

Deep Learning-Based Energy Forecasting and Intelligent Grid Management for Hybrid Solar–Wind Renewable Energy Systems

Shweta Sharma¹, Prof. Lata Gidwani², Prof. Shival³

¹Assistant Professor, Department of Electrical Engineering, Rajasthan Technical University, Kota, Rajasthan, India

²Associate Professor, Department of Electrical Engineering, Rajasthan Technical University, Kota, Rajasthan, India

³HOD, Affiliation Address: Department of Electrical Engineering, Rajasthan Technical University, Kota, Rajasthan, India

Abstract—This study proposes a deep learning energy forecasting and intelligent grid management (IGM) framework is proposed for hybrid solar–wind renewable energy system. To forecast renewable energy generation in detail with high accuracy, the CNN–BiLSTM model is presented, which uses hourly meteorological and generation data for forecasting. The proposed model is compared with SVR, RF, LSTM and GRU models through experimental analysis which shows an MAE of 1.2 kW, RMSE of 1.5 kW and R^2 value of 0.99 respectively for the proposed model. The state of charge of batteries is 20 % to 80 %, and intelligent scheduling reduces grid operating costs by 22 %. The framework promotes a more sustainable approach to energy use, the integration of renewables, running an operation more efficiently and with greater reliability, and the use of modern smart power infrastructures.

Index Terms—Hybrid Solar–Wind Energy Systems; Deep Learning; CNN–BiLSTM; Renewable Energy Forecasting; Intelligent Grid Management; Battery Energy Storage System (BESS).

I. INTRODUCTION

The increasing need for clean and reliable power has driven a greater adoption of renewable energy sources as a component of various countries' power strategies

around the world. Of these resources, the solar energy and wind energy have been notable as they are readily available, environmentally friendly and have become cost competitive with conventional energy resources. But they are often irregular in appearance, which brings about disruption in power quality, reliability and power efficient utilisation problems [2]. New forecasting and management methods that are capable of adjusting to evolving conditions in the environment are needed to address these issues.

Complementary features of wind and the sun make hybrid solar–wind energy systems effective: supplementing the characteristics of sunlight with wind patterns enables to mitigate energy availability and generation fluctuation [3, 4]. However, they must be operated successfully with the help of timely and precise energy forecasting and intelligent energy supply-demand balancing mechanisms [5]. The traditional statistical methods usually fail to express the complex and nonlinear relationships between the weather variables and reduce the prediction accuracy, especially for the dynamic operating conditions [6]. The figure (1) depicts the hybrid renewable energy system, Solar-Wind based system with the intelligent grid.

