Enhancing Long-and-Short-Term Forecasting for Optimized Microgrid Energy Management Through Advance Hybrid Deep Learning Models

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DOI: https://doi.org/10.56293/IJASR.2025.6302

IJASR 2025
VOLUME 8
ISSUE 1 JANUARY - FEBRUARY **ISSN: 2581-7876**

Abstract: Solar power, while abundant, is unpredictable due to its intermittency, causing instability in energy supply and imbalances between supply and demand, which can threaten grid reliability. To address these challenges, innovative solutions are required, especially as electricity demand fluctuates. Energy Storage Systems (ESS) help manage peak shaving and load shifting, but erratic energy sources can degrade batteries, leading to high costs. Accurate forecasts of energy consumption (EC) and solar energy generation (EG) are crucial for optimizing solar microgrids. This study evaluates deep learning models, including Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and a hybrid CNN-GRU model, to predict both EC and EG. A multi-input, parallel processing approach was used to capture temporal and spatial patterns for real-time applications with reduced data drift and improved accuracy. The model was tested using 47 months of historical data from the Sceaux microgrid near Paris, France, spanning from December 2006 to November 2010, from the University of California, Irvine repository. The data was also used to optimize the photovoltaic (PV) system sizing. The proposed method achieved excellent results for EG prediction with a Mean Absolute Error (MAE) of 3.974 and a Root Mean Squared Error (RMSE) of 6.603. For EC prediction, it obtained an MAE of 4.869, an RMSE of 6.527, and a Mean Absolute Percentage Error (MAPE) of 0.113, demonstrating its effectiveness for both short-term and long-term forecasting.

Keywords: Parallel Processing Approach, Solar Power Generation Prediction, Energy Consumption Prediction, Convolution Neural Network, Bidirectional Gated Recurrent Unit, Long-and-short term prediction.

1. Introduction

The world is rapidly becoming more interconnected and energy demands are on the rise from a variety of demographics due to essential human needs in areas like healthcare, welfare, and economic growth, yet the earth's natural state doesn't change [1]. Therefore, to achieve a sustainable future that keeps pace with human advancement and demand for energy, two major issues must be resolved: guaranteeing dependable energy supply and lessening the energy sector's contribution to climate change [2].

Power generation reliant on fossil fuels (coal, oil, gas) remains predominant, resulting in yearly CO2 emissions rises of 2.3% since 1990 [3]. This trend has been intensified by global population increase, heightening the demand for energy and further quickening CO2 emissions [2]. 75% of total global greenhouse gas (GHG) emissions is generated by CO_2, with 31% from electricity generation [4]. Hence, global temperatures are greatly impacted by rising CO_2 concentrations, which have major negative effects on the environment and climates.

The United Nations responded through the Copenhagen Accord of 2021 and its Sustainable Development Goals (SDGs) by urging nations to keep CO2 emissions between 7% and 16% by utilizing energy in a sustainable way [5]. Hence, the deployment of renewable energy, characterized by low carbon emissions and sustainability, has emerged as a critical response to the global energy crisis. These is further enhanced by strong legislative efforts and investment incentives which has made renewable energy technologies gained momentum [6]. Therefore, integration of renewable energy into modern power grids presents a viable solution for mitigating climate change and global warming [7].

Due to advancements in solar technology, which allow power to be generated even in cloudy weather, solar energy has become more popular among renewable energy sources [8]. Solar energy has thus become a cornerstone to reduce carbon emissions and address climate change.

Despite the advantages of solar energy, solar electricity is still erratic because of seasonal cycles and weather patterns. This causes instability to energy supply, and this intermittency poses a serious threat to the broad deployment of renewable energy sources [9]. Additionally, renewable energy output is less adaptable to fluctuating demand cycles compared to conventional energy sources, presenting further challenges in aligning generation with consumption patterns. Addressing this mismatch between dynamic energy demand and renewable supply requires innovative solutions.

