Solar Power Generation Prediction Using Advanced Deep Learning Approach for EV Applications

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***Abstract*—Accurate solar power prediction plays a pivotal role in the effective management of Electric Vehicle (EV) charging systems, especially in smart energy networks. This paper presents an advanced Deep Learning (DL) based approach for solar power generation forecasting. Historical and real-time solar power generation datasets are collected and undergo comprehensive preprocessing, including data cleaning and normalization, to ensure quality and consistency. The pre-processed dataset is then split into training and testing sets to develop a reliable predictive model. A hybrid DL architecture combining Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and an attention mechanism is utilized to extract spatial-temporal features and focus on critical input parameters, thereby improving forecasting accuracy. Furthermore, model optimization is carried out using the Chimp Optimization Algorithm (ChOA), which efficiently tunes models hyperparameter by simulating intelligent search behavior. The proposed work implemented using Python and demonstrates strong forecasting capability, achieves MAE of 0.03 and RMSE of 0.09.**

***Keywords*—Solar power prediction, EV, CNN-GRU with attention, Chimp optimization algorithm, Renewable energy.**

I. Introduction

The depletion of fossil fuels and increase in greenhouse gas emissions have accelerated the world's transition to RES, with solar energy emerging as an important option due to its availability and environmental benefits. Solar Photovoltaic (PV) systems are particularly useful in areas with limited grid infrastructure since they provide both on- and off-grid possibilities [1-2]. While integrating several climatic parameters improve forecasts, it also increases processing demands, making it critical to select the most important inputs for precise and efficient modeling [3-4]. Furthermore, the growing popularity of EV is changing energy consumption patterns and boosting the demand for clean, reliable power sources. Distributed Energy Resources (DERs), such as solar PV and energy storage systems, contribute to grid stability, especially during peak demand periods [5-6]. EVs, with their longer idle intervals, serve as mobile energy storage units to aid with load balancing. Charging them with solar electricity improves system reliability while minimizing reliance on fossil fuels [6-7]. In this context, advanced DL models are an effective tool for precisely estimating solar generation, enabling better energy management and faster EV integration for more sustainable energy future.

Solar PV forecast models are commonly classified as physical and AI based methodologies. Physical models are not depending previous solar data, but rather on current weather and geographical data [8]. While statistical models use both historical and real-time data, they frequently suffer from data quality difficulties and processing limits. In contrast, AI based systems improve prediction by learning complicated patterns. ANN manage huge, non-linear, and noisy datasets, making it suited for dynamic solar forecasting scenarios [9-11]. Nevertheless, it requires significant training data and processing resources, and performance is heavily dependent on parameter tuning. In comparison, SVM performs well with smaller datasets and high-dimensional domains, but it struggles with kernel selection and scalability in real-time, data-intensive applications such as EV-based solar forecasts [12]. Further performance improvement achieved by optimization approaches such as Artificial Bee Colony (ABC) algorithm, which increases the model's global search ability by emulating honey bees' intelligent foraging behavior. However, convergence in high-dimensional spaces take longer. The Adam optimizer speeds up training by adaptively altering learning rates, however it occasionally results in poor generalization [13-15]. To overcome this challenges by using hybrid DL model combining CNN-GRU with attention mechanism. Additionally, the ChOA process refines model parameters by balancing exploration and exploitation, resulting in faster convergence and more reliable predictions.

The main contribution of this paper as follows,

- **Preprocessing:** A robust preprocessing stage ensures data quality and dependability by cleaning, standardizing, and separating train and test sets.
- **Develop hybrid DL model:** Provide a hybrid architecture uses CNN, GRU, and an attention mechanism to collect spatial-temporal data and increase solar power forecasting accuracy.
- **Tune model using the optimization algorithm:** The ChOA automatically fine-tune hyperparameters, resulting in improved prediction accuracy and computing efficiency.
- **Increase the accuracy of solar energy forecasts:** Extensive simulations provide high precision solar power estimates with low error rates, outperforming existing methods.

