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Deep Learning Based Prediction of Renewable Energy Using Hybrid CNN & LSTM Model

Mr. Riyas P P[1], Musammil Hamza[2], Anoop P[3], Mohammed Swalih V[4], Muhammed Jasil P[5], Shabeeb Rahman P[6]
[1]Assistant Professor, [2, 3, 4, 5, 6]B-Tech Students, Department of Electrical and Electronics Engineering, MEAEC, Perinthalmanna–679325

Abstract: Renewable energy sources such as solar photovoltaic (PV) and wind power are vital for sustainable development and reducing dependence on fossil fuels, but their power generation is highly intermittent due to changing meteorological conditions like solar irradiance, temperature, wind speed, and cloud cover, which creates challenges in maintaining grid stability and efficient energy management. Accurate forecasting is therefore essential for reliable power system operation, enabling optimal energy dispatch, reserve planning, and cost reduction. Conventional forecasting methods based on physical and statistical models rely on historical and weather data but often fail to capture complex nonlinear relationships and dynamic variations. To overcome these limitations, a hybrid deep learning approach combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is proposed, where CNN extracts important features from input data and LSTM captures temporal dependencies and long-term patterns in time-series data, improving prediction accuracy. The model is implemented in MATLAB Simulink and evaluated using performance metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), with results demonstrating improved accuracy and robustness compared to traditional methods, thereby supporting effective integration of renewable energy into modern power systems.

I. INTRODUCTION

Energy is essential for economic growth and improved living standards, but traditional fossil fuels such as coal, oil, and natural gas are non-renewable and contribute to environmental pollution and climate change. This has increased the adoption of renewable energy sources like solar photovoltaic (PV) and wind power due to their clean nature and abundant availability [1], [2], [3]. However, these sources are highly variable as their output depends on meteorological conditions such as solar irradiance, temperature, wind speed, and cloud cover, which creates challenges in maintaining grid stability and power balance [4], [5]. Accurate forecasting of renewable energy generation is therefore important for reliable power system operation, energy scheduling, and cost reduction [6]. Conventional forecasting methods based on physical and statistical models often fail to capture complex nonlinear and dynamic patterns in data [7]. Machine learning techniques improve prediction accuracy but have limitations in modeling long-term dependencies [10], [11]. Deep learning models such as CNN and LSTM overcome these issues by effectively learning spatial and temporal features from data [8][10][11][12][13]. Therefore, this work proposes a hybrid CNN–LSTM model to improve prediction accuracy and support efficient renewable energy integration.

II. PROPOSED HYBRID CNN-LSTM MODEL

A. *Overview of the Proposed System*

The proposed method aims to develop an intelligent and accurate renewable energy prediction system using a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. This hybrid model is designed to exploit the complementary strengths of CNN and LSTM for forecasting wind and photovoltaic (PV) power generation. CNN is employed to extract meaningful spatial features from meteorological and historical power data, while LSTM is used to capture temporal dependencies and long-term sequential patterns in time-series data. The overall objective of the proposed system is to improve prediction accuracy and reliability compared to traditional statistical and standalone machine learning approaches. By combining spatial feature extraction and temporal sequence learning within a single framework, the system can effectively model the nonlinear and dynamic behavior of renewable energy sources. The proposed method follows a structured workflow consisting of data acquisition, data preprocessing, feature extraction using CNN, temporal modeling using LSTM, prediction generation, and performance evaluation. The proposed model is implemented using MATLAB Simulink and Deep Learning Toolbox, which provide a suitable environment for data processing, neural network design, training, and testing. The system is designed to support short-term and medium-term forecasting for both wind and PV power generation, making it suitable for smart grid and microgrid applications.

B. Block Diagram

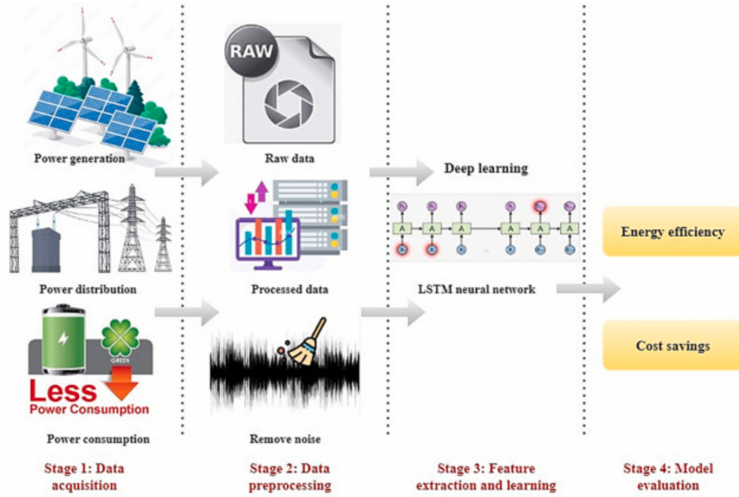

Fig-1- Proposed Hybrid CNN–LSTM Model for Wind and PV Power Prediction

1) Data Acquisition and Input Parameters

The input vector at a time t:

$$Xt = [It, Tt, Ht, WSt, WDt, Pt - 1]$$

- *I_t : Solar irradiance*
- *T_t : Ambient temperature*
- *H_t : Humidity*
- *WS_t : Wind speed*
- *WD_t : Wind direction*
- *P_{t-1} : Previous power output*

The first stage of the proposed method is data acquisition. Historical and real-time datasets related to renewable energy generation are collected from meteorological stations, energy monitoring systems, and open-access databases. The input dataset includes both weather-related parameters and historical power generation records. For PV power forecasting, the main input parameters are solar irradiance, ambient temperature, humidity, and previous PV power output. For wind power forecasting, the key parameters are wind speed, wind direction, air density, atmospheric pressure, and historical wind turbine power output. These parameters are selected because they directly influence the power generation capability of solar panels and wind turbines. Solar irradiance determines the amount of sunlight available for PV conversion, while temperature affects the efficiency of PV modules. Similarly, wind speed and air density strongly influence the mechanical power captured by wind turbines. Including historical power output helps the model learn operational patterns and system behavior under different environmental conditions. The collected dataset is organized in time-series format with fixed sampling intervals such as hourly or daily records. This time-series structure is essential for training the LSTM network, which relies on sequential data to learn temporal relationships.

