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Refining solar energy forecasting with optimization and feature engineering

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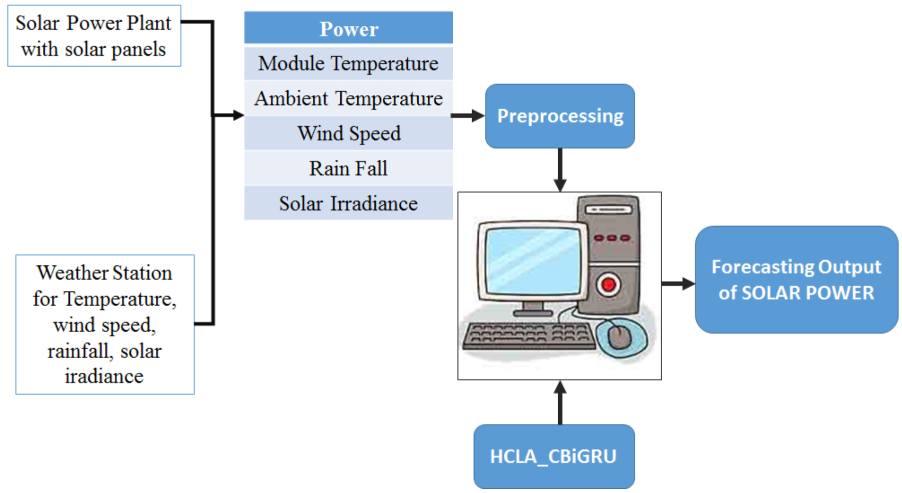
Article



ABSTRACT

This research article addresses the imperative need for precise solar power generation forecasting to efficiently integrate solar energy into existing power grids. It introduces a holistic approach, considering multiple parameters and employing advanced modeling techniques. Emphasizing the importance of reliable raw input data, including solar irradiance, temperature, humidity, wind speed, and power generated, the study applies preprocessing methods such as data cleaning, outlier removal, and normalization for data integrity. A unique method for handling missing entries and feature extraction using LTF-MICF modeling captures essential characteristics. The HOpt_CLA-CBiGRU network model combines hierarchical optimization, CLA, and CBiGRU techniques for forecasting, while Mod_MUD optimizes hyperparameters. The proposed architecture demonstrates practical implementation, significantly contributing to forecasting accuracy and facilitating solar energy integration. Experimental results showcase superior performance in RMSE and MAE compared to baseline methods, highlighting the model's efficacy in supporting reliable power supply through optimal resource utilization and grid integration. The proposed strategy offers a foundation for efficient, sustainable energy management, heralding a future rich in green energy.

Keywords: Feature extraction, Hyperparameter optimization, LSTM-based models, Multivariate time series,Solar power generation forecasting.

INTRODUCTION

Over the past decade, solar energy-based power generation has witnessed remarkable popularity, owing to its sustainable nature and classification as a renewable source of energy. As societies worldwide strive to transition towards cleaner and more environmentally friendly energy alternatives,[1] in renewable energy sector, solar power has emerged as a key player. Accurate forecasting of solar power generation is crucial to fully exploit the potential of solar energy and ensure its seamless integration into the existing power grid infrastructure.[2] Accurate forecasting of PV power generation plays a vital role, as it can greatly assist in scheduling electricity and managing power grids.[3]

Solar power plants are highly dependent on both the availability and intensity of solar irradiance. Solar irradiance, defined as the amount of solar energy per unit area, plays a crucial role in influencing electricity generation.[4] It offers a valuable guideline for selecting solar irradiance forecasting models according to the desired time horizon. Accurate solar irradiance prediction is crucial for assessing the potential power generation of solar power plants.[5] Environmental factors such as temperature, humidity, and wind speed also significantly affect the efficiency and performance of solar power plants.[6] Therefore, researchers and industry professionals have recognized the need to develop robust forecasting models that consider these diverse parameters.[7] At the distribution level, solar power consideration in terms of quality and quantity is having major challenges including factors of environmental dependency.[8]

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An improved forecasting of solar irradiance is of paramount importance due to its direct correlation with subsequent power generation. Precise predictions enable power plant operators to anticipate the amount of electricity that will be generated over specific time periods.[9] This knowledge facilitates effective grid integration, optimizing energy distribution, load management, and resource allocation. Moreover, the enhanced performance of the system facilitates the integration of solar power with other renewable and conventional energy sources, contributing to a reliable and stable power supply.[10]

In response to the increasing importance of solar power generation forecasting, researchers and scientists have invested considerable effort into developing advanced methodologies and models.[11] These efforts are focused on enhancing the accuracy, reliability, and efficiency of solar power generation predictions. Through data acquisition, preprocessing, feature extraction, and network modeling techniques, researchers have sought to uncover the underlying relationships and patterns that govern solar power generation.[12]