- **Enable reliable EV charging operations:** Improve EV charging energy planning by incorporating accurate solar forecasts, increasing grid resilience, and decreasing dependency on fossil fuels.

II. PROPOSED SYSTEM DESCRIPTION

Fig. 1 displays a block diagram for estimating solar power generation using an enhanced DL approach for EV applications. Raw data is collected and pre-processed using techniques such as data cleaning to eliminate noise and irrelevant information, followed by data normalization to uniformly scale the features and prepare the data for model training. Following preprocessing, the enhanced dataset is divided into training and testing sets, allowing for efficient model creation and precise performance measurement.

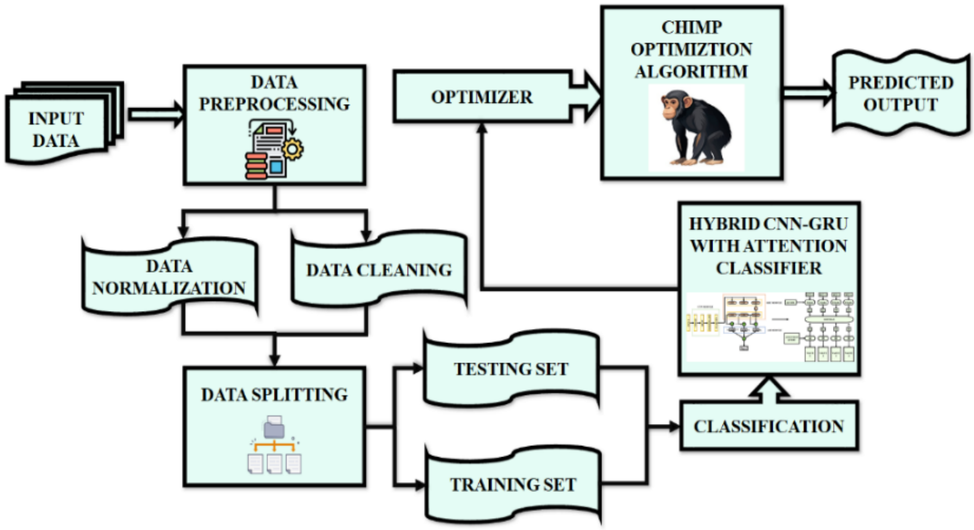

Fig. 1. Block diagram of the proposed work

After data is prepared, the technique continues on classification phase, where hybrid CNN-GRU with attention classifier is used to predict solar power generation. This advanced DL model uses CNN to extract spatial data, GRU to capture temporal correlations, and an attention mechanism help the model focus on the most important input elements, improving prediction accuracy. To increase model performance, the ChOA, an approach based on intelligent chimp behavior efficiently explore the solution space and fine-tune model parameters. The approach leads with the generation of predicted output, which provides the accurate solar power projections required to ensure the efficiency and dependability of EV chargers.

III. PROPOSED SYSTEM MODELLING

A. Data Preprocessing

Data preparation is a crucial step in calculating solar power output for EV applications since it ensures that DL models use accurate, consistent, and thorough data. It consists of a set of operations designed to improve raw data collected from many sources, including solar irradiance, temperature, humidity, panel voltage, and current measurements. These techniques dramatically improve data quality, resulting in increased prediction model performance and reliability.

Data Cleaning: It involves finding and correcting errors, inconsistencies and missing values in a dataset. This phase is critical as DL models demand precise and consistent real-time inputs. To ensure that the dataset is free of noise and errors techniques such as imputation, outlier detection and correction, and validation checks are used, resulting in accurate model training and enhanced energy management in EV charging systems.

Data Normalization: Following cleaning, data normalization is used to standardize the range and distribution of detector inputs, which differ greatly in size. Furthermore, controlling for deviation in data distribution ensures that normality-based models work effectively. Together, these efforts ensure a balanced feature contribution, improve prediction accuracy, and enable successful control of EV energy systems.

After preprocessing, the dataset is split for training and testing, followed by solar power prediction using a Hybrid CNN-GRU with attention classifier.