2) Data Preprocessing

Before feeding the data into the deep learning model, preprocessing is performed to improve data quality and ensure compatibility with the neural network architecture.

- Noise filtering
- Missing value interpolation
- Min–Max normalization

$$X' = \frac{X - X_{\{min\}}}{X_{\{max\}} - X_{\{min\}}}$$

$\boldsymbol{X}$ = *The orginal value of variable*
$\boldsymbol{Xmin}$ = *The minimum value of* $\boldsymbol{X}$ *in the dataset*
$\boldsymbol{Xmax}$ = *The maximum value of X in the dataset*

- Dataset split:
  - 70% Training
  - 15% Validation
  - 15% Testing

Data reprocessing consists of several steps including noise removal, handling of missing values, normalization, and data formatting. Noise in weather and power data can occur due to sensor errors or communication issues. Filtering techniques are applied to remove abnormal spikes and outliers. Missing values are handled using interpolation or mean substitution methods to maintain data continuity. Normalization is performed to scale all input parameters into a common range, typically between 0 and 1, to prevent dominance of any single feature during training and to improve convergence speed.After normalization, the dataset is divided into training, validation, and testing sets. Usually, 70% of the data is used for training, 15% for validation, and 15% for testing. The training set is used to adjust network weights, the validation set is used to tune hyperparameters, and the test set is used to evaluate final model performance.The preprocessed data is then reshaped into an appropriate format required by the CNN and LSTM layers. For CNN processing, the data is arranged in matrix or vector form to allow convolution operations. For LSTM processing, the data is organized as sequences of time steps.

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3) Convolutional Neural Network (CNN)

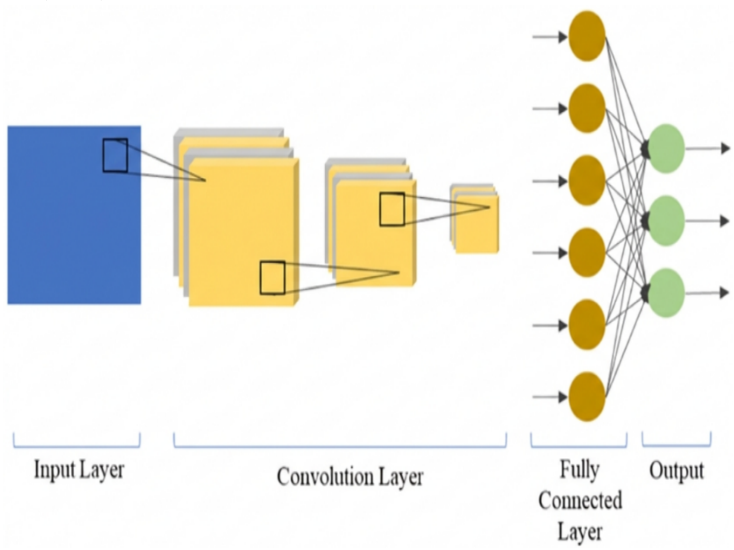

Fig-2-Convolutional Neural Network

Convolutional Neural Network (CNN) is a deep learning model that is highly effective in extracting features from structured and unstructured data. In the proposed method, CNN is used to extract spatial features and correlations from meteorological and power data. The CNN consists of convolution layers, activation functions, and pooling layers. The convolution layer applies a set of filters to the input data to detect local patterns and relationships among variables. For example, it can learn how solar irradiance and temperature jointly affect PV power output or how wind speed variations influence wind turbine generation. Each filter generates a feature map that highlights important patterns in the input data. The activation function, typically Rectified Linear Unit (ReLU), introduces nonlinearity into the network and enables it to model complex relationships. Pooling layers are used to reduce the dimensionality of feature maps while preserving essential information. This reduces computational complexity and prevents overfitting. CNN, a deep learning algorithm frequently used for image, text, and signal inputs, consists of stacked layers that extract object features. Figure 1 shows the basic architecture of a CNN. The model performance is based on the number of stacked layers and the type and size of the kernel. The data in the input layer goes through convolution and pooling layers to extract deep features. These features are then input in the fully connected layer, where the result values are classified. A CNN is used for extracting hierarchical features from an image. Accordingly, a CNN can extract important information from the one-dimensional sequential and two-dimensional input data.