This research article offers a comprehensive approach to improving solar power generation forecasting by incorporating multiple parameters and utilizing advanced modeling techniques. It makes several significant contributions to the field of solar energy forecasting. Firstly, the significance of acquiring reliable and comprehensive raw input data from solar power plants is emphasized. This includes data on solar irradiance, temperature, humidity, wind speed, and power output, capturing key variables that impact the solar power generation process.Secondly, the preprocessing of raw input data is addressed, ensuring the generation of relevant outcomes for effective forecasting. This stage involves crucial steps such as data cleaning, outlier removal, and normalization, ensuring data integrity and reliability for subsequent analysis. Thirdly, a novel approach for handling missing entries within the collected data is proposed. Employing techniques such as interpolation or imputation effectively fills gaps in the dataset, enabling a more comprehensive and accurate analysis.

Additionally, the concept of feature extraction is employed to capture the crucial characteristics of the data. The study adopts the log term frequency based modified inverse class frequency (LTF-MICF) modeling approach, providing a robust method for extracting informative features that play a key role in improving the accuracy of solar power generation forecasting.

The research article presents the HOpt_CLA-CBiGRU network model, a novel integration of hierarchical optimization, Contrastive Learning Architecture (CLA), and Convolutional Bi-GRU (CBiGRU) techniques, to model the forecasting process. This advanced modeling approach is designed to capture complex relationships and patterns within the data, enhancing the accuracy of solar power generation forecasting.

The network model's performance is enhanced by optimizing hyperparameters through the use of the Mod_MUD approach.This optimization step refines the forecasting process and ensures the model's reliability and effectiveness in generating precise power generation forecasts.

By presenting a comprehensive workflow of the proposed architecture, the research article demonstrates the practical implementation of the approach and provides a valuable research resource for the solar power generation forecasting community.

This research article significantly contributes by integrating data acquisition, preprocessing, feature extraction, and network modeling techniques in forecasting task. The proposed method can improve the accuracy and reliability of solar power generation forecasts, promoting optimal resource use and supporting the efficient integration of solar energy into the existing power grid infrastructure.

RELATED WORK

Improving forecasting accuracy is vital for reducing the negative impact of random photo voltaic (PV) power fluctuations on the grid and providing reliable data for grid operators. Accurate forecasts are essential for optimal power distribution planning. As solar power generation grows globally, the demand for precise solar forecasting has increased. Ensemble forecasting, which averages predictions from multiple models, reduces bias and improves accuracy. It also mitigates the impact of outliers in weather data, minimizing errors. However, ensemble models require substantial computational resources due to the simultaneous simulation of several models.

Eseye et al. [13] applied regression model of support vector regression in forecasting work. The linearization in the input data was achieved with the use of particle swarm optimization and wavelet transform based preprocessing method. The actual recordings btained from the system equipped with Supervisory Control and Data Acquisition (SCADA) were used. Based on deviations in predictions, optimization algorithm was reiterated for optimal solution and error minimization.

Semero et al.[14] applied a genetic algorithm (GA) alongside Gaussian regression analysis to determine the critical factors impacting power generation. They also explored the use of adaptive neuro fuzzy inference system (ANFIS) for fuzzy nature consideration and prediction. The combination of K-mean clustering and GRA was used by Lin et al.[15] Additionally Elman methods were used for the prediction. To incorporate the environmental effects on power forecasting, meteorological data was also used. The data such as wind speed and rainfall were considered. Park et al.[16] employed a hierarchical clustering process to identify seasonal and defective data patterns within clusters. The combination of probability density function and spatio-temporal features of the records were considered by Agoua et al. [17]. The genetic algorithm (GA) based optimization was applied with SVM classifier by VanDeventer et al. [18]. The Markov Chain based multivariate method was applied for forecasting method in combination of solar and wind power generation work by Sanjari et al. [19]. The stochastic correlational operator was applied for time adaptive window mechanism and pattern matching analysis of the pre-recorded data for combined solar and wind power forecasting. The simultaneous inputs were given during the training phase. They observed that solar irradiance and temperature had little impact on wind power generation, while wind speed showed minimal impact on solar power generation.