B. Hybrid CNN-GRU with Attention Mechanism

An enhanced CNN-GRU model is developed to accurately estimate solar power generation in EV applications as shown in fig. 2. It handles concerns such as a lack of historical data and the limitations of long-sequence forecasting by preprocessing and validating incoming data in order to boost efficiency. A 1D CNN captures essential time-series features, which are then enhanced with GRU layers and an attention module that applies dynamic weights to improve prediction. This integrated architecture generates exact and dependable estimates for effective energy management in EV systems.

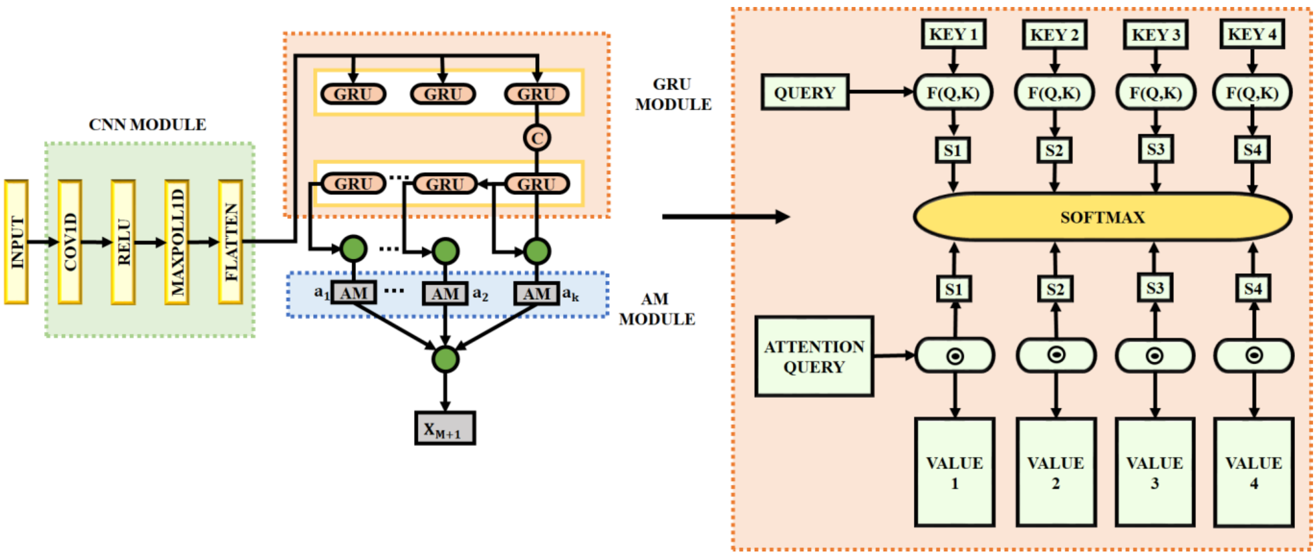

Fig. 2. Hybrid CNN-GRU with attention

CNN Model: This study uses 1D-CNN to estimate solar power generation for EV applications by efficiently analysing smart grid time-series data. The network, which contains convolutional, pooling, flattening, and output layers, extracts complex temporal features. By activating ReLU and extracting features at many scales, the model ensures accurate and efficient solar energy predictions. The convolution formula is illustrated as follows:

$$g(i) = \sum_{x=1}^{m} \sum_{y=1}^{n} \sum_{z=1}^{p} a_{x,y,z}\omega_{x,y,z}^{i} + b^{i}, \; i = 1,2, \ldots\ldots q \quad (1)$$

Where, $g(i)$ designates the ith feature map, a is the input data, i represents the ith convolution kernel, b is the bias term, and x, y, z represent the three dimensions of the input. Given the one dimensional nature of the data, a 1D CNN is used to process it using the convolution formula.

$$g(i) = \sum_{x=1}^{m} a_x \omega_x^{i} + b^{i}, \;\; i = 1,2, \ldots, q \quad (2)$$

Time-series characteristics are extracted using sliding window with step size l. Pooling layers combine window elements to preserve important features, which retrieved in high dimensions with additional convolutional layers. The CNN module output is completed with flattening and fully connected layers.