4) Long Short Term Memory

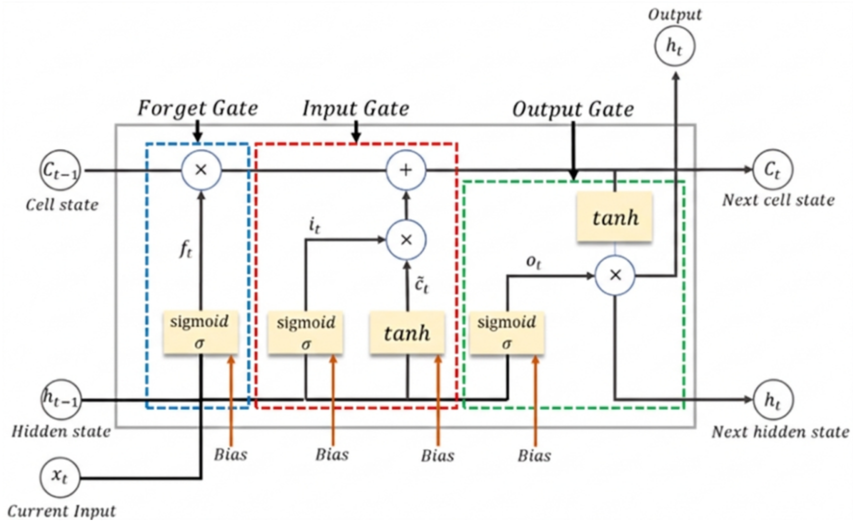

Fig-3- Silicon Photo Diode

LSTM receives current input data and long- and short-term memory of the previous cell in each time step. Short-term memory represents the hidden state and represents $ht-1$, while long-term memory represents the cell state $Ct-1$. A cell adjusts the information to be maintained or discarded in each time step before delivering short-term and long-term information to the next cell using a gate. This gate is called the input, forget, or output gate and accurately performs filtering through training. The first step of LSTM is identifying and removing unnecessary information in a memory cell. This process is performed in the forget gate that determines an output value between 0 and 1 based on a sigmoid function. The closer the value is to 1, the more information about a previous state is maintained. The information of a previous state is forgotten as the value approaches 0, and omitted parts are decided. After passing the forget gate, the information to be stored is selected. If the previous time is forgotten, new information to be remembered is added, and the value of each element is decided as the newly added information. In this case, new information is not stored in the memory cell unconditionally; instead, an appropriate value is selected using an input gate. The sigmoid function is added with the last LSTM cell and the current state and time activation feature. The value passed through the sigmoid layer is expressed as a number between 0 and 1 and indicates the degree of new information being updated. The value that has passed through the tanh function has a value between −1 and 1. Then, the output is multiplied, and the final value is stored in the long-term memory. The following process is used to select the output information. The output gate generates a new short-term memory (hidden state) to be delivered to the cell in the next step using the current input, previous short-term memory, and newly generated long-term memory. The output of the current time step can also be imported from the hidden state. The short- and long-term values generated by this gate are transferred to the next cell as the process is repeated. The output of each time step can be obtained from short-term memory or a hidden state.

$$f_t = \sigma\left(x_t w_f + h_{\{t-1\}w_f} + bias_f\right)$$
$$g_t = tanh\left(x_t w_g + h_{\{t-1\}w_g} + bias_g\right)$$
$$i_t = \sigma(x_t w_i + h_{\{t-1\}w_i} + bias_i)$$
$$c_t = f_t \otimes c_{\{t-1\}} + g_t \otimes i_t$$
$$o_t = \sigma(x_t w_o + h_{\{t-1\}w_o} + bias_o)$$
$$h_t = o_t \otimes \backslash tanh(c_t)$$

The gating mechanism enables long-term memory retention.

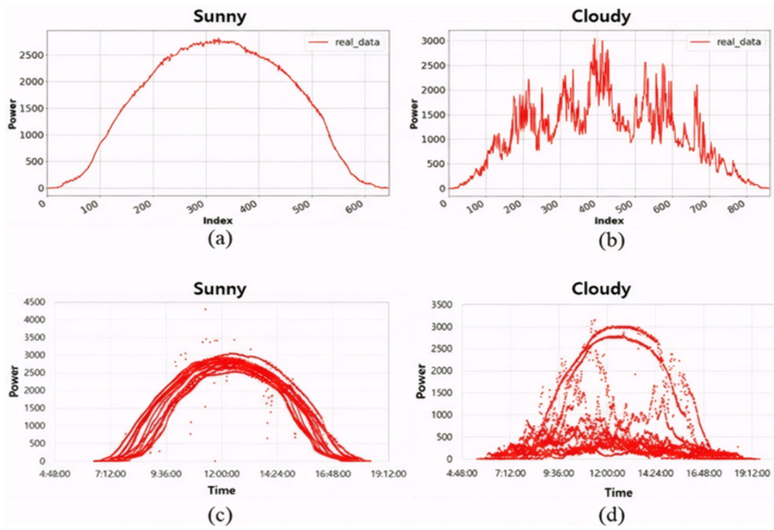

Fig-4- PV power generation graphs; (a) sunny day, (b) cloudy day, (c) scatter plot of sunny days, (d) scatter plot of cloudy days.

5) Hybrid CNN–LSTM Architecture

The hybrid CNN–LSTM architecture integrates CNN and LSTM networks into a unified model. The CNN block extracts spatial features from the input data, while the LSTM block models temporal dependencies in these features. This integration enables the model to handle complex nonlinear relationships and time-series variations simultaneously. The architecture typically consists of an input layer, one or more convolution layers, pooling layers, LSTM layers, and a fully connected output layer. The fully connected layer maps the learned features into predicted power output values for wind and PV systems. The hybrid structure is advantageous because CNN alone cannot effectively model long-term temporal dependencies, and LSTM alone may struggle to extract meaningful spatial features. By combining both models, the proposed method achieves improved forecasting performance compared to standalone CNN or LSTM models.

Output layer:

$$\widehat{P_t} = W_o h_t + b_o$$

$\widehat{P_t}$ = *The predicted output at time step t*
Wo = *The output weight matrix*
h_t = *The hidden state at time step t*
b_o = *The output bias term*

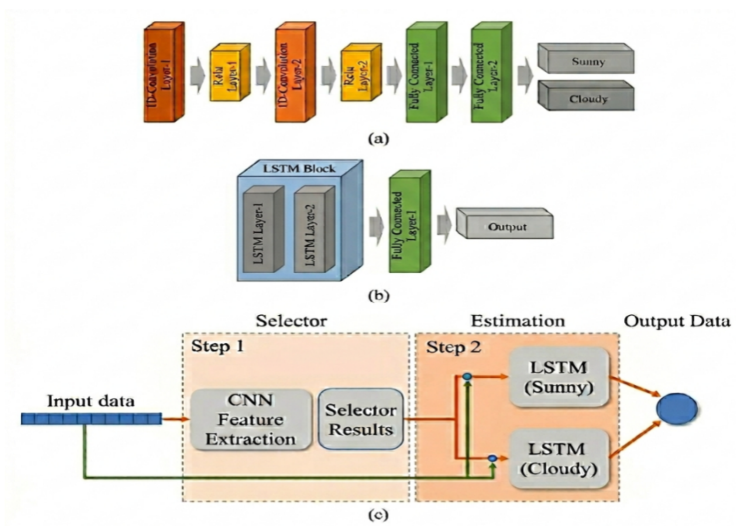

Fig -5- Proposed CNN-LSTM hybrid model; (a) CNN architecture for weather classification, (b) LSTM architecture for PV power generation forecasting, (c) Overall CNN-LSTM hybrid model.