The multivariate time series forecasting is essential in various domains,[20] but existing methods often overlook intrinsic connections between variables, impacting accuracy. To address this, authors proposed TDLSTM-LS, a deep long short term memory (LSTM) neural network model. It incorporates tensor processing. Additionally, the optimization algorithm was applied to achieve the attention mechanism. The deep LSTM with linking gates to preserve, enhance, and convey intrinsic connections. Experiments across five domains demonstrate that TDLSTM-LS outperforms state-of-the-art methods in evaluation metrics. Liu et al.[21]addressed challenges in accurate prediction and discussed that LSTM has excelled with time series data. However, it lacks the ability to pay sufficient attention to multivariate data. The combinational approach included MLP and LSTM model. Experimental results demonstrate the effectiveness of this framework in extracting multivariate features and outperforming baselines.

Thus, Ensemble forecasting reduces biases and improves accuracy. Various techniques such as SVM, GA, ANFIS, and LSTM have been employed for prediction, considering factors like weather data and multivariate analysis. The proposed TDLSTM-LS model outperforms existing methods.

METHODOLOGY

The geographic location of a solar power plant significantly influences its power generation capacity. A key factor in forecasting solar power generation is estimating production based on solar irradiance, which represents the solar energy received per unit area. This measurement is essential for determining the plant's potential output. By accurately assessing irradiance levels, operators can make informed decisions about energy production and distribution.

Beyond irradiance, researchers and industry professionals have acknowledged the significance of incorporating additional environmental factors in solar power generation forecasting. These factors, typically gathered from weather stations, include temperature, humidity, wind speed, and cloud cover. By integrating these parameters into forecasting models, a more thorough and accurate analysis of solar power generation can be achieved.

This research analyzes the influence of different parameters on solar power generation forecasting (Figure 1), highlighting the importance of irradiance and other environmental factors. The findings improve projection accuracy, supporting better decision-making for power plant operators, grid managers, and policymakers. This knowledge helps optimize resource use and facilitates the seamless integration of solar energy into the power grid.

- Acquisition of raw input data
- Data pre-processing
- missing entry filling
- Feature Extraction
- Model Training
- Power Forecasting

The initial step involves collecting input data, including solar irradiance, temperature, humidity, wind speed, and power output, from the solar power plant for the forecasting process. The pre-processing steps are carried out over the raw input data to generate the relevant outcomes beneficial for effective forecasting. After pre-processing, effective features are extracted using LTF-MICF modelling approach. After extracting the features, the effective forecasting through HOpt_CLA-CBiGRU network model. The overall performance in the network are optimized by tuning the hyper parameters using Mod_MUD approach. The proposed HOpt_CLA-CBiGRU network model helps to enhance the forecasting process and serves as an excellent research source. The work flow of proposed architecture is portrayed in Figure 1.

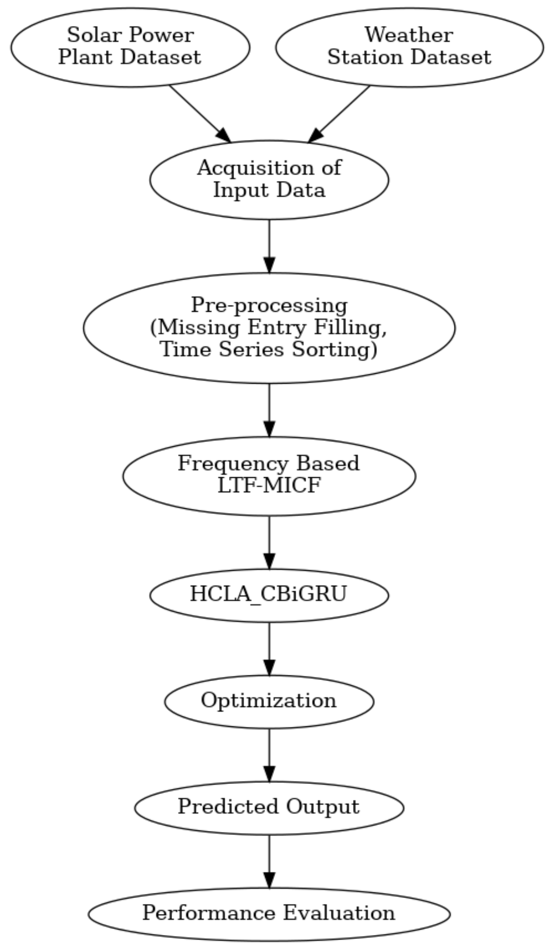

Figure 1: Overall schematic architecture of proposed model

3.1 PRE-PROCESSING OF RAW INPUT DATA

Data were collected over two years (2018-2019) from two main sources. The first dataset includes power generation records from an operational inverter, providing details on power output, module temperature, ambient temperature, and solar irradiance.The second dataset, obtained from Skymet Weather Services Pvt. Ltd., includes meteorological parameters such as maximum and minimum temperatures, humidity, wind speed, and rainfall, with data recorded every 15 minutes. Wind speed affects solar panel temperature, cloud movement, and dust accumulation, impacting solar efficiency. It also integrates with weather models for precise forecasting and aids in hybrid system optimization, improving overall solar power prediction accuracy.