GRU Model: The GRU is more straightforward and efficient alternative to LSTM for dealing with long-term dependencies in time series data. It employs only two gates reset and update to control information flow and eliminate fading gradients, resulting in faster and more effective temporal feature modeling.

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \quad (3)$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \quad (4)$$

$$\widetilde{h_t} = f\left(W_1 x_t + U_h (r_t \odot h_{t-1})\right) \quad (5)$$

$$h_t = z_t \odot \widetilde{h_t} + (1 - z_t) \odot h_{t-1} \quad (6)$$

Where, r_t is reset gate, z_t is update gate, x_t is input data, and σ is sigmoid activation function. The previous hidden layer state is indicated byh_{t-1}. σ Denotes sigmoid activation function. The input x_t and preceding hidden layer are denoted by h and t, respectively, with f representing the tanh activation function.

Attention Mechanism: The attention mechanism, which is inspired by human perception, enhances model focus by weighting key parts of sequential input data. Widely used in activities such as machine translation, it improves prediction by allowing the model to select essential time-series data, making it appropriate for solar power forecasting in EV applications. The attention mechanism generates hidden states and selectively emphasizes critical information based on its formula.

$$a_i = \frac{exp(s(h_i, h_t))}{\sum_{i=1}^{N} exp(s(h_i, h_t))} \quad (7)$$

$$O = \sum_{i=1}^{N} a_i h_i \quad (8)$$

The feature vector's score is indicated by $(s(h_i, h_t))$. In attention mechanism, a_i represents the weight value of ith input feature, as well as feature vector's score ratio to the total. The final vector$O$, is calculated by combining and averaging all vectors. To further enhance model performance, ChOA is applied to efficiently tune parameters through intelligent exploration of solution space.

Chimp Optimization Algorithm: The ChOA modelled after chimps intelligent and socially oriented hunting behavior, is used to optimize DL models for solar power prediction in EV applications. The program assigns the chimp population to four strategic roles, attacker, barrier, chaser, and driver, which represent different exploration and exploitation strategies as shown in fig. 3. Standard ChOA requires initializing N chimps with locations X_i and designating the top four solutions as attacker, barrier, chaser, or driver. These roles recreate advanced hunting strategies by commanding the chimps to alter their positions based on equations that simulate encircling and catching prey, hence boosting the search for optimal solutions.

$$A = f.(2.r_1 - 1), C = 2.r_2 \quad (9)$$

$$m = chaotic\_value \quad (10)$$

In ChOA, r_1 and r_2 are random vectors in $[0,1]$, while f is a non-linear decay factor that linearly declines from 2.5 to 0 over iterations$t$. A random vector A exists within $[-f, f]$ and influences exploration. The chaotic factor (m) represents how sexual behavior incentives influence position updates. Prey impact is determined by a coefficient (c) ranging from 0 to 2 weak when $0 < 1$ and high when $0 < 1(C > 1)$. These factors work together to guide the chimps' movements toward optimal outcomes.

The remaining chimps' positions are adjusted based on the attacker, barrier, chaser, and driver positions, using specific equations to guide the population to optimal solutions through cooperative and adaptive movement.

$$\begin{cases} X_1 = X_{Attacker} - A_1 * D_{Attacker} \\ X_2 = X_{Barrier} - A_2 * D_{Barrier} \\ X_3 = X_{Chaser} - A_3 * D_{Chaser} \\ X_4 = X_{Driver} - A_4 * D_{Driver} \end{cases} \tag{14}$$

$$X(t+1) = (X_1 + X_2 + X_3 + X_4)/4 \tag{15}$$

Where, $(C_1, C_2, C_3, and\ C_4)$ are comparable to C, whilst $(A_1, A_2, A_3, and\ A_4)$ are similar to A. And m1, m2, m3, and m4 are all equivalent to m. The procedure involves the creation of displayed output, which provides the accurate solar power predictions required to assure the efficiency and dependability of EV chargers.

