their rivals. This option had the least impact on import expenses, which in turn resulted in a decrease in export revenue, but it was still the most advantageous choice. The strength of the MILP lies in its all-encompassing objective of cost minimization that simultaneously supports revenue growth and reduction of expenses. The measurements taken from the batteries provide insights into the operational tactics of the optimizers. DP was the one that cycled the most energy across the storage unit by means of aggressive and high-throughput arbitrage. CP was the one that took the most conservative approach as it opted for direct export rather than storage. MILP adopted a balanced and tactical approach by using the battery to shift solar energy and trim peak import times with minimal cycling, which might eventually benefit the long-term health of the storage system while doing so profitably. MILP guarantees systematic, cost-driven scheduling; DP allows for highly flexible, real-time responses; and CP operates under rule-based, logically possible constraints. To sum up, the high-accuracy TCN-Attention forecaster and the cost-driven MILP optimizer have a synergistic effect in terms of better predictions, higher economic returns, and the energy in microgrids being efficient and sustainable.

6 CONCLUSION

The research certainly presents a convincing case for the dual-stage microgrid supervision system which, on top of that, is a very effective one which combines accurate forecasting and eco-friendly energy scheduling. The TCN-Attention hybrid model has shown a significant improvement in predictability ($MAE = 7.2864$, $RMSE = 10.093$, $R^2 = 0.923$) and that is why it has been compared with the traditional TCN, BiLSTM, and LSTM techniques which only got the advantage of the temporal dependencies at the very beginning and the end of the whole process of solar PV generation. The generation estimate accuracy that was improved right away has reacted positively in making decisions in the optimization phase. Out of all the optimization methods that were tested, Mixed-Integer Linear Programming (MILP) came out as the most effective one with the highest cost reduction of 131.6% and a net profit of £8.34. The MILP controlled the grid import (35.9 kWh), export (94.4 kWh), and battery usage (90.2% efficiency) very effectively leading to a reduction in the cost of running the system, and at the same time, guaranteeing the proper functioning of the system by very smooth dynamics. On the other hand, Dynamic Programming (DP) emphasized the bold cycling of energy, whereas Constraint Programming (CP) strictly adhered to the operational limits and thereby lost profitability. The combined TCN-Attention

+ MILP approach is the top performer among all approaches in predictive correctness, operational effectiveness, and sustainability, and as a result, it becomes a large-scale, data-driven framework for intelligent microgrid energy management that not only increases the economic viability but also enhances the consumption of renewable resources.

CONFLICTS OF INTEREST

The authors declare that there are no known financial interests, personal relationships, or institutional affiliations that could have appeared to influence the work reported in this paper. The research was conducted independently, and the results presented are solely based on scientific analysis without any external commercial or competitive bias.

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