Additional features were derived by calculating the yearly mean temperature, as well as the standard deviation of ambient and module temperatures on a daily basis. A total of six input features were used for each 15-minute interval during model training, with the target being power generation output. The mean temperature was computed as follows:

$$Tm = \frac{\sum_{i=1}^{N} T(i)}{N} \quad ...(1)$$

N represent the total number of temperature values in a year. The standard deviation of these values is calculated using thefollowing formula:

$$\sigma\ (i) = Tm - T(i),\quad i=1,2,...,N \quad ...(2)$$

3.2 Feature Extraction using LTF-MICF

According to Parveen et al. [22], the feature extraction method called LTF-MICF is the amalgamation of two weighting structures. The calculation of how often a term is obtainable within dataset contents is performed by the term frequency. By using the alone tends to add an enlarged weight on the document that is totally inappropriate. For producing effective power forecasting, the supervised methods are employed with increased attentions. Hence, the proposed research work intended to combine with MICF. The inverse class frequency refers to the inverse of the proportion of each class relative to the total number of classes. In contrast, the term related to training historic records pertains to data spanning all classes.

Initially, LTF is evaluated in this research work that measures of every term obtained from the pre-processed data. After that, log normalization is performed over the outcome of data which is indicated as LTF. Next MICF, an advanced version of is assessed for all terms. The disparate class specific scores of all terms possess varied significance and to enhance the performance, modification is performed. The particular scores of varied weights of varied classes are strictly assigned and for total term score, the particular scores of weighted sum across every class is employed. The mathematical formulation of LTF-MICF is indicated as,

$$LTF\_MICF(s_a) = LTF(s_a) * \sum_{x=1}^{n} w_{bx} . \left[{}^{u}C_b(s_a)\right] \quad ...(3)$$

From the above expression, w_{bx} indicates the specific weighting factor of term s_a for class C_b and can be stated as,

$$w_{bx} = \log\left(1 + \frac{q_u \vec{s}}{Max(1, q_u \vec{s})} . \frac{q_u \tilde{s}}{Max(1, q_u, \hat{s})}\right) \quad ...(4)$$

The weighting factor W_r is utilized for weight consideration over the given input data. The overall amount of data in class C_b is signified as q_u which includes the term s_a, an amount of q_u in additional classes that include the term s_a is indicated as $q_u \vec{s}$. The amount of s_a in class C_b that cannot combine the term s_a is represented as $q_u \hat{s}$. The amount of q_u that cannot include s_a in other classes is stated as $q_u\ \hat{s}$. To eradicate the negative weights, the fixed value of '1' is employed in the proposed LTF-MICF feature extractor approach. When $q_u \hat{s}$ or $q_u \vec{s}$ equals to zero, the lowermost denominator is fixed to '1'for lessening the zero-denominator problem in a serious case. A progressive term weighting strategy LTF-MICF (s_a) is produced over MICF (s_a). The expression for $LTF(s_a)$ and ${}^{u}C_b(s_a)$ can be indicated as,

$$LTF(s_a) = \log(1 + TF(s_a, q_u)) \quad ...(5)$$

From the above expression, $TF(s_a, q_u)$ denotes the raw number of a term s_a over the given data. The total number of term s_a obtainable over the input data can be mathematically expressed as,

$${}^{u}C_b(s_a) = \log\left(1 + \frac{x}{C(s_a)}\right) \quad ...(6)$$

From the above expression, x indicates the total classes in a delivered dataset and the amount of classes offering the term s_a is stated as $C(s_a)$. The semantic features extracted from the pre-processed dataset are represented as

$$F_u = \{F_1, F_2, F_3, ...F_n\}$$

3.3 HOpt_CLA-CBiGRU Model for Forecasting

After extracting the features, the proposed method has employed a new Hybrid Optimal Cross-Layer Attention based Convolutional Bidirectional Gated Recurrent Unit (HOpt_CLA-CBiGRU) model for forecasting the power. HOpt_CLA-CBiGRU model is the combination of bidirectional gated recurrent unit (BiGRU), cross-layer attention and output layer. The model utilized GRU for capturing the long-term dependencies rather that utilizing transformation in single shot, thereby it encodes the vector representation increasingly through recurrent process. For forecasting of power, the model do not directly use BiGRU output as final output instead a cross-layer attention has employed to improve the feature representation. Then, to retain the valuable significant information, row-max-pooling layer has employed. Figure 2 indicates the architecture of HOpt_CLA-CBiGRU model.