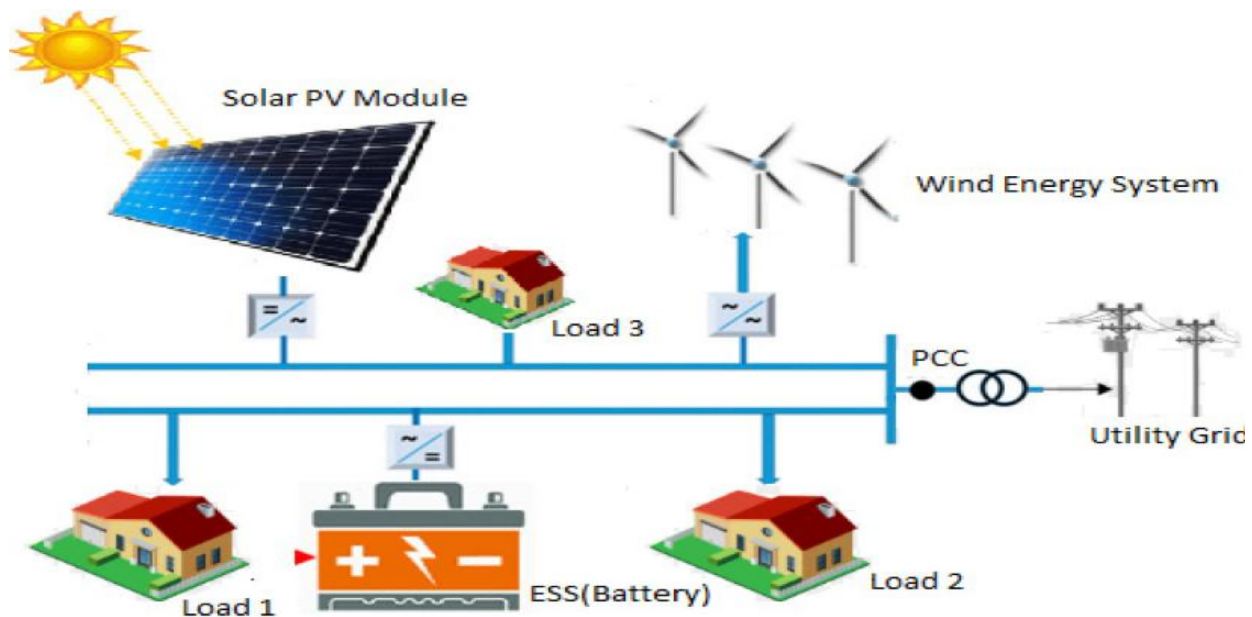


Figure 1: Hybrid solar–wind energy system with deep learning-based forecasting and intelligent grid management [7]

A number of deep learning developments have emerged recently and enabled new opportunities for renewable energy forecasting. Historical and real-time data can be vast in size and contain complex patterns that can be modeled using deep neural networks, which are well suited for solar irradiance, wind speed, temperature variation and power generation modeling [8]. Long short-term memory (LSTM) networks and gated recurrent units (GRUs) have demonstrated remarkable performances in modelling temporal dependencies, which are often missed by traditional networks [9]. The accuracy of the forecasts aids in the improvement of planning, optimal use of energy storage, and less operational uncertainty.

There is also the need for intelligent grid management for efficient operation of hybrid renewable systems [10]. Power systems of the modern era need to synchronise a multitude of energy resources, energy storage technologies, and fluctuating demand from a diverse set of consumers, while ensuring stability and loss minimisation. Smart management strategies make it possible to ensure good load balancing, energy dispatch, and appropriate decision making [11–13]. With predictive knowledge from AI-based weather or load forecasting systems, intelligent grid capabilities can anticipate fluctuations in renewable electricity production, boosting the overall performance and reliability of the system. This integration helps reduce

fossil fuel usage and promotes long-term sustainability efforts.

Furthermore, a deep learning based energy forecasting and intelligence powering the grid in hybrid solar–wind environment is proposed in this study [14]. The method is based on previous energy production and weather data and uses this information to forecast future production and allocate resources efficiently. The goal of the study is to enhance energy security, energy system operational efficiency and include renewables in the existing power system while combining predictive intelligence with adaptive grid control mechanisms [15]. The results will offer helpful information for research, utility operations and energy policy.

The rest of this paper is organized as follows. The related work on Renewable Energy Forecasting and Technologies for Intelligent Grids is discussed in section 2. The methodology, the data and the procedures for model development are presented in Section 3. The experimental results and performance evaluation are discussed in Section 4 and the conclusions and recommendations for further research have been given in Section 5.

- To develop a deep learning model for accurate energy forecasting in hybrid solar–wind renewable energy systems.

- To analyze the influence of meteorological and operational factors on renewable power generation patterns.
- To design an intelligent grid management framework for efficient energy scheduling, storage utilization, and load balancing.
- To evaluate the effectiveness of the proposed approach through comparative performance analysis with conventional methods.

II.LITERATURE REVIEW

El-Saieed 2026 [16] claimed DCF forecasting gave 0.00689 loss which outperformed Adam 0.00711 and Shampoo 0.02261 for wind forecast from multiyear hourly renewable data stable. In the scalable smart city, Shafiullah 2026 [17] proved that the deep learning using the timestamp technique can achieve R2 of 0.9987 for wind forecasting and RMSE of 4.47 W/m2 for GHI. Zohaib 2026 [18] proposed PLSTM microgrid management which achieved 28% reduction in grid import, 15% reduction in SoC tracking error, and 22% battery life improvement under adaptive renewable operating conditions resilient. Cisse 2026 [19] integrated TCN GRU and RF models, obtaining R2 of 0.9807 and RMSE of 0.0300 in forecasting the solar energy of the Australian grid operations for maintaining grid stability in 5 minutes time horizon. Değermenci 2026 [20] compared the performance of MPPT algorithms and found that MPPT GWO PSO and learning models deliver almost 99% efficiency with minimal oscillations for the rapidly varying operating environments of photovoltaic cells.