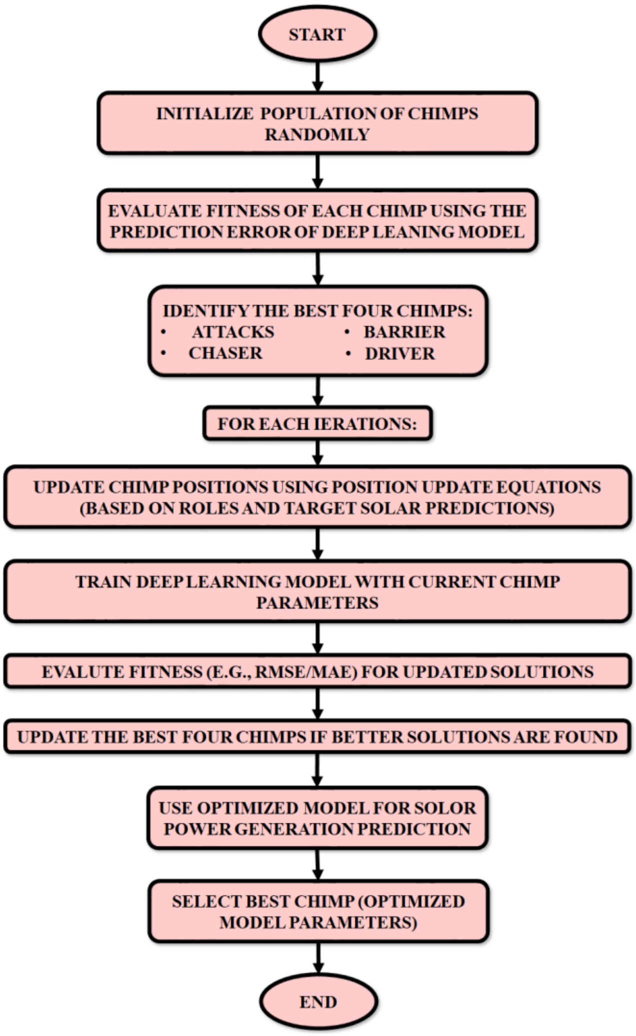

Fig. 3. Flowchart of ChOA

IV. Results and Discussion

The proposed research uses hybrid CNN-GRU attention model optimized with the ChOA for solar power generation prediction in EV applications. This model is used for the solar power generation dataset [16] and implemented in Python, and the results are discussed below.

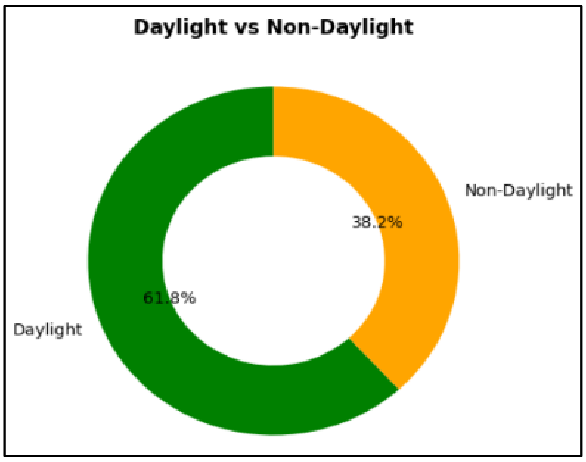

Fig. 4. Daylight vs non-daylight

Fig. 4 displays the contrast between daylight and non-daylight times, revealing that 61.8% of the time is spent during daylight hours, with the remaining 38.2 falling outside of them.