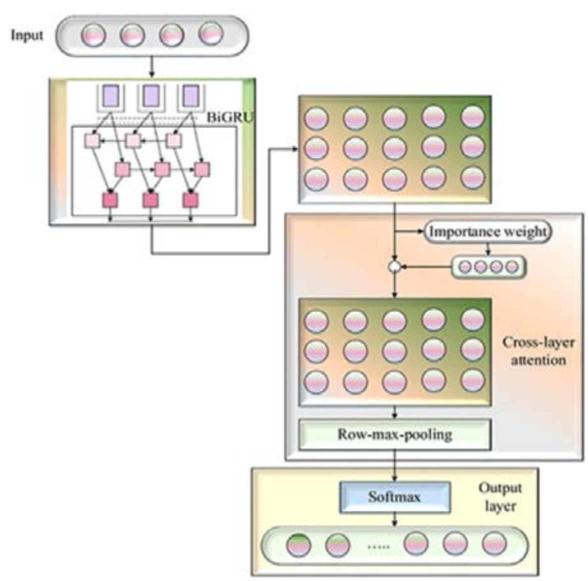

Figure 2: Structure of HOpt_CLA-CBiGRU model

BiGRU- In natural processing, LSTM has prominently applied neural network. While analyzing with classical RNN, LSTM has the capability to learn the long term dependency effectively between the words and resolves the issues of gradient disappearance. However, the operation of LSTM is very slow so to leverage this problem Bi-GRU, the gating model of LSTM has used and accelerated the speed of training while managing the performance. Generally, the GRU's are the gating approach encompassing of gates that modulate the present input and preceding hidden states. The GRU encompasses update gate and reset gate. The reset gate recognizes the amount of past memory requires to be forget. The update gate recognizes how much of the past memory needed to be transferred along into future. The entire evaluations of the reset gate, update gate, candidate hidden state and new hidden state are stated in the below expressions as follows.

$$M_v = \{Sigmoid * (w_m A_v + w_m H_{v-1} + B_t)\} \quad ...(7)$$

$$S_v = \{Sigmoid * (w_s A_v + w_s H_{v-1} + B_s)\} \quad ...(8)$$

$$H_v^{'} = \tanh * (wB_v + wS_v \otimes Hlv - 1) \quad ...(9)$$

$$H_v = \{M_v \otimes H_{v-1} + (1 - M_v) \otimes H_v^{'}\} \quad ...(10)$$

From the above expression, the reset gate, update gate, candidate hidden state and new hidden state are represented as M_v , S_v, $H_v^{'}$ and H_v. The weights, hidden state at preceding time step and bias term are represented as w, H_{v-1} and B. The sigmoid function enables the evaluation outcomes of two gated units within the range [0, 1] that regulates the memory and forget degree at the preceding moment. The hyperbolic activation function is denoted as $\tanh$ and hadamard product is denoted by the symbol $\otimes$. The data are memorized in GRU based on the above given equations whereas past information is correlated with the present information. The GRU accomplishes the degree over data memory, considers necessary information to avoid redundancy and avoids gradient explosion issues.

In Bi-GRU, the hidden state of every unit contains not only the old information, but it also consists of future information. This has been attained by considering two GRUs processing text in different directions, one from right to left to achieve the hidden state consisting of future information and the other from left to right to achieve the hidden state consisting of past information. Therefore, Bi-GRU has been utilized to quickly determine the feature weight of the input. Then, for the given matrix, the feature weight can be obtained as,

$$I = [i_1, i_2, ..., i_u, ...i_Z] \in S^{Z \times 2E_i} \quad …(11)$$

From the above expression, E_i resembles the hidden state of Bi-GRU and Z represents the length.

Cross-layer attention: Here, the weights have employed to determine the significant features that express the meaning of the sentences since different terms exhibits dissimilar meanings. Let the number of BiGRU be M. The input is considered as $Y = [y_1, y_2, y_3, ..., y_p]$, where $Y \in \Re^{p \times f}$. f Represents the dimension and p resembles the feature length. The hidden outcome of L^{th} BiGRU $I^L = [i_1^L, i_2^L, i_3^L, ..., i_p^L]$, where $I^L \in \Re^{p \times 2f^L}$, f^L represents the hidden dimension of L^{th} GRU. Here, row-max-pooling of hidden output $I^M = [i_1^M, i_2^M, i_3^M, ..., i_p^M]$ of M^{th} BiGRU is utilized, and it is expressed as follows:

$$r = i_t^M = Maxpooling_{Row}(I^M) \quad …(12)$$

From the above expression, $r \in \Re^{2f^M}$, f^M indicates the hidden dimension of M^{th} GRU. The query matrix is resembled as R, in which $R \in \Re^{p \times 2f^M}$.