Energy Storage Systems (ESS) plays a crucial role in integrating solar energy into the grid Battery-based Energy Storage Systems (BESS) are effective for peak shaving and load shifting, thereby, enhancing utilization of distributed generation Distributed generation (DG) refers to producing power close to the point of consumption through small-scale, decentralized sources. A key factor in BESS management is the State of Charge (SoC), which indicates the amount of energy stored in the battery. Maintaining optimal SoC levels within DG is critical for ensuring the efficiency and longevity of BESS and this is influence by renewable energy variation

Microgrids which is a localized energy systems that can operate independently or in conjunction with the main grid, benefit significantly from Integration of Photovoltaic (PV) solar power with BESS. This system presents a transformative approach to meet the demands of energy systems. It enhances energy sustainability, resilience, and reliability, offering greater flexibility and control over energy resources. However, managing efficiency is vital to mitigate the challenges posed by solar power's intermittency, demand variations, and battery storage limitations, which can lead to grid instability.

Maximizing the advantages of solar energy and BESS integration requires holistic energy system optimization. But only by utilizing data from previous solar production, weather data, and patterns of energy consumption for predictive models and advanced forecasting techniques, grid operations can be dynamically modified to account for these changes. This proactive approach minimizes the impact of fluctuating solar irradiance and consumption patterns, thereby, enhances grid stability and reliability. Meanwhile, the application of machine learning for forecasting in solar microgrids offers numerous benefits, but it also faces challenges. One major issue is the need for large, high-quality datasets that include details on energy output, consumption trends, and weather conditions. Making decisions based on incomplete or erroneous facts might be problematic. Furthermore, establishing and integrating a thorough data collection system can be expensive and technically difficult, particularly in places with limited resources.

The computational complexity and continuous maintenance needed are further disadvantages. Training sophisticated machine learning models demands significant computing power and expertise. These models also need regular updates with fresh data, which can be resource intensive. Overfitting remains a risk, potentially undermining the reliability of microgrid operations. Deep learning, however, offers advantages for real-time applications by automating multiple tasks and adapting over time.

The main objectives of this research are twofold: first, to create accurate and reliable deep learning models for predicting short- and long-term electricity generation (EG) and consumption (EC); and second, to showcase the practical effectiveness of hybrid deep learning models for real-time and smart grid applications. This is accomplished by applying a data-driven methodology to address issues related to the intricate spatiotemporal features of data on solar energy generation and electricity use. The primary aim is to contribute to the field of energy consumption and generation introducing a two input and parallel processing with hybrid deep learning techniques that combines innovative architecture, featuring a Convolutional Neural Network (CNN) and bidirectional Gated Recurrent Unit (GRU).

The approach in this work aims to address the shortcomings of traditional forecasting models that includes their inability to generate precise predictions and challenges in capturing intricate relationships between variables. Hence, this study is motivated because precise forecasting of electricity generation and consumption (EC and EG) is critical to power management optimization and can result in substantial energy and cost savings. The data-driven model is unique in that it handles issues with noisy data and complex variable interactions for both short- and long-term EC and EG is what makes it distinctive.

The analysis of datasets that represent home electricity consumption demonstrates the relevance of this research, which extends beyond theoretical contributions and into useful real-world applications. Precise forecasts of electricity generation (EG) and consumption (EC) are essential for efficient resource management in power systems. Optimised power distribution, effective grid operation, and improved integration of renewable energy sources like solar and wind are all made possible by reliable forecasts.

The analysis of datasets that represent home electricity consumption demonstrates the relevance of this research, which extends beyond theoretical contributions and into useful real-world applications. Precise forecasts of electricity generation (EG) and consumption (EC) are essential for efficient resource management in power systems. Accurate forecasting enables better integration of solar energy and efficient grid management, thus, the approach used in this work reduces carbon emissions, increases energy savings, and lowers operational costs. Also, this study seeks to give a robust solution for both short-term and long-term forecasting by tackling the difficulties caused by noisy data and the intricate interactions among variables in EC and EG. The novel hybrid deep learning approach employed in this work enables more reliable and precise forecasts, which are essential for the smooth functioning of smart grids and other real-time power management systems.