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6) Training and Learning Process

The hybrid CNN–LSTM model is trained using historical datasets. During training, the network weights are updated using optimization algorithms such as Adam or stochastic gradient descent. The loss function, typically Mean Squared Error (MSE), measures the difference between predicted and actual power values.The training process involves multiple epochs, during which the model gradually learns the relationships between input parameters and power output. Hyperparameters such as learning rate, number of layers, number of neurons, and batch size are selected based on validation performance.Overfitting is controlled using techniques such as dropout, early stopping, and regularization. These methods prevent the model from memorizing training data and improve generalization to unseen data.

III. OUTPUT GENERATION AND PERFORMANCE EVALUATION

After training, the model is used to generate predictions for future wind and PV power generation. The predicted output is compared with actual measured values to evaluate performance. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used to quantify prediction accuracy. Lower MAE and RMSE values indicate better model performance. Graphical analysis using predicted and actual power curves is also performed to visualize model accuracy.

A. Model Implementation

The model is implemented using MATLAB Deep Learning Toolbox.

Hyperparameters:

PARAMETER	VALUE
Convolution Filters	32
Kernel Size	3
LSTM Units	100
Optimizer	1
Learning Rate	0.001
Epochs	50
Batch Size	32

Loss Function:

$$\boldsymbol{MSE = \left(\frac{1}{N}\right)\sum\left(\left(Y_{pred} - Y_{actual}\right)^2\right)}$$

Over fitting is controlled using dropout and early stopping.

IV. RESULTS AND PERFORMANCE ANALYSIS

A. Evaluation Metrics

Mean Absolute Error (MAE):

$$MAE = \left(\frac{1}{N}\right)\sum\left(\left|Y_{pred} - Y_{actual}\right|\right)$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum\left(\left(Y_{pred} - Y_{actual}\right)^2\right)}$$

Lower MAE and RMSE indicate better performance.

B. Performance Comparison

Model	MAE (kW)	RMSE (kW)	Performance Level	Remarks
ANN	0.185	0.240	Low	Poor handling of nonlinear & temporal patterns
LSTM	0.120	0.165	Moderate	Good temporal learning but weak spatial feature extraction
CNN	0.135	0.178	Moderate	Good spatial feature extraction but limited long-term

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				memory
CNN–LSTM (Proposed)	0.072	0.098	Best	Excellent spatial + temporal learning capability

The hybrid model demonstrates improved prediction accuracy due to combined spatial-temporal learning.

- *Training Vs Validation Plot:*

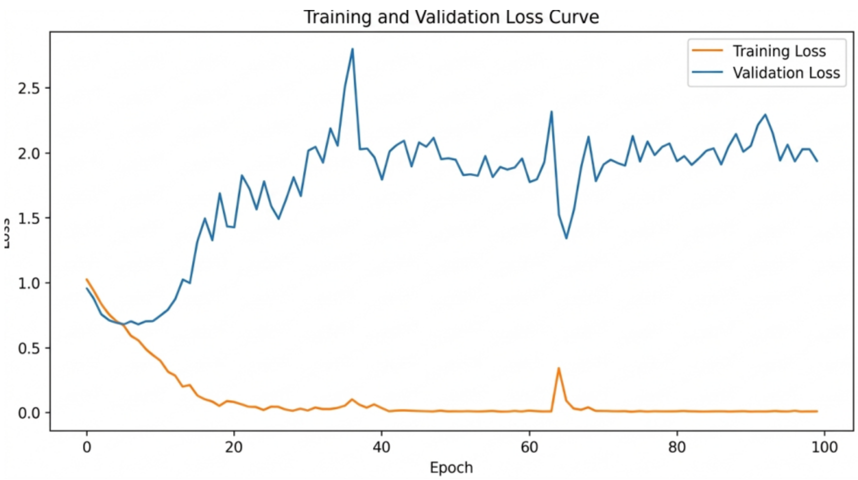

Fig -6- Training and validation convergence curve.

- *Experimental Results -*

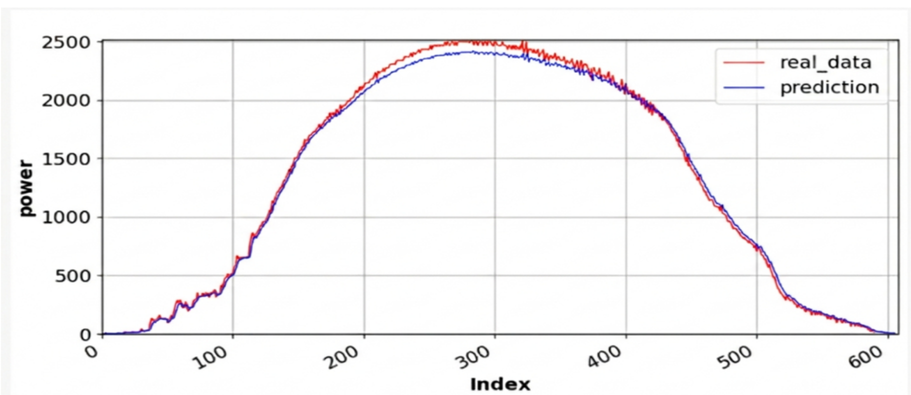

Fig -7- Forecasting result of sunny day power generation data.

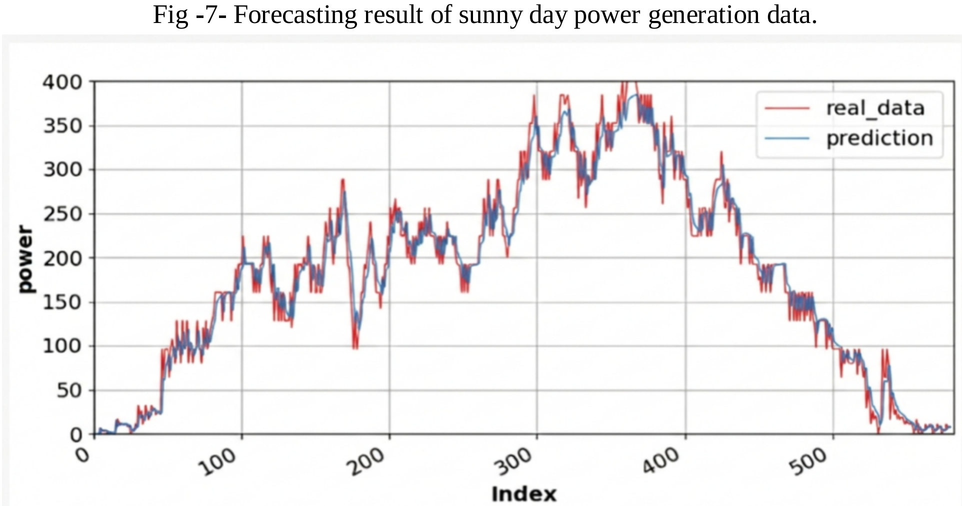

Fig-8- Forecasting result of cloudy day power generation data.