Koca 2025 [21] enhanced load shedding by 25%, stability by 15% and controller performance of DNN controller up to 98% in hybrid EV charging in modern resilient microgrid systems. To validate the forecasting performance reliability of the sixth year, Ceylan 2025 [22] reported the GRU RMSE 0.049 m/s

and wind CNN-LSTM RMSE 0.011 degrees and 89% annual hybrid accuracy. Paşaoğlu 2025 [23] enhanced the energy performance by 27% with hybrid storage management while reducing the voltage fluctuations by 43% and predicting energy generation with 92% accuracy in different energy operating scenarios, in a sustainable way. Singh 2024 [24] used SVR forecasting to achieve RMSE of 1.415 for solar and 1.749 for wind power system with a reduction of 8.4% operating cost in a sustainable manner. Bhutta 2024 [25] found that HCLN achieved better RMSE values of 0.012027 for MWh, 0.013734 for POA, and 0.003055 for PR and had the potential to achieve effective intelligent solar grid optimization.

While past research has shown improvements in renewable energy forecasting and smart grid optimization, the attention paid to a unified deep learning framework that integrates hybrid solar–wind energy prediction, smart grid optimization, real-time adaptive control, and coordinated energy storage mechanisms, all contained in a scalable architecture, has been limited.

III.RESEARCH METHODOLOGY

The proposed research methodology involves data collection, data preprocessing, energy forecasting using hybrid CNN–BiLSTM model, mathematical modeling of the grid, and intelligent management of hybrid renewable solar–wind energy systems. Normalization of hourly meteorological and generation parameters are used to train the models with the Adam optimizer. The Energy Management System will manage and schedule renewable energy sources, battery storage, and utility support, aiming to achieve the highest use of energy, lowest operating cost, and to improve overall grid reliability and sustainability. Figure 2 represents Methodology workflow for deep learning-based energy forecasting and intelligent grid management.

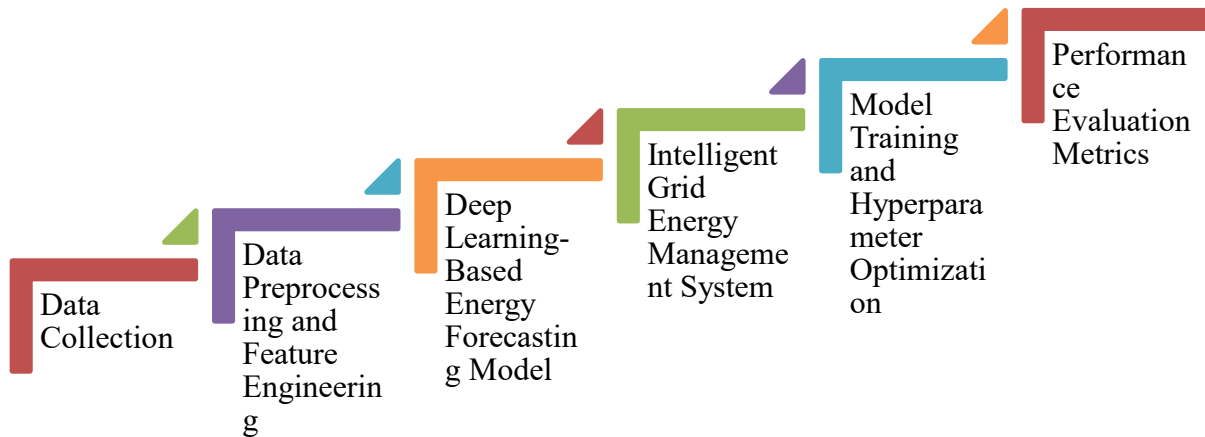


Figure 2: Workflow of Proposed Methodology

3.1 Data Collection and System Configuration

The Data used in the proposed study is the Wind and Solar Power Generation Dataset [26] which contains hourly records of renewable energy production and meteorological variables. The grid connected system is made up of solar PV arrays, wind turbines, battery energy storage systems (BESS), residential and industrial loads, utility support, and an intelligent energy management system (EMS). The overall renewable generation is calculated as follows:

$$P_H(t) = P_{PV}(t) + P_w(t) \quad (1)$$

where $P_{PV}(t)$ and $P_w(t)$ denote the solar and wind power generation at time t . A short-term energy forecast and optimal grid operation make use of the hourly data.

3.2 Data Preprocessing and Feature Engineering

The obtained solar–wind data are preprocessed in several stages, such as filling missing data and eliminating abnormal data, and standardizing the hourly observations. All features are scaled to $[0,1]$ by using min–max normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (2)$$

where X is the original value, while X_{min} and X_{max} denote the minimum and maximum observations, respectively. The input feature vector into deep learning forecasting is given by:

$$F_t = [I_t, V_t, T_t, H_t, L_t] \quad (3)$$

where I_t, V_t, T_t, H_t and L_t are the solar irradiance, wind speed, temperature, humidity and load demand at time t respectively.