Further, the attention weight is computed by employing additive approach and it is expressed as follows:

$$b = x^U \tanh(X^{(1)}R + X^{(2)}I^L) \quad …(13)$$

$$q(Z \mid I^L, R) = Soft\max(b) \quad …(14)$$

From the above expression, $q(Z \mid I^L, R)$ resembles the significance of j^{th} hidden outcome of L^{th} BiGRU and $\tanh$ indicates the activation function.

Conferring to the normalized attention weight $q(Z \mid I^L, R)$, the weighted average hidden output representation of L^{th} BiGRU has obtained as follows:

$$i_t^L = \sum_{j=1}^{p} q(Z = j \mid I^l, R) i_j^L \quad …(15)$$

From the above expression, $i_t^L \in \Re^{2f^L}$, f^L represents the hidden dimension of l^{th} GRU. To obtain the final representation i_t, i_t^M and i_t^L are concatenated and it is expressed as follows:

$$i_t = [i_t^M \oplus i_t^L] \quad …(16)$$

From the above expression, $i_t \in \Re^{p \times 2(f^L + f^M)}$. The value of L is based on the value of M. L resembles the subset of each set made by the components from $\{1, 2, 3, ..., M-1\}$. The value of M and L is specified by considering the semantic features in each layer, parameters, running time, and amount of dataset.

Output layer: For power forecasting, the data are output required is numeric data and not the class number. The output layer is thus linear activated. Here, the Linear activation is employed for predicting the power based on input data vector. Then, the outcome $\hat{z}$ can be computed as follows:

$$\hat{z} = SoftMax(Wh + b) \quad …(17)$$

Further, the cross-entropy loss has specified as follows.

$$K(\phi) = -\frac{1}{n}\sum_{j=1}^{n} u_j \log(\hat{z}) + \gamma\|\phi\|_G^2 \qquad \ldots(18)$$

From the above expression, $u_j \in U^n$ represents the one-hot representation of true label, γ specifies the L_2 regularization hyper parameter and $\hat{z}$ resemble the outcomes of cross entropy loss. Here, modified mud ring optimization (Mod_MUD) algorithm is employed as an optimizer.

3.3.1 HYPER PARAMETER TUNING

To enhance the overall performance of power forecasting system, Mod_MUD algorithm is employed for tuning the hyperparameters. The Mud ring algorithm pretends the foraging performance of bottlenose dolphins initiating from dolphin's swarm prey searching through echolocation. The behavior ends with the formation of mud ring for feeding. By hunting process initiation, the dolphin's swarm gets nearer to the prey which is indicated with S parameter. The parameter acts as the sound loudness which is minimized every time when the swarm converges to the prey and this regulates the prey searching transition. The transition between prey searching or exploration and mud ring or exploitation process. During the exploration phase, global searching is performed and during exploitation, optimal solution is discovered in mud ring algorithm.

Foraging behavior or Exploration phase

In order to evaluate the distance, the dolphins utilize echolocation during prey searching. The dolphins swim randomly while utilizing velocities *P* at *W* positions with *S* sound loudness for prey searching. Based on the prey closeness, every dolphins modify the sound loudness. The assumption is made that the loudness variations depends upon time step and pulse rate $R \rightarrow 0 to 1$ whereas 0 denotes no emission pulses and 1 represents high emission pulses. The *S* can be mathematically evaluated as,

$$\vec{S} = 2\vec{b}.\vec{R} - \vec{b} \qquad (19)$$

From the above expression, $\vec{R}$ denotes the random vector between 0 and 1.

$$\vec{b} = 2\left(1 - \frac{t}{T_{Max}}\right) \qquad \ldots(20)$$

The virtual dolphins are employed during exploration and in d-dimensional parameter space, dolphins explore a random position. Hence, $\vec{S}$ which is greater than 1 or less than -1 is utilized to determine the fittest prey. The randomly chosen dolphin is selected as the best dolphin whereas $|\vec{S}| \geq 1$ indicates exploration for the global search. In order to update the positions and velocities, the workability $\vec{W}^t$ dependent on $\vec{P}^t$ velocity at time step t is given as,

$$\vec{W}^t = \vec{W}^{t-1} + \vec{P}^t \qquad \ldots(21)$$

The random vector is given as P and the random velocity is assigned from $[P_{Min}, P_{Max}]$ which is chosen based on the problem of interest size.