Fig8 is the graph of the cloudy day dataset in which the maximum power output is 400 W. In contrast, on a sunny day, the maximum power output is 2500 W. This result implies that the amount of solar radiation is minimal, resulting in severe fluctuations in overall power generation. The blue line shows the measured data from the device, while the red line shows the prediction data. A quantitative evaluation was performed using MAPE, RMSE, and MSE to validate the LSTM forecasting model. The LSTM model adequately followed the trend of the observation data for accurate forecasting.

C. MATLAB SIMULINK MODEL & OUTPUT:

- *PV POWER :*

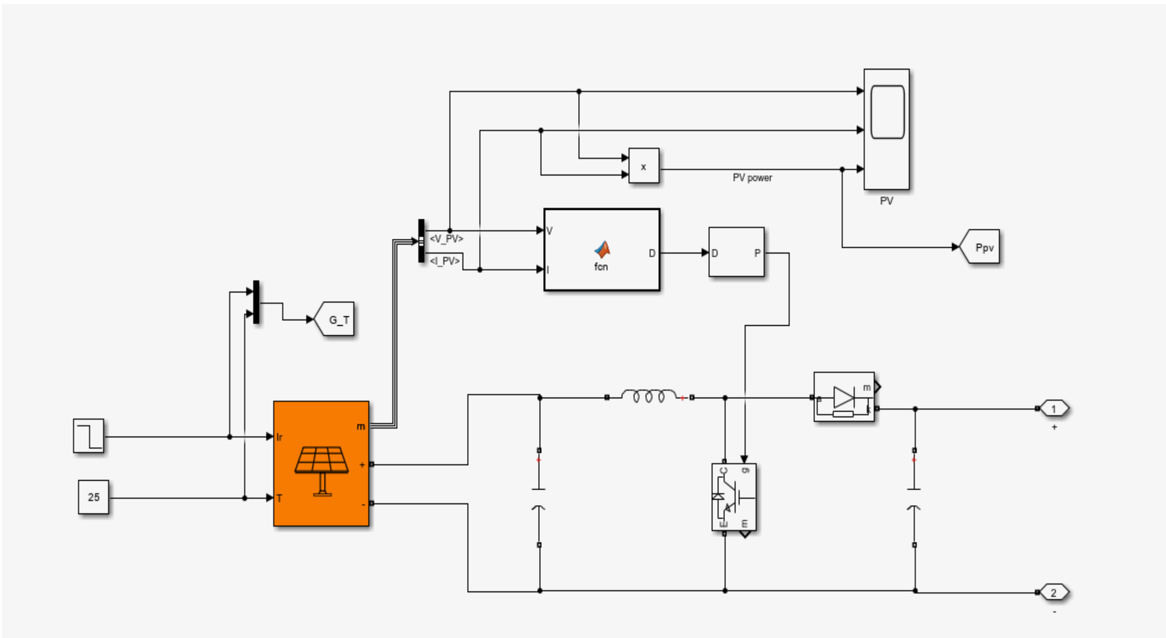

Fig-9- PV POWER

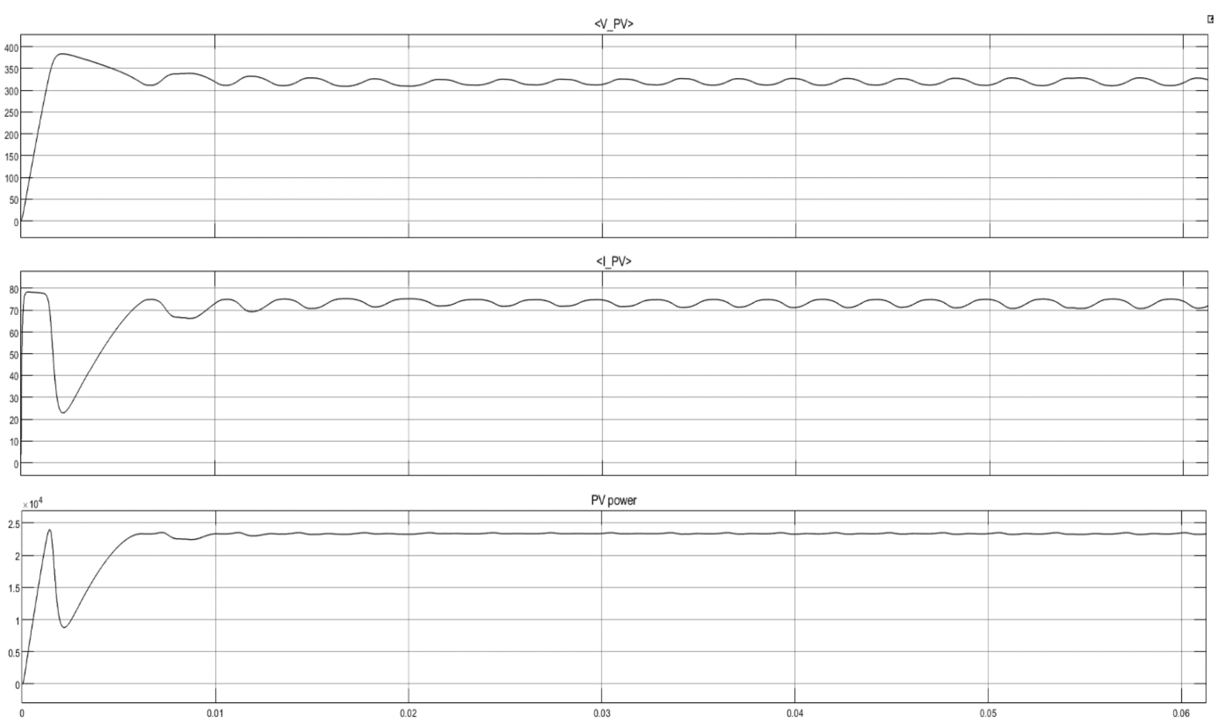

Fig-10- PV SYSTEM OUTPUT

Figure 10 presents the dynamic performance of the photovoltaic (PV) system, including the PV output voltage (V_PV), PV output current (I_PV), and generated PV power under controlled operating conditions. During the initial startup period, the system exhibits a transient response characterized by overshoot and oscillatory behavior due to converter switching and maximum power point tracking (MPPT) controller action.