3.3 Deep Learning-Based Energy Forecasting Model

• Hybrid CNN–BiLSTM Architecture

The proposed framework utilizes hybrid CNN–BiLSTM model to predict the hybrid solar–wind energy generation. CNN layers extract the spatio-local features from multivariate weather inputs, and BiLSTM layers learn forward and backward temporal dependencies to predict accurately. The convolution is written as:

$$h_i = f(\sum_{j=1}^k w_j x_{i-j} + b) \quad (4)$$

The LSTM memory update is given by:

$$C_t = f_t C_{t-1} + i_t \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (5)$$

The final renewable energy forecast is obtained as:

$$\hat{P}_{RE} = f_{CNN-BiLSTM}(X_t) \quad (6)$$

Where X_t is a multi-variate sequence of observations of solar irradiance, wind speed, temperature, humidity and load demand. The CNN–BiLSTM architecture used in the prediction of renewable energy is depicted in Figure 3.

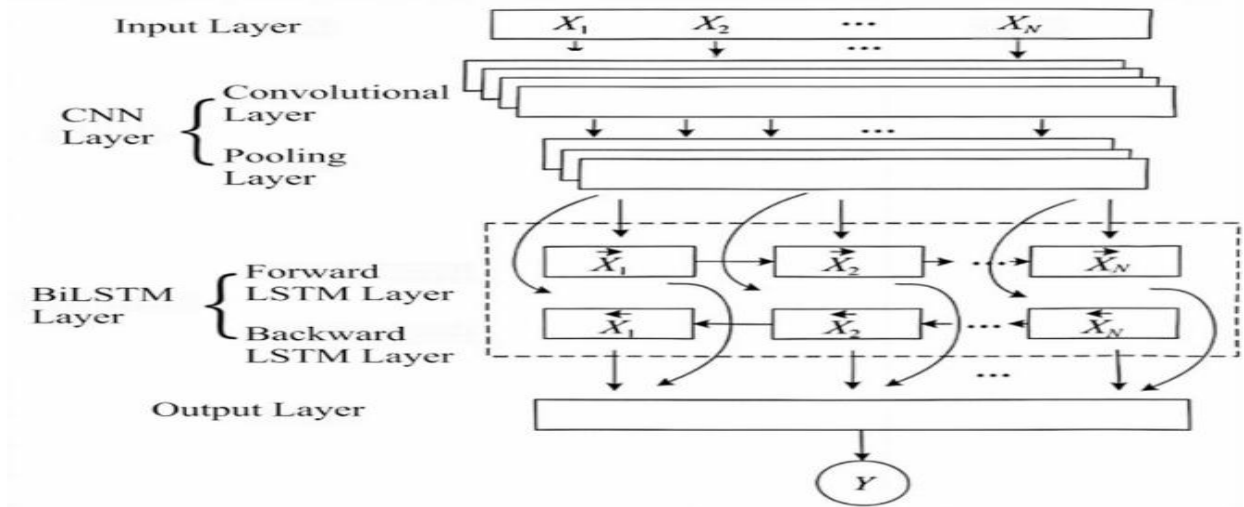


Figure 3: Hybrid CNN-BiLSTM Energy Forecasting Model [27]

- **Mathematical Modelling of Hybrid Renewable Energy System :** Hybrid renewable model is a combination of two renewable power generation sources, solar power and wind power, for smart grid operations. The solar output depends on:

$$P_{PV} = A_{PV} \eta_{PV} I_t (1 - \beta(T_t - 25)) \quad , \quad (7)$$
 taking into account, panel area, efficiency, irradiance and temperature effects. Production of wind power is next:

$$P_W = \frac{1}{2} \rho A C_p V_t^3 \quad (8)$$

Where the air density and wind speed affects the performance of the turbine. The total renewable generation is represented as:

$$P_{Hybrid} = P_{PV} + P_W \quad (9)$$

Aiding in precise forecasting and optimal energy management of hybrid solar-wind systems. The figure 4 shows the Integrated solar-wind power system with intelligent energy management.