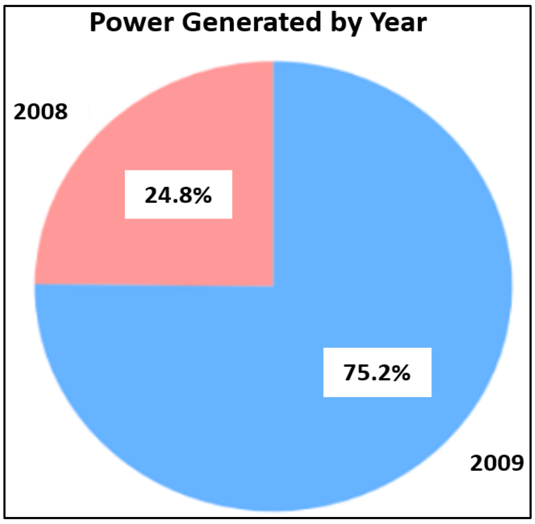

Fig. 5. Power generated by year

Fig. 5 depicts the annual power generation distribution, with 24.8% of total power generated in 2008 and 75.2% in 2009, demonstrating a large increase in power generation in 2009.

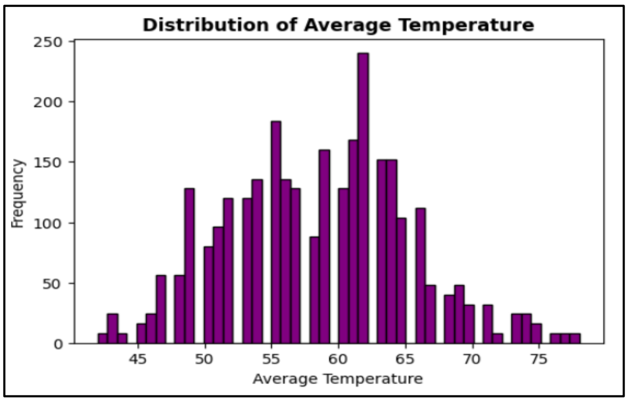

Fig. 6. Distribution of average temperature

Fig. 6 shows distribution of average temperatures. Temperature readings typically range from 44°F to 76°F, with a high frequency at 61°F. The histogram shows a near normal distribution, with the majority of days (almost 240) having temperatures between 58°F and 64°F.

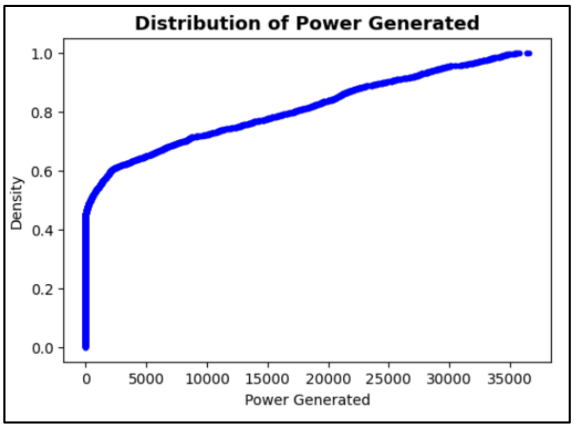

Fig. 7. Distribution of power generated

Fig. 7 displays the cumulative power generation distribution, which reaches up to 35,000 units, with about 60% falling below 10,000 units, showing frequent low power values.

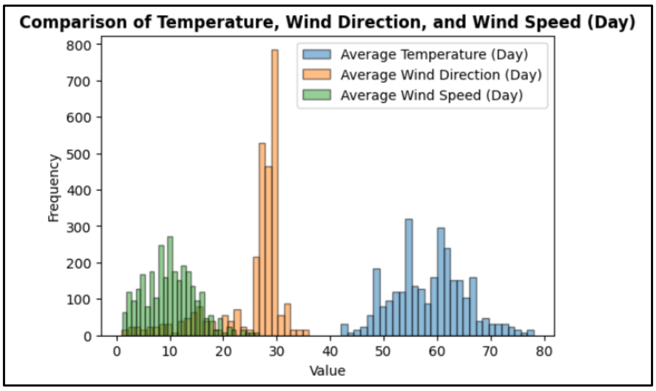

Fig. 8. Comparison of temperature, wind direction and speed

Fig. 8 depicts overlapping histograms of daylight temperature, wind direction, and wind speed. The temperature peaks near 60°F, the wind direction clusters around 20°, and wind speed peaks between (7-9).