2. DEEP LEARNING ALGORITHMS

Supervised models, CNN and RNN, will predict energy demand by capturing spatial and temporal data. The models will be trained on historical data segmented into hourly intervals for accuracy.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) utilize convolutional filters to identify patterns or features in input data. For time series data, these filters move along the time dimension, applying the convolution operation described in equation (1).

$$(f * x)(t) = \sum_{i=0}^{k-1} f(i) . x(t-i) \quad (1)$$

Here, f represents the filter (or kernel) of size k, and $x(t)$ denotes the input time series. The convolution operation generates a feature map, emphasizing specific patterns within the time series. This feature map is then passed through an activation function, such as ReLU, which introduces non-linearity, enabling the model to capture more complex relationships.

The most notable features can be highlighted by pooling the output from several convolutional layers to minimise dimensionality (using methods like max pooling). After that, the data is compressed and run through a series of fully connected layers to make forecasts, like future value forecasting. CNNs are particularly good at automatically identifying significant patterns in the data, which makes them ideal for jobs like anomaly detection, classification, and time series forecasting.

Recurrent Neural Networks (RNNs)

Because recurrent neural networks (RNNs) are designed to handle sequential data by maintaining a hidden state that stores information about previous inputs, they are suitable for applications like time series prediction.

At each time step t, an RNN updates its hidden state h_t using equation 2 based on the current input x_t and the previous hidden state h_{t-1}:

$$h_t = \tanh(W_h . h_{t-1} + W_x . x_t + b) h_t \quad (2)$$

where W_h and W_x are weight matrices, and b is a bias term. However, long-term dependency learning is a challenging task for RNNs due to vanishing gradients and other issues.

Gated Recurrent Units (GRUs)

To solve these issues, a kind of RNN known as Gated Recurrent Units (GRUs) employs gating techniques to control the input flow. The two main gates of the GRU are the update gate (z_t) and the reset gate (r_t).

Equations 3 and 4, respectively, define these:

$$Z_t=\sigma(W_z.[h_{t-1}, x_t])Z_t=\sigma W_z.h_{t-1}, x_t \quad (3)$$
$$r_t=\sigma(W_r.[h_{t-1}, x_t]) \quad (4)$$

The update gate z_t regulates how much of the new candidate state h_t in Equation 5. adds to the current state $\dot{h}_t$ in Equation 6, whereas the reset gate r_t chooses how much of the prior state h_{t-1} to forget:

$$\dot{h}_t = \tanh(w_h.x_t + r_t.(w_h.h_{t-1}) + b_h) \quad (5)$$
$$h_t = z_t.h_{t-1} + (1 - z_t).h_t \quad (6)$$

Compared to conventional RNNs, GRUs are more effective and less susceptible to the vanishing gradient issue, which helps them better capture long-term dependencies in sequential data.

3. PROPOSED METHOD

The selected novel approach, "Dual Sequence with Dual Stream Prediction Mechanism," is a multi-input, parallel processing technique intended to capture both EG and EC with an emphasis on spatiotemporal aspects. This technique uses two concurrent sequences, one for temporal dynamics and the other for simulating the spatial properties of the data. Through the integration of two streams, it effectively leverages Gated Recurrent Unit (GRU) for temporal pattern recognition and Convolutional Neural Networks (CNNs) for spatial feature extraction. With the help of this dual technique, complicated relationships in the temporal and spatial domains can be captured simultaneously, offering a comprehensive and detailed comprehension of the data. This methodology is very appropriate for advanced EG and EC forecasting because it addresses the special difficulties that time-series data bring and improves prediction accuracy, especially when combined with changeable consumption patterns and fluctuating weather. Figure 1. depicts the suggested method's workflow. By capturing spatiotemporal features comprehensively through separate but integrated CNN and RNN streams, the proposed method improves forecasting accuracy and robustness, reduces overfitting, and provides scalable adaptability for a range of energy forecasting scenarios. This will improve microgrid and integration of effective energy management system, lowering operating costs and reducing reliance on non-renewable energy backup systems.