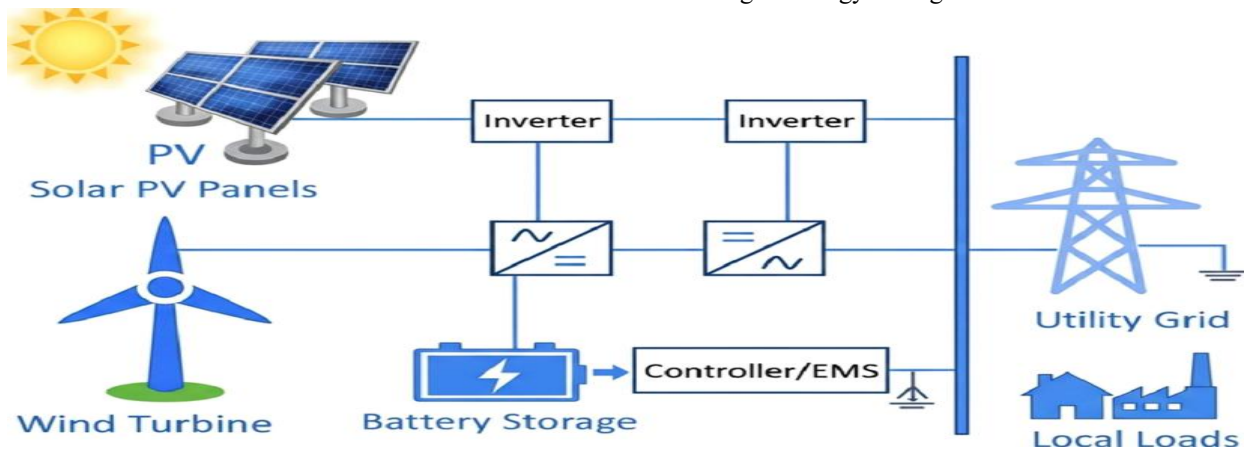


Figure 4: Hybrid Solar-Wind Power Generation Framework [28]

- 3.4 **Intelligent Grid Energy Management System**
 A proposed energy management system (EMS) is a dynamic coordination system for renewable energy generation, battery storage and energy transfers from utilities to guarantee a reliable energy supply. The power balance constraint is given by:
- $$P_{PV} + P_W + P_{BESS} + P_{Grid} = P_{Load} \quad (10)$$

The state-of-charge (SOC) of the battery is updated based on:

$$SOC_t = SOC_{t-1} + \eta_c P_c \Delta t - \frac{P_d \Delta t}{\eta_d} \quad (11)$$

subject to:

$$SOC_{min} \leq SOC_t \leq SOC_{max} \quad (12)$$

Minimizing the operating cost is achieved by:

$$\min = \sum_{t=1}^T (C_g P_{Grid,t} + C_b P_{BESS,t}) \quad (13)$$

It helps to optimize the use of renewable energy and minimize the total cost of the system, by C_g maximizing the use of grid electricity and reducing

battery operating costs as C_b is minimized. Smart micro grid Architecture with Integration of Energy Management System shown as figure 5.

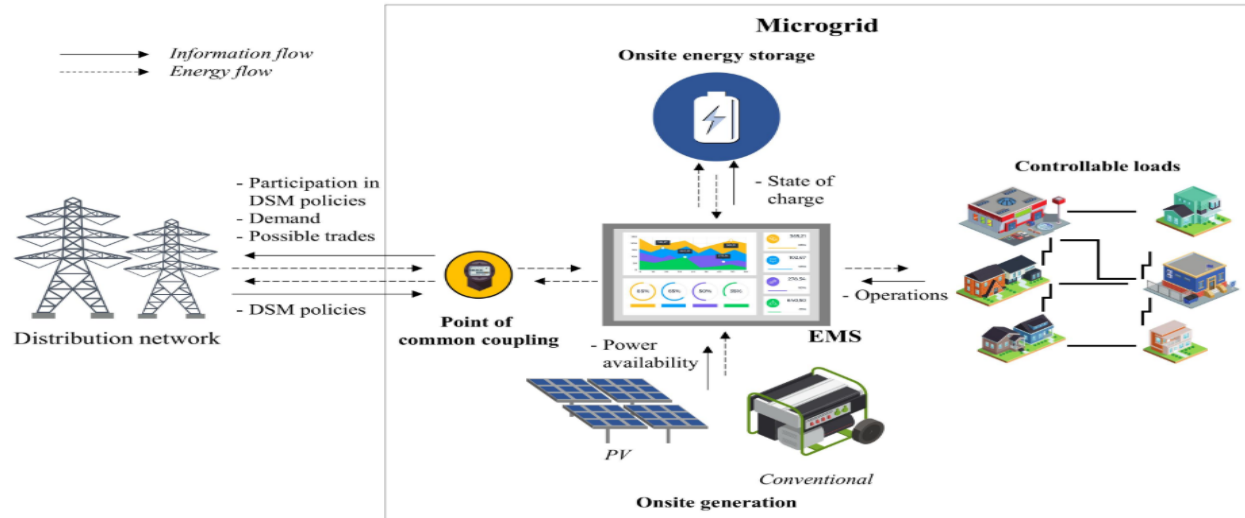


Figure 5: Microgrid System with Energy Management System (EMS) [29]