The PV voltage rapidly increases and stabilizes around its rated operating value with minor steady-state ripple. Similarly, the PV current shows an initial dip before converging to a stable value. The PV power output rises sharply during system initialization, briefly oscillates, and then settles at approximately 2.3×1042.3 \times 10^42.3×104 W, indicating effective maximum power extraction.

The small steady-state oscillations observed in voltage, current, and power waveforms are attributed to high-frequency switching dynamics of the DC–DC converter. Overall, the results demonstrate stable system operation, fast transient response, and efficient MPPT performance.

- *WIND POWER:*

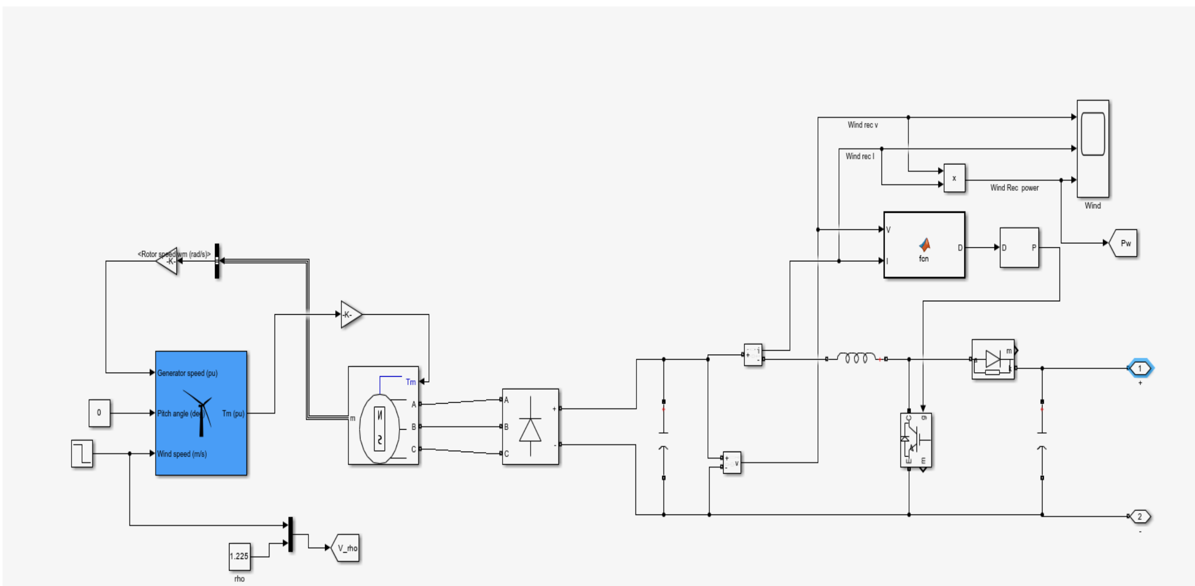

Fig-11- WIND POWER

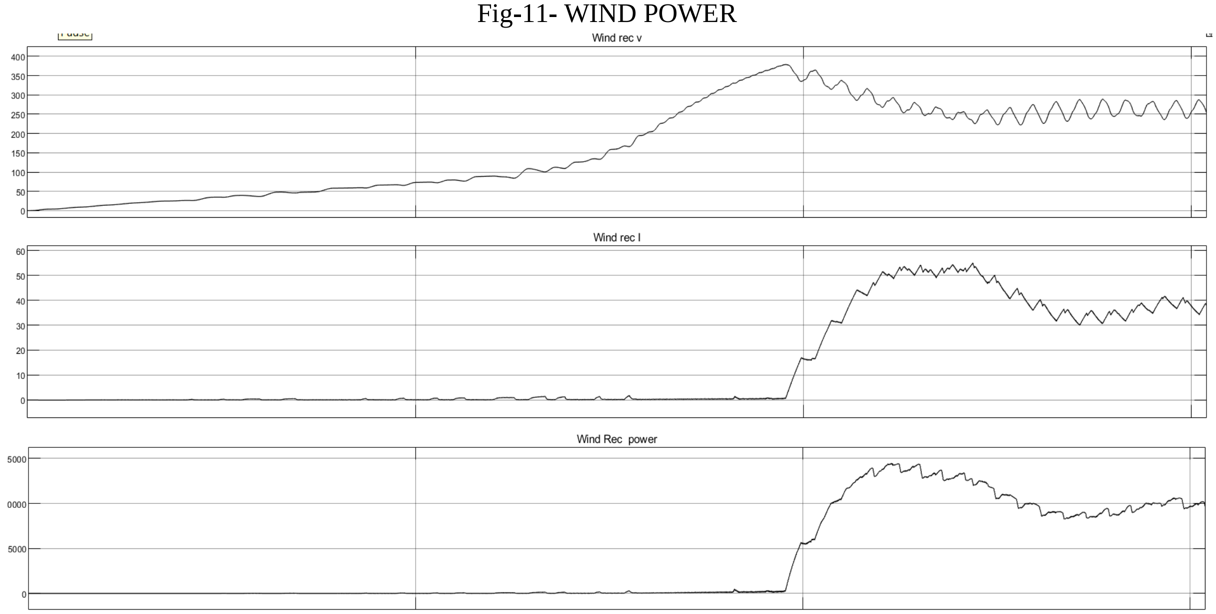

Fig-12- WIND POWER OUTPUT

Figure 12 presents the short-term photovoltaic (PV) power forecasting results obtained using the proposed hybrid CNN–LSTM model under clear-sky (sunny day) conditions. The predicted power output closely matches the measured PV generation profile, indicating high forecasting accuracy and strong temporal generalization capability. The model effectively captures the smooth and continuous variation of solar irradiance throughout the day, resulting in minimal deviation between actual and predicted curves.