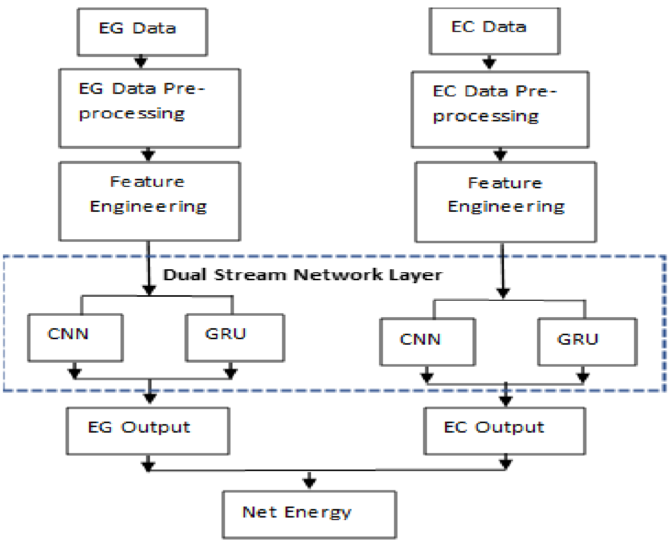

Figure 1: Proposed Method Workflow

4. DATA SOURCES, PRE-PROCESSING, AND FEATURES ENGINEERING

The energy consumption data as shown in Table 1. is a one-minute sampling rate over a period of almost 4 years for Sceaux microgrid (7km of Paris, France) between December 2006 and November 2010 (47 months) [13]. The data collected from the sensors and their measurement unit contains 2,075,257 instances with 9 features. The weather data for sceaux was gotten from Solcast API website which was created using a global fleet of weather satellites. The weather data extracted is a 5-minute interval data for a period of 4 year. The extracted data has 9 features with 410,652 instances, and the data description is shown in Table 2.

Table 1: Energy consumption data

Features	Description	unit
Date	Date format	dd/mm/yy
Time	Time format	hh:mm:ss
Global Active Power	Total power consumed	kw
Global Reactive Power	Reactive power consumed.	kvar
Voltage	Voltage levels during consumption.	volts
Global Intensity	Total current intensity.	Amp
Sub-metering_1	Electricity consumed in kitchen.	Watt-hour
Sub-metering_2	Electricity consumed in laundry room.	Watt-hour
Sub-metering_3	Electricity consumed by electric water-heater and air-conditioner.	Watt-hour

Table 2: Sceaux weather data

Measurement	Description	Unit
Air temp	Ambient air temperature.	^{o}C
Cloud opacity	Degree to which clouds block the transmission of light.	%
Dni	Direct Normal Irradiance.	W/m^2
Ghi	Global Horizontal Irradiance.	W/m^2
gti	Global Tilted Irradiance.	W/m^2
Precipitable water	Amount of water vapor in a column of the atmosphere.	mm
Relative humidity	Amount of water vapor present in the air compared to the maximum amount of water vapor that the air can hold at a given temperature.	%
Snow depth	Height of snow accumulated on the ground.	cm
Wind speed 10m	wind velocity at a height of 10 meters.	m/s

Data pre-processing

The dataset was explored with Pandas after importing necessary libraries on jupyter notebook. All attributes were numerical (integers or floats), missing values were forward-filled, and no duplicates were found. Statistical analysis and visualizations, including seasonal patterns, were performed for energy consumption and solar generation

Features Engineering

By using feature engineering, one can increase the prediction capacity of statistical or machine learning models by turning a bunch of meaningless data into a set of useful features. The timestamp was used to extract several temporal elements, including the year, month, day, hour, day of the week, and week of the year. The lag_1, lag_2, and lag_3 features were developed to record the prior values of the targets in the respective data sets. To reduce noise and spot patterns, rolling statistics—such as the rolling mean and standard deviation over 30- and 10-day windows were calculated. To get cumulative trends over time, expanding statistics were computed, such as the expanding mean and standard deviation of target values.

By smoothing the data, an exponential weighted moving average (EWMA) with span and alpha values of 0.1 and 0.3 was used to highlight the most recent changes in electricity generation and consumption. In order to identify seasonality and eliminate trends from the worldwide active power data, differencing was used with shifts of 1 and 2. Time-based features were further strengthened by converting the hour into sine and cosine components to reflect daily periodicity. Resampling aggregations were carried out on a daily, weekly, monthly, quarterly, and annual basis to examine trends of power generation and consumption over various time periods.