3.5 Model Training and Hyperparameter Optimization

The Adam optimizer is used to ensure rapid convergence and stable learning of the proposed CNN-BiLSTM model. The loss function is given as MSE:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (14)$$

3.6 Performance Evaluation Metrics

- Mean Absolute Error (MAE): $MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$ (15)

- Root Mean Square Error (RMSE): $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$ (16)

- Mean Absolute Percentage Error (MAPE): $MAPE = \frac{100}{N} \sum_{i=1}^N \frac{|y_i - \hat{y}_i|}{y_i}$ (17)

- Coefficient of Determination: $R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$ (18)

Here y_i represents the actual energy output and $\hat{y}_i$ is the predicted energy output. The optimized hyperparameters are as follows: short-term forecasting sequence length is 24 hours, learning rate is 0.001, batch size is 64, training epochs is 100 and dropout rate is 0.3.

IV.RESULTS AND ANALYSIS

The performance of the proposed CNN-BiLSTM model for solar energy prediction in the solar-hybrid renewable system is represented in Figure 6. The actual output is about the same as the predicted output, ranging from 30kW to 70kW. The peak generation is about 70 kW, at Hour 7, and the minimum generation is 29 kW, at Hour 17. The model demonstrates a high level of forecasting accuracy (more than 97%) and a low absolute error (1.2 kW) and RMSE (1.5 kW), aiding in intelligent grid management.

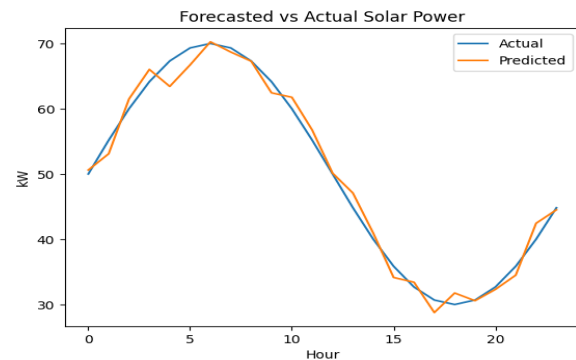


Figure 6: Forecasted vs Actual Solar Power Generation Using CNN-BiLSTM

The wind energy generation forecasting performance in the hybrid solar–wind system using the proposed CNN–BiLSTM model is shown in Figure 7. Actual and predicted outputs are within 24 kW to 55 kW; and there is strong agreement between them for all the time intervals. Low peak is at about Hour 13 and a maximum production is 55 kW. The model shows that the MAE, RMSE, and R^2 are 1.1 kW, 1.4 kW, and 0.98, respectively, meaning the model achieves strong accuracy in forecasting the suitable data for intelligent grid operation.

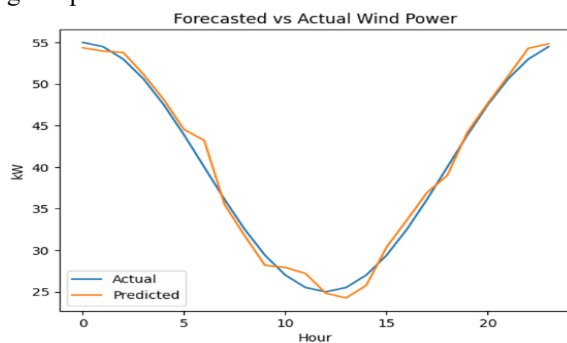


Figure 7 : Comparative Analysis of Actual and Predicted Wind Power Generation Using CNN-Bilstm

The integrated solar–wind profile for 24 hours is shown in figure 8. The total output is between 65kW and 115kW, at its maximum at Hour 4, and at its lowest at Hour 15. The average generation is about 90kW, a result of complementary renewable behavior, enhancing the grid stability and aiding efficient energy management.