The slight discrepancies observed at certain intervals are primarily attributed to minor irradiance fluctuations and inherent system nonlinearities. However, no significant phase shift or amplitude distortion is evident, confirming that the hybrid architecture successfully models both spatial correlations among meteorological inputs and long-term temporal dependencies in the time-series data.

The close alignment between predicted and measured outputs demonstrates the robustness, stability, and reliability of the proposed CNN–LSTM framework for short-term PV power forecasting under stable atmospheric conditions. These results highlight the model's suitability for real-time energy management and smart grid applications.

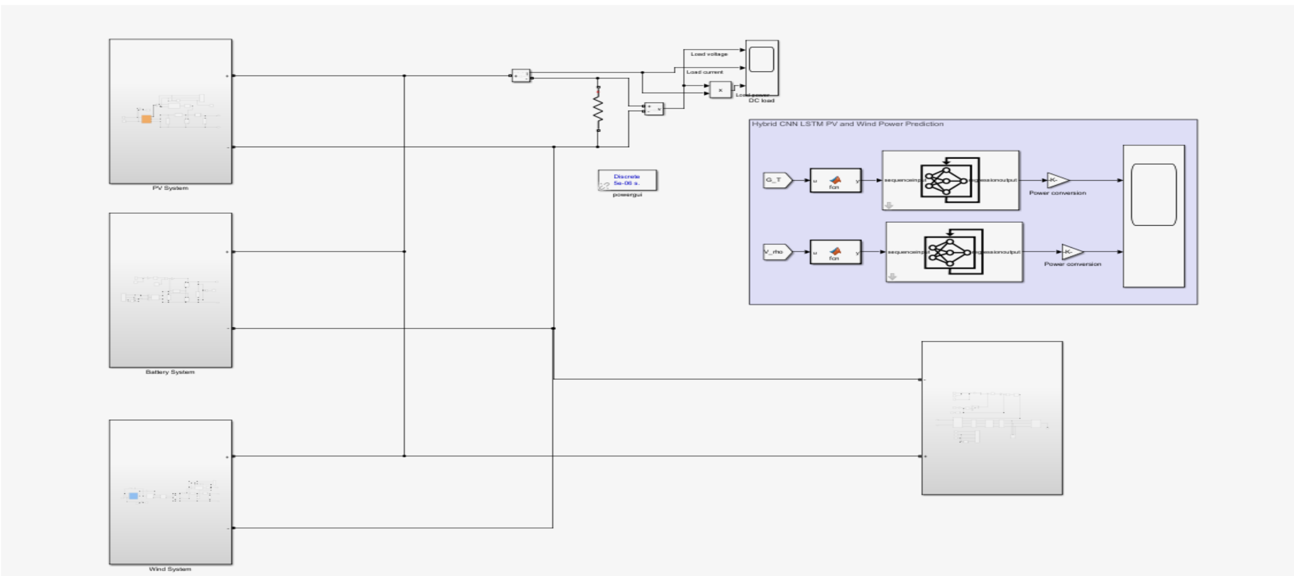

Fig-13- OVERALL VIEW HYBRID CNN & LSTM

The CNN extracts high-level spatial features, which are passed as sequential inputs to the LSTM network. The final dense layer maps learned features into predicted renewable power output.