To track general trends, the cumulative totals of reactive and active power consumption were also computed. The target values were transformed using a quantile transformer to produce a normal distribution, which increased the modelling accuracy. Finally, seasonal indicators were found by categorizing months into spring, summer, fall, and winter based on their respective calendar periods.

Solar PV generation sizing

By calculating the mean of the daily value, the daily load demand and daily solar irradiance are determined. PV system efficiency and inverter system efficiency were set at 15% and 95%, respectively [14]. After that, the following formula was used to get the necessary PV size: Required pv size = average daily consumption / (average daily irradiance * PV system efficiency * inverter efficiency).

(7)

5. Integration of deep learning algorithms for EG and EC prediction

Train test validation data splitting:

The dataset of both the energy consumption (EC) and energy generation (EG) is separated into training, testing and validation of 60:20:20.

Normalization: By dividing the mean and value subtraction by the standard deviation, the EC and EG data were normalised.

Function for prediction: For short-term predictions, the next hour was predicted using data spanning six hours, and for long-term predictions, the next year was predicted using data spanning three years.

Implementation of CNN and GRU individual models

The input shape for EC data is (6 ,37) while EG is (6, 48) after feature engineering. The best hyper-parameter was selected by keras tuner. These individual models were used for EC and EG data separately.

Implementation of hybrid CNN and GRU

For improved prediction, the CNN and GRU models were concatenate and separately applied to EC and EG.

Implementation of dual input dual stream techniques

The EG and EC data are simultaneously fed into the two deep learning models in the dual input dual stream technique. Keras tuned the ideal hyper-parameter, and attention technique was used to support parallel processing and long-term dependency management. In order to capture information from both past and future contexts in the sequence and provide predictions that are more accurate, bidirectional GRU was chosen. Figure 2 shows the dual stream / dual sequence paradigm for the EC and EG prediction.

The Kullback-Leibler Divergence (KLD) technique is used to detect the difference between two probabilities after concatenating the output from the CNN and GRU. This allows one to determine the difference between electricity generation and consumption. This makes it possible to manage electricity more effectively, transferring adequate energy to clients while lowering surplus depletion.

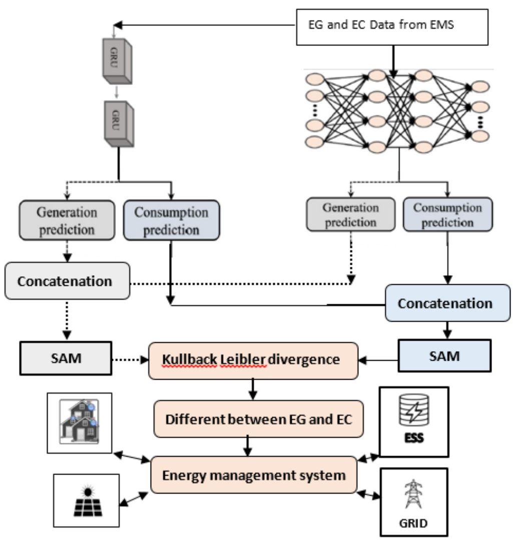

Figure 2: Dual Input Dual Stream Workflow

6. EVALUATION METRICS

Mean Absolute Error (MAE) measures the mean magnitude of errors between predicted values and actual values, without taken cognisance of their direction (i.e., whether the prediction is higher or lower than the actual value). MAE is calculated as the mean of the absolute differences between the predicted values $(\dot{y}_i)$ and the actual values (y_i) across all data points n [14].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \dot{y}_i| \qquad (8)$$

Root Mean Squared Error (RMSE) is a metric that quantifies the average magnitude of errors between predicted values and actual values in a regression model [14]. It is calculated using the equation 9.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \dot{y}_i)^2} \qquad (9)$$

Mean Absolute Percentage Error (MAPE) is a metric used to measure the accuracy of a forecasting mode. It expresses the prediction error as a percentage and is calculated using equation 10. The closer to zero the better the model [14].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \dot{y}_i}{y_i}\right| \times 100\% \qquad (10)$$

7. RESULTS AND DISCUSSION

Model Performance Comparison

The comparison between the selected model using MAE, RMSE and MAPE for energy generation and energy consumption is shown in Table 3 and Table 4 respectively.