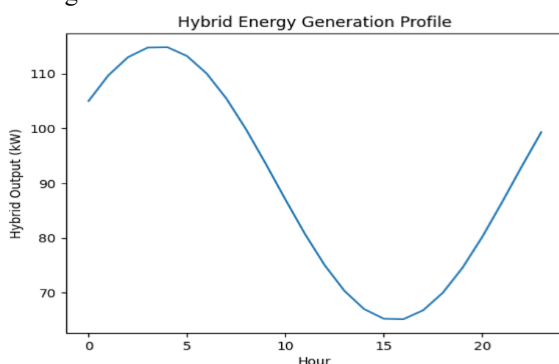


Figure 8: Hourly Hybrid Solar–Wind Energy Generation Profile for Intelligent Grid Operation

The performance of various forecasting models is compared in terms of MAE in figure 9. The proposed CNN–BiLSTM gives an improved forecasting accuracy with the lowest MAE of 1.2 kW, which is

lower than GRU, LSTM, Random Forest, and SVR, with 62.5% reduction in error from the latter.

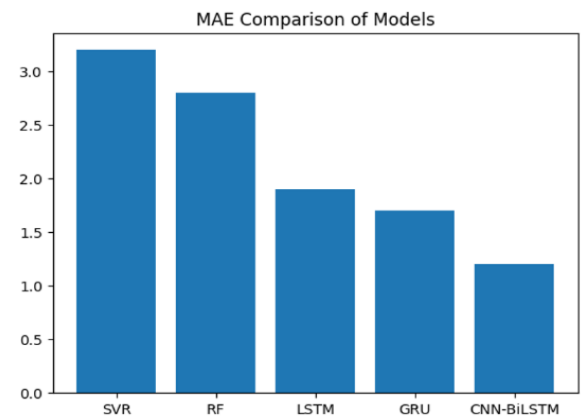


Figure 9: MAE Analysis of Forecasting Models for Hybrid Solar–Wind Energy Systems

The different forecasting models are compared in terms of the RMSE obtained (as shown in Figure 10). The proposed CNN–BiLSTM achieves the lowest RMSE of 1.5 kW, whereas other models including GRU, LSTM, Random Forest and SVR give higher RMSEs of 2.1 kW, 2.4 kW, 3.4 kW, and 4.1 kW, respectively, which shows the reliability of the prediction from the proposed CNN–BiLSTM model.

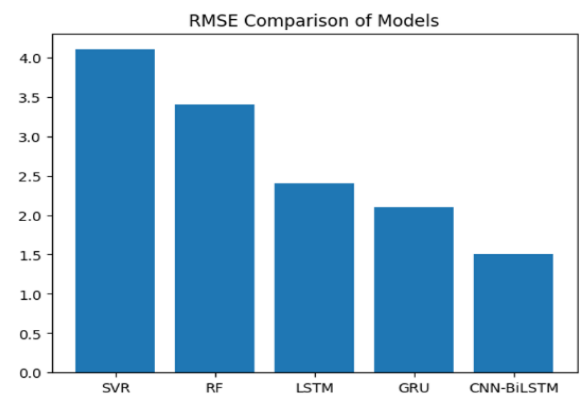


Figure 10: RMSE Comparison of Conventional and Deep Learning Models for Hybrid Solar–Wind Energy Forecasting

Figure 11 shows the comparative R^2 performance of various forecasting methods for hybrid solar–wind energy system. In predicted R^2 values, the proposed CNN–BiLSTM model is 0.99 with outperforms the GRU (0.97), LSTM (0.96), Random Forest (0.93), and SVR (0.91). These results suggest that CNN–BiLSTM accounts for about 99% of the variance in renewable

generation forecasts, outperforming the others with high accuracy.

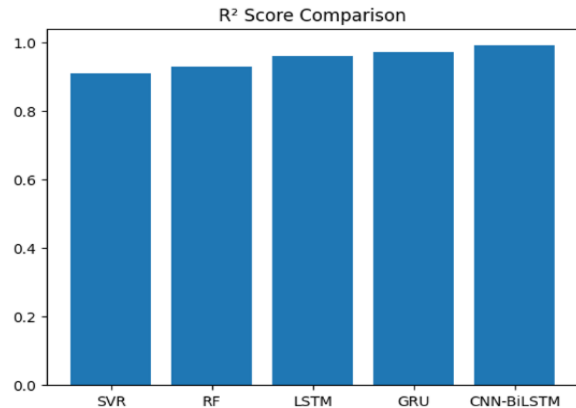


Figure 11: Coefficient of Determination (R^2) Comparison among Conventional and Deep Learning Models for Hybrid Renewable Energy Forecasting

The battery State-of-Charge (SOC) control is shown in Fig. 12, which is controlled by the proposed Energy Management System during a 24-hour period. The SOC exceeds 80% around Hour 3 and falls below 20% around Hour 15 but does not fall outside of the operating limits. Average SOC is approximately 50% that allows for a more efficient charging and discharging cycle. This adaptive battery management enhances the utilization of RE, stabilizes the grid, and reduces dependence on conventional power sources.