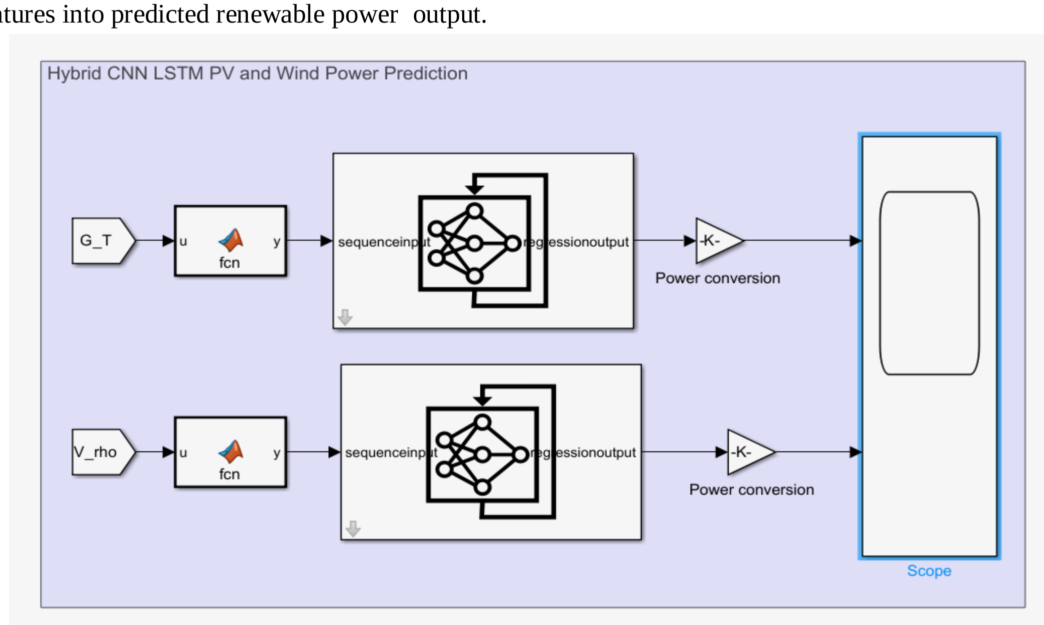

Fig-14- HYBRID CNN & LSTM MATLAB SIMULINK

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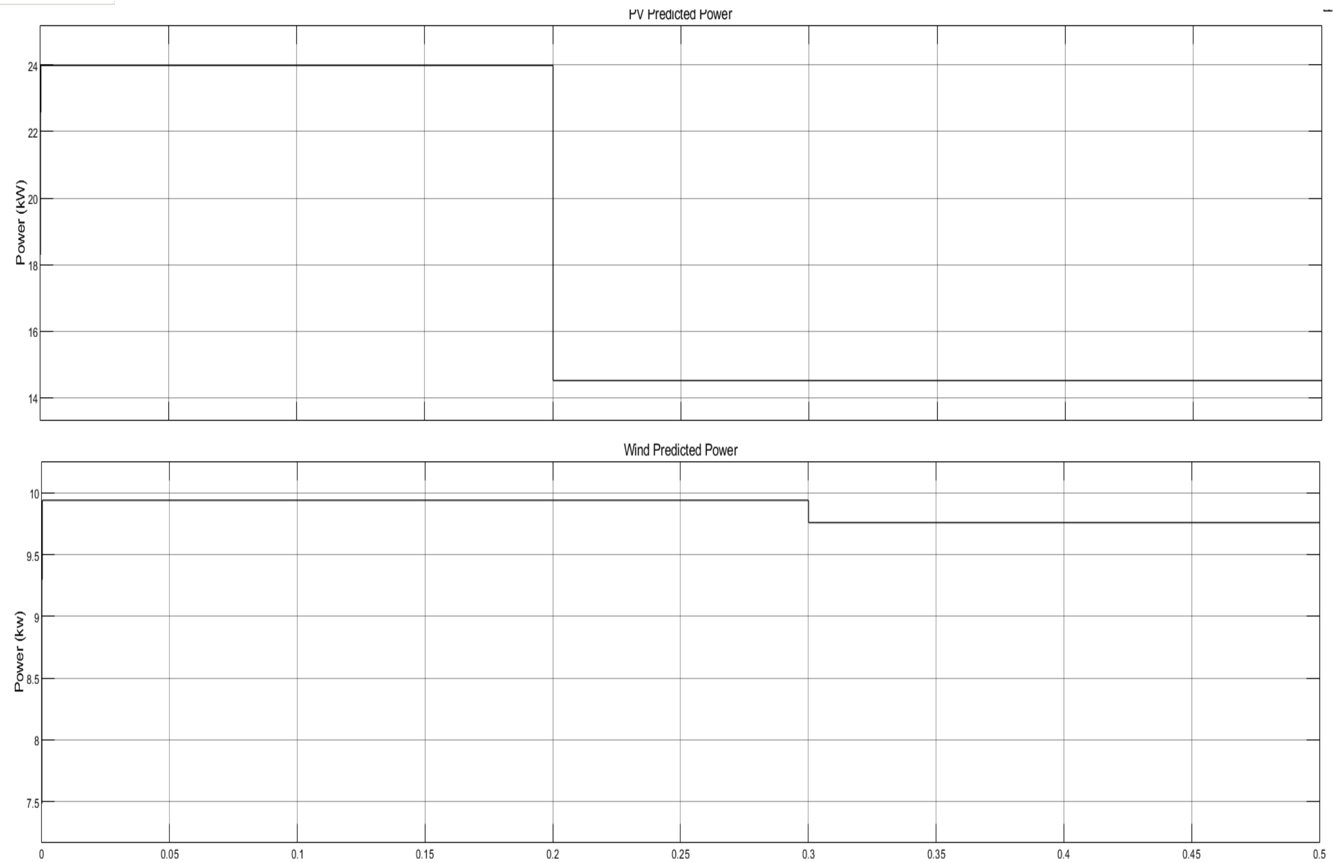

Fig-15- PV & WIND POWER PREDICTION

Figure 15 illustrates the overall prediction performance of the proposed hybrid CNN–LSTM model for combined photovoltaic (PV) and wind power generation. The figure presents the predicted renewable power output compared with the actual measured data under varying operating conditions. The predicted curves demonstrate strong agreement with the real power profiles, confirming the effectiveness of the hybrid architecture in capturing both spatial correlations among meteorological variables and temporal dependencies in sequential data.

The model accurately tracks fluctuations in renewable power output caused by variations in solar irradiance and wind speed. Minor deviations observed during rapid transitions are attributed to sudden environmental changes and inherent system nonlinearities. Nevertheless, the absence of significant lag or amplitude distortion indicates stable convergence and good generalization capability.

Overall, the results validate that the integrated CNN–LSTM framework provides improved forecasting accuracy and reliable performance for multi-source renewable energy prediction, making it suitable for smart grid and microgrid energy management applications.

V. CONCLUSION

The increasing integration of renewable energy sources into modern power systems has introduced significant operational challenges due to the intermittent and stochastic nature of solar photovoltaic (PV) and wind energy. Variations in meteorological parameters such as solar irradiance, temperature, and wind speed result in fluctuating power generation, which affects grid stability, reserve management, and economic dispatch. Accurate forecasting of renewable energy output is therefore essential for ensuring reliable system operation and efficient utilization of sustainable resources. This paper presented a hybrid deep learning framework based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for renewable energy prediction. Conventional statistical and physical forecasting methods often struggle to model the nonlinear and time-varying relationships between environmental conditions and power output. Although standalone machine learning models offer improved performance, they typically require manual feature extraction and exhibit limitations in capturing long-term temporal dependencies. The proposed CNN–LSTM architecture integrates spatial feature extraction and temporal modeling within a unified framework.

The CNN component automatically learns meaningful correlations among meteorological variables and historical power data, eliminating the need for handcrafted features. The LSTM component effectively captures sequential dependencies and long-term trends in time-series data through its gated memory mechanism. By combining these capabilities, the hybrid model enhances prediction accuracy and robustness compared to standalone CNN or LSTM approaches. Performance evaluation using statistical metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) demonstrates the effectiveness of the proposed method in forecasting wind and PV power generation. Improved prediction accuracy contributes to optimized energy scheduling, enhanced grid reliability, and better renewable energy integration within smart grid and microgrid systems. Future work may focus on incorporating attention mechanisms, probabilistic forecasting techniques, and real-time data acquisition to further improve forecasting performance and adaptability.

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