Table 4 shows that the proposed method has the lowest MAE and RSME for EG compared to the individual deep-learning model despite predicting two data streams sequentially, which is necessary for real-time prediction. MAPE is not reported for EG prediction because many actual values of energy generation (y_{actual}) are zero, therefore making the MAPE value to be very high.

However, the proposed method lack behind the individual model in terms of MAE, RSME and MAPE for EC prediction due to overfitting and the attention mechanism layer which focuses more on EG prediction. Adjusting it will increase the error in the EG prediction, EG prediction is more difficult and has more variability than EC prediction, so it is better to achieve more accuracy in generation as compared to EG.

Table 3: Model performance comparison of EG prediction

Model	MAE	RSME
CNN	4.483	7.602
GRU	6.118	8.73
CNN+GRU	4.601	7.88
Proposed method	**3.974**	**6.603**

Table 4: Model performance comparison of EC prediction

Model	MAE	RMSE	MAPE(%)
CNN	4.678	6.238	0.109
GRU	**3.451**	**5.014**	**0.07**
CNN+GRU	4.205	5.877	0.092
Proposed method	4.869	6.527	0.113

Visualization of Results

The results of the proposed model (dual sequence dual stream) is discussed in this section. For discussion purpose and clarity, only the next 48 hours prediction profile was shown. However, the prediction of up to a year can be getting from the model.

Prediction vs. Actual Comparison

The Energy consumption prediction vs Actual for the CNN+GRU model when EG and EC data are fed at the same time is shown in Figure 3, while the energy generation prediction vs actual is in Figure 4. It can be observed from the EC results profile (Figure 3) that the predicted follows the actual consumption pattern, however, most of the predicted value are slightly higher than the actual value which is safer for this type of scenario as the excess can be stored or sold to the grid.

Similarly, from Figure 4, it can be observed that the actual energy generation profile and the predicted energy follows the same pattern, but it can be seen that most of the errors occurs when there is sudden change in solar generation pattern which depict the transition between day and night. Overall, the EG prediction is more accurate than the EC prediction as shown from the metric table and the prediction profile.

The difference between the EG and EC for the entire validation set (equivalent to 9 months) is shown in Figure 5, The net energy above the zero-difference line shows more EG are available for that period, while below the zero-difference line shows there is more EC.