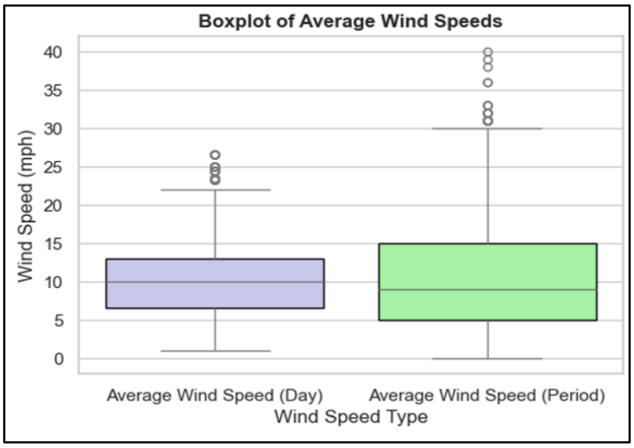

Fig. 9. Boxplot of average wind speeds

Fig. 9 depicts boxplot of average wind speeds, with daylight speeds ranging from 5 to 15 mph, outliers above 25 mph, and entire period speeds above 40 mph, indicating slightly more variability.

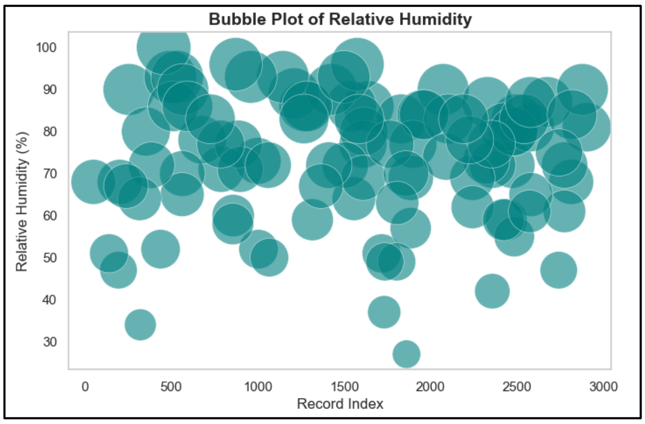

Fig. 10. Bubble plot of relative humidity

Fig. 10 depicts relative humidity, with the majority of values ranging from 60% to 90% and a few as low as 30%, indicating significant humidity variation between datasets.

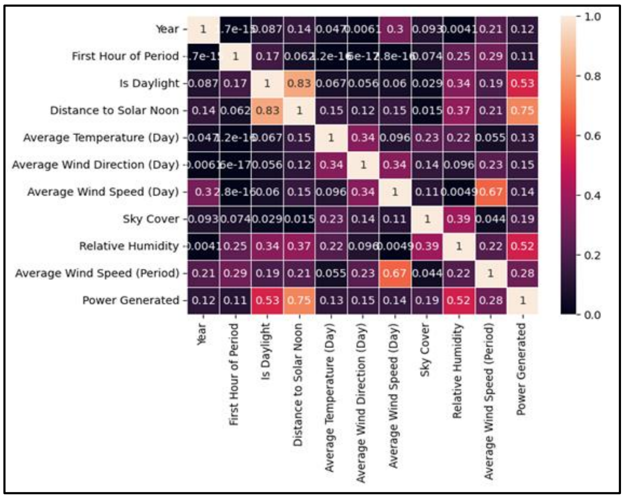

Fig. 11. Correlation heat map

Fig. 11 depicts a correlation heat map that shows large positive connection (0.75) between average temperature (Day) and power generated, as well as a substantial negative correlation (-0.52) with sky cover, indicating key environmental impacts on energy output.