Exploitation phase

After the prey exploration, dolphins locate and surrounds the prey. The mud ring algorithm considers target prey as the optimal location. The other dolphins update the positions based on the best position. The exploitation behavior can be expressed as follows.

$$\vec{M} = \left|\vec{V}\vec{W}^{*t-1} - \vec{W}^{t-1}\right| \qquad \ldots(22)$$

$$\vec{W}^t = \vec{W}^{*t-1}.Sin(2\pi l) - \vec{S}.\vec{M} \qquad \ldots(23)$$

From the above expressions, the coefficient vectors are denoted as $\vec{V}$ and $\vec{S}$. The dolphin's position vector is denoted as $\vec{W}$ and the best position is signified as $\vec{W}^*$. The best dolphin migrates in a circle with its tail movement in the mud producing a sine wave to make other dolphins follow. The $\vec{M}$ can be estimated as,

$$\vec{M} = 2.\vec{R} \qquad \ldots(24)$$

Through the random vector $\vec{R}$ determination, any position can be attained. The best dolphin position is chosen when $|\vec{S}| < 1$ and when $|\vec{S}| \geq 1$, random positions are chosen. To enhance the convergence and decrease time consumption, Mod_MUD is used. In Mod_MUD, opposition based learning (OBL) is used whereas it searches for an optimal solution in the direction opposite to present solution and delivers better results. Because of this, the solution gets closer to the optimal solution and the convergence rate gets faster. The chief focus of OBL is to evaluate the original and matching opposite solution concurrently. The best solutions are selected through this and the equivalent matching solution can be defined as,

$$L_i' = UPB + LOB - L_i, \quad L_i \in [UPB, LOB] \qquad \ldots(25)$$

From the above expression, L_i' denotes the updated best solution, the lower and upper bounds of search space are denoted as UPB and LOB respectively. The algorithm for Mod_MUD for tuning the hyper parameters is described in Table 1.

Table 1: Pseudo code for Mod_MUD algorithm

Input- Textural Features
Output- Optimal solutions for hyperparameter tuning
Start
Initialize the dolphin population randomly, and velocities
Evaluate the fitness function of every dolphin
Determine the best dolphin position
While (
For to
    Change and
If , then
    Produce new solutions by changing velocity using equation (21)
Else
    // Formation of Mud ring
    Update the present position of dolphin using equation (23)
End If
End For

Update the dolphin bounds outside the search space
Obtain the fitness functions of dolphins
Update in case of best position determination
Set
End While
\\ as the best position
Initialize opposition based learning in mud ring optimization
Modify the obtained position using equation (25)
\\ Optimal outcomes
Stop

The tuned model has hyper parameters with total number of neurons in second last dense layer as 128. the model requires 110 training epochs with 32 batch size.

RESULTS AND DISCUSSION

4.1 RMSE AND MAE ANALYSIS

The RMSE is estimated as,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - y'(i)\|^2}{N}} \quad \ldots(26)$$

The Mean Absolute Error (MAE) is estimated as,

$$MAE = \frac{\sum_{i=1}^{N} (y(i) - y\prime(i))}{N} \quad \ldots(27)$$

Where y′ represents the predicted value for the i^{th} sample, and y is the actual value across a total of NN samples. Figure 3 illustrates the analysis of power output prediction in relation to various parameters. Each parameter was individually and collectively input into the HOpt_CLA-CBiGRU model. The graph indicates that irradiance is the most influential parameter.

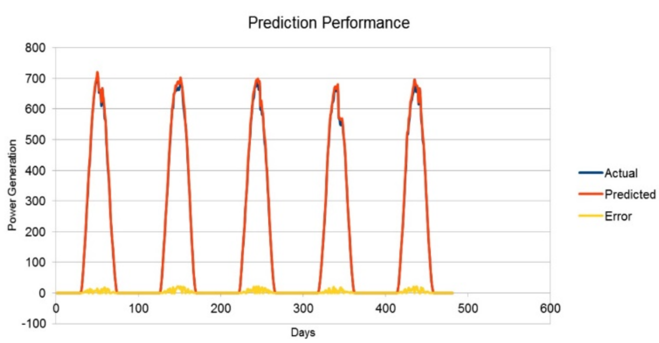

Figure 3: Individual parameter based analysis compared with actual Power Generation

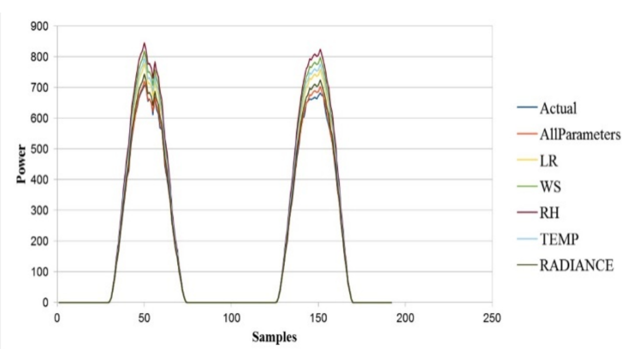

Figure 4: Prediction performance

A 5-fold K-fold cross-validation was used for training, showing improved RMSE in the 5th fold. The dataset of 35,040 yearly samples was split 80%-20% for training and validation in each fold. With random validation sets, the average RMSE decreased progressively, reaching its lowest in the 5th fold.