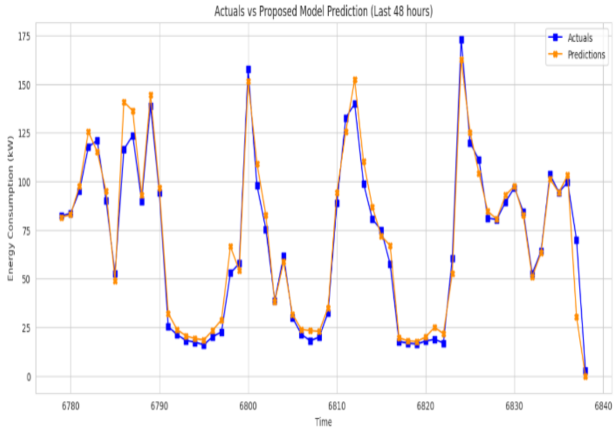

Figure 3: Actual consumption vs predicted consumption profile

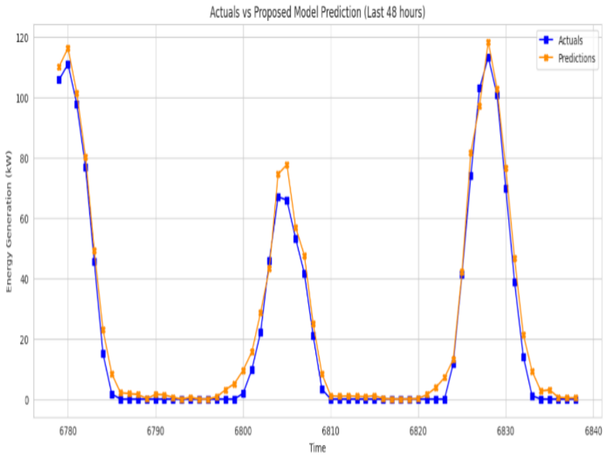

Figure 4: Actual energy generation vs predicted generation profile

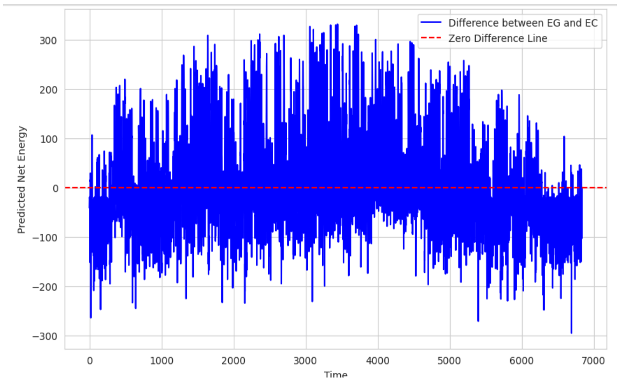

Figure 5: Predicted net energy for 9 months

Error Analysis

Figure 6 and Figure 7 shows the training versus validation MAE for both the EG and EC respectively. It can be observed that both the training MAE and validation MAE decreases and converge to low values, this suggests that the model is learning well and generalizing appropriately to the validation set.

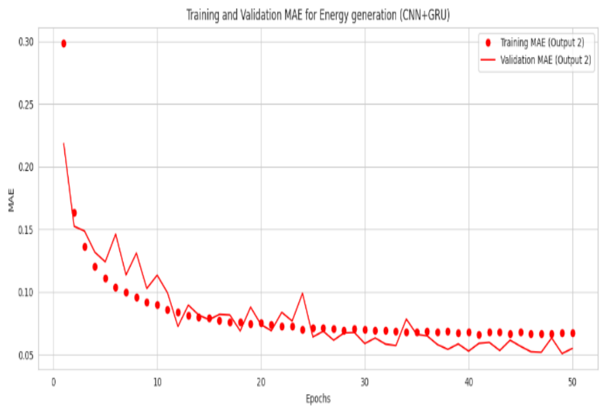

Figure 6: EG training and validation MAE for the proposed method

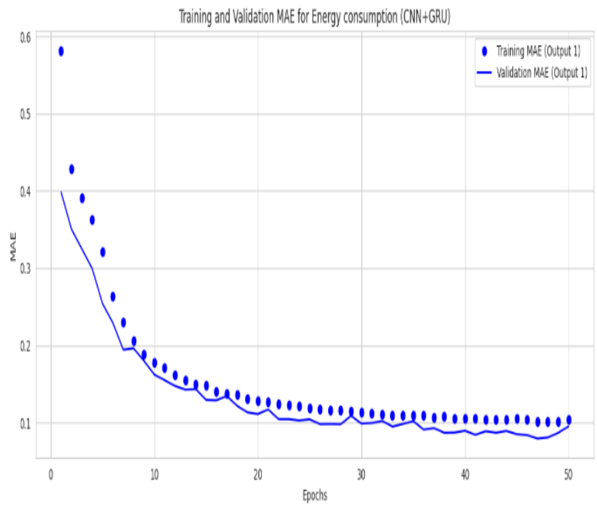

Figure 7: EC training and validation MAE for the proposed method

8. CONCLUSION

This study presents a comprehensive approach to optimizing microgrids by accurately predicting energy consumption (EC) and generation (EG) for real-time applications. A hybrid CNN-GRU model captures spatial and temporal features, achieving low data drift and losses. The model achieved a MAE of 3.974 and RMSE of 6.603 for EG, and MAE of 4.869, RMSE of 6.527, and MAPE of 0.113 for EC, outperforming other deep learning models. The CNN extracts important features, while the GRU handles temporal dependencies in longer sequences. Improved prediction accuracy enhances solar microgrid efficiency and resource management. Future work will explore reinforcement learning for further improvements in prediction and optimization.

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