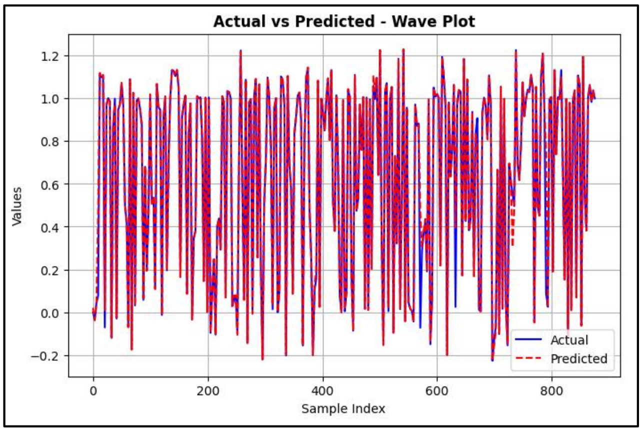

Fig. 12. Actual vs predicted

Fig. 12 shows a wave plot of actual vs predicted values, illustrating that the model closely tracks real data trends, with just slight differences across about 900 samples.

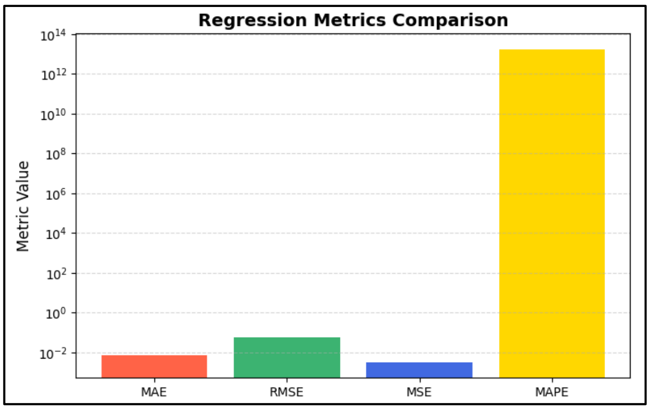

Fig. 13. Comparison of regression metrics

Fig. 13 compares regression measures and shows that the model is effectively for MAE (0.03), RMSE (0.09), and MSE (0.01). The MAPE (10^{14}) is excessive, showing difficulties in dividing by small or zero integers.

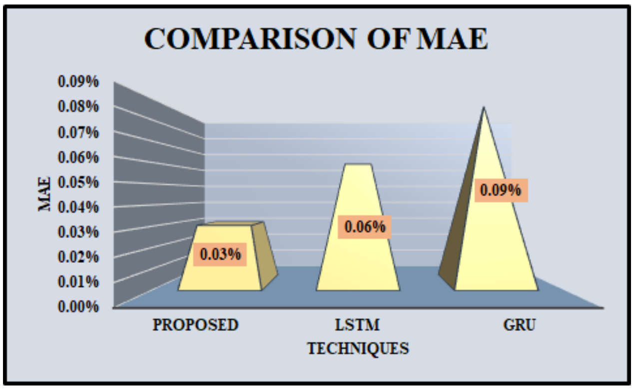

Fig. 14. Comparison of MAE

The Proposed model with the lowest MAE at 0.03%, outperforming both LSTM [13] (0.06%) and GRU [14] (0.09%), indicating better accuracy in predictions as shown in fig. 14.

TABLE I. COMPARISON OF RMSE

Techniques	RMSE
Proposed	0.09
LSTM [13]	0.093
GRU [14]	10.56

The Proposed model with the lowest RMSE at 0.09%, outperforming both LSTM [13] (0.093%) and GRU [14] (10.56%), indicating better accuracy in predictions as shown in Table I.

V. CONCLUSION

The proposed solar power forecasting system presents a highly effective solution for optimizing EV charging within smart energy networks. By combining historical and real-time solar data with advanced preprocessing techniques and a hybrid deep learning architecture featuring CNN, GRU, and an attention mechanism, the model accurately captures spatial-temporal dependencies in solar generation patterns. The integration of the ChOA further refines model performance through intelligent hyperparameter tuning. The proposed work implemented using python and achieving a low MAE of 0.03 and RMSE of 0.09, the system demonstrates strong predictive capabilities. This approach supports efficient energy planning, enhances the reliability of EV charging infrastructure, and promotes sustainable smart grid operations.

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