Table 3: Comparative Results

Method/Parameter	RMSE	MAE	MAPE
ANN6 [18]	0.32	0.042	4.2%
RNN [19]	0.231	0.036	3.6%
RNN-LSTM-AutoGRU[20]	0.129	0.0877	8.7%
CNN-LSTM[21]	0.4387	0.034	3.4%
HOpt_CLA-CBiGRU	0.062	0.019	1.9%

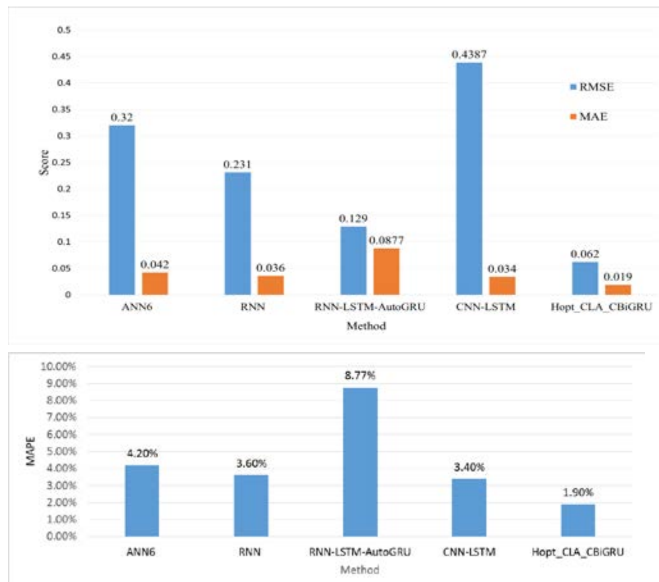

Figure 5: State-of-the-art methods compared with HOpt_CLA-CBiGRU performance

4.2 COMPARATIVE ANALYSIS

González Ordiano et al. [23]developed a PV output forecasting system using data-driven models without incorporating weather data. Their approach utilized an artificial neural network (ANN) with six neurons, showing a lower RMSE than other models in the study. We compare this with the HOpt_CLA-CBiGRU model to identify the more effective approach.

G. Li et al.[24] employed LSTM for PV output forecasting. Their comparative analysis, based on intra-day data inputs, identified LSTM as a more effective model. The authors evaluated performance using mean absolute percentage error (MAPE) at various time horizons. For our comparative analysis, we applied data with 15-minute intervals to the same LSTM model.

AlKandari et al.[25] developed an RNN model that combines LSTM and Auto-GRU layers. Their hybrid approach employs ensemble methods, including weighted averaging with both linear and nonlinear techniques, as well as simple averaging.

Lim et al.[26] developed a hybrid model that combines CNN and LSTM. The 1D CNN forecasts weather data, and the predicted vector is passed to the LSTM layer, which then predicts the power output. The mean absolute percentage error (MAPE) is provided in table 3.

Conclusion

The growing popularity of solar energy as a sustainable power source highlights the need for accurate forecasting of solar power generation. This research article has presented a comprehensive approach that considers various parameters and employs advanced modelling techniques to enhance solar power generation forecasting. The significance of acquiring reliable raw input data, including solar irradiance, temperature, humidity, wind speed, and power generated, has been emphasized. Pre-processing techniques like data cleaning, outlier removal, and normalization are crucial for maintaining data integrity and enabling accurate forecasting. Additionally, a novel approach for handling missing entries has been proposed, further improving the accuracy of the forecasting process.

The LTF-MICF approach was used for feature extraction to capture key data characteristics, improving the accuracy of solar power generation forecasts. The integration of hierarchical optimization, CLA, and CBiGRU techniques in the HOpt_CLA-CBiGRU network model has allowed for the modelling of complex relationships and patterns, resulting in improved forecasting performance.

The optimization of model performance through hyperparameter tuning using the Mod_MUD approach further enhances the reliability and effectiveness of the proposed architecture. The practical implementation of the proposed model offers a valuable tool for the solar power forecasting community, helping researchers and industry professionals make informed decisions. Importantly, the experimental results have demonstrated that the proposed model achieves superior performance in terms of RMSE and MAE when compared to baseline methods. This enhanced accuracy in forecasting supports effective grid integration, load management, and resource allocation, ensuring a reliable and stable power supply from solar energy.

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