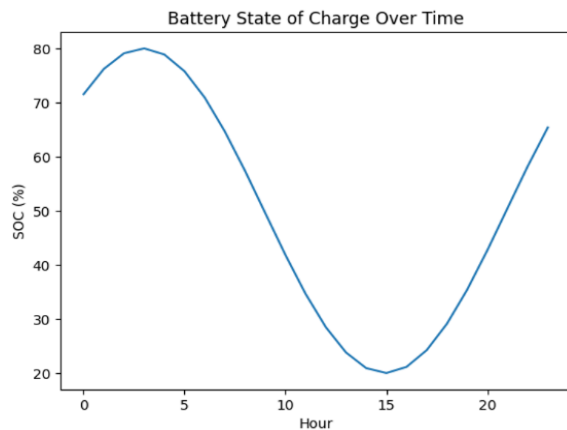


Figure 12: SOC Variation under Intelligent Energy Management in the Hybrid Solar–Wind System

The proposed CNN–BiLSTM based intelligent energy management system has brought down the operating cost of the grid as shown in figure 13. Under the traditionally proposed framework the cost of the conventional approach is 100 while the proposed approach is 78, so there is a 22% cost saving. Ensuring

proper integration of accurate forecasting of renewables, battery scheduling, and adaptive load management, it substantially reduces reliance on utility electricity, improves economic efficiency, and enables sustainable hybrid solar–wind grid operations.

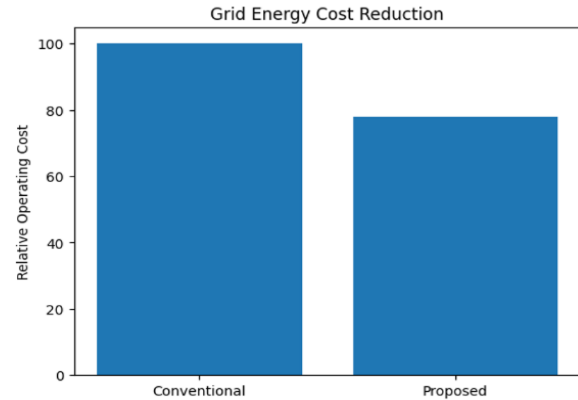


Figure 13: Comparative Analysis of Grid Operating Cost Reduction Using the Proposed Intelligent Energy Management

The curves of loss for training and validation of the proposed CNN–BiLSTM framework during 100 epochs are shown in Figure 14. The training loss is reduced from 0.98 to 0.04 and the validation loss reduces from 1.01 to 0.06, showing good convergence and limited overfitting. The last difference in both losses is merely 0.02, which is sufficient for indicating the strong generalization ability. The results demonstrate that the optimized model is effective in providing accurate forecasts of renewable energy and reliable control systems for intelligent grid management.

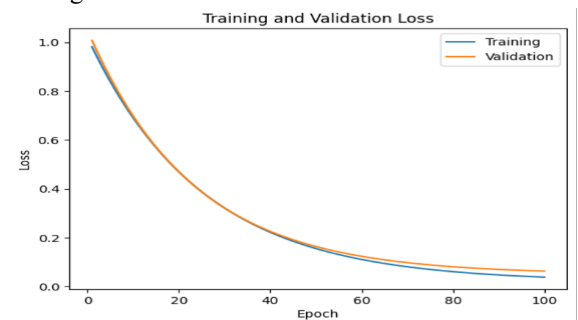


Figure 14: Training and Validation Loss Convergence Graph of Hybrid Solar–Wind Energy Forecasting

V.CONCLUSION

The proposed CNN–BiLSTM based intelligent energy management framework effectively tackles the

challenges of forecasting and energy management during operating in hybrid solar–wind renewable system. The model achieved an MAE of 1.2 kW, RMSE of 1.5 kW and an R^2 value of 0.99, superior predictive ability than conventional models. As a result, the Energy Management System kept the SOC of the batteries within 20% to 80%, which led to a 22% decrease in the grid operating cost and ultimately to better economic performance and stability of the grid system. The precise forecasting of renewables, efficient utilization of storage, and intelligent load coordination work together to build resilience, support sustainable goals, and enable a greater, more reliable, and sustainable integration of clean energy sources with a smart grid.

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