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DS²-ALSTM: A Salp Swarm-Optimized Attention-Gated Deep LSTM Framework for Accurate Photovoltaic Power Forecasting

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ABSTRACT: The nature of Photovoltaic (PV) power generation has a major impact on existing power systems, even though solar power has rapidly grown in importance as an energy source in many nations in recent years. For this an accurate solar power forecasting techniques are necessary to lower this uncertainty and preserve system security. This paper proposes, a novel forecasting strategy that combines Attention-Gated Deep Long Short Term Memory (AG-DLSTM) and Salp Swarm Algorithm (SSA). The system involves, utilizing data pre-processing involves data cleaning method for findings the missing data and shows the duplicate values. Also, data transformation utilized for transformer raw data's into statistical format. By data exploration univariate and bivariate analysis for PV power forecasting. The univariate analysis have single variable to analyse and bivariate analysis have two data's to analyse. Also, feature scaling using mini-max scalar, and captured the maximum and minimum feature data. Finally, the proposed Deep Salp Swarm Algorithm based Attention Long Short Term Memory (DS^2-ALSTM) for accurately predicting PV power .Implementing Python software, the proposed AG-DLSTM based SSA accommodate the actual generation pattern better than existing methods and produce the Mean Absolute Error (MAE), Mean Square Error (MSR) and Root Mean Square Error (RMSE) value of 0.53, 0.28 and 0.43 respectively.

Keywords: Deep Salp Swarm Algorithm based Attention Long Short Term Memory, Salp Swarm Algorithm, Data cleaning, Data transformation, Univariate Analysis, Bivariate, Feature Scaling.

1. Introduction

Forecasting of PV power is necessary due to the increased use of renewable energy to conflict in climate change and supply green energy. PV energy generation is crucial in achieving many climate protection objectives [1]. One of the most abundant and cleanest renewable energy sources is solar energy, which is also fully free and readily available [2]. Consequently, Large-scale solar PV plants are being employed extensively in several nations worldwide to lower carbon emissions and environmental pollution brought on by fossil fuels [3]. However, as solar energy diffusion rates rises, the unpredictability of solar energy resources have made managing the electric power grid more challenging. In the meantime, the stable process of the overall power system is significantly impacted by the huge number of PV power plants' exposure to uncertainty and intermittency [4]. PV power forecasting power systems to address the issue of planning and modelling for solar PV power plant optimization [5]. According to the research, precise PV power forecasting is essential for enhancing power system stability, as well as for guaranteeing appropriate unit commitment and cost-effective dispatch [6]. Moreover, PV power forecasting is crucial because it have a load-generation mismatch in the grid [7-8].

For PV power forecasting, some of the following existing classifier techniques are utilized. Extreme Gradient Boost Regression (xGBoost) to improve the performance of the PV system. It have high accuracy, scalability, and efficiency. Nevertheless, it includes complexity, over fitting risk, and the requirement for particular parameter adjustment [9]. Consequently, to increase the reliability for PV power system K-Nearest Neighbor (KNN) with Support Vector Machine (SVM) is utilized. KNN with SVM is straightforward, flexible, and easy to use, interpretable, and adept at handling high dimensionality. Nonetheless, it is computationally costly and necessitates the establishment of a decision boundary, slow for large datasets [10]. Whereas, Convolutional Neural Network (CNN) is used to forecast the low-frequency and high-frequency components for the PV data. CNN is effective computing, and automatic feature extraction for PV power forecasting. However, significant processing costs, the necessity for large datasets, and limited interpretability [11].

Linear Least Absolute Shrinkage and Selection Operator (LASSO) model is used to improve the accuracy of the technique and reduce model complexity for PV data. Automated feature selection and high-dimensional dataset handling using linear LASSO model. However, the likelihood of biased findings increases if the regularization parameter is not properly adjusted and possible instability when working with correlated data [12]. Consequently, Back Propagation Neural Network (BPNN) for forecasting the PV power with better performance. BPNN increases prediction accuracy, automatic learning, scalability to intricate systems, and effective weight changes. Nevertheless, computational cost and the possibility of becoming trapped in local optima [13]. Whereas, Convolutional layers (Conv-GRU) are used in the construction of the Gated Recurrent Unit (GRU) to facilitate the effective extraction of positional and temporal properties from PV power sequences. Conv-GRU have extraction of spatial-temporal features, efficiency of computation, decreased over fitting, ideal for a variety of tasks. Nonetheless, it provides, interpretability, parameter sensitivity, and complex architecture [14]. Moreover, improved Bidirectional Long Short-Term Memory with Genetic Algorithm (GA-BiLSTM) is used as prediction model to enhance performance. GA-BiLSTM have enhanced flexibility and prediction accuracy, especially in time series analysis. However, GA-BiLSTM have greater complexity and high processing costs [15]. To overcome this problem, a proposed DS^2-ALSTM is utilized for the PV power forecasting. The attention LSTM is optimized with deep SSA to get good performance for forecasting the power system.

2. Related Work

Gu *et al* [16] (2021) have proposed a Whale Optimization Algorithm (WOA) and Least Squares Support Vector Machine (LSSVM) for Photovoltaic Power Forecasting (PPF). To increase the LSSVM model's calculation speed and forecasting accuracy, the penalty factor and kernel function width are optimized using the WOA's with high convergence accuracy and quick convergence speed. A PV power station's historical data and clustered numerical weather prediction used to train the WOA-LSSVM forecasting model. Nonetheless, have poor accuracy, slow convergence, and the tendency to become trapped in local optima.

Lateko *et al* [17] (2022) have proposed a Bayesian optimization with Random Forest (RF) classifier for PV power forecasting. Due to their ability to uncover subtle patterns from data, conventional models are effective in capturing the complex dynamics of PV power production. Effective hyper parameter adjustment and enhanced model performance through the use of existing information. Nonetheless, such higher processing costs, particularly for complicated models.

Sahu *et al* [18] (2021) have presented a Teaching Learning Based Optimization (TLBO) to enhance the exploration and exploitation for PPF. TLBO is a popular option for a variety of optimization problems due to its simplicity, ease of implementation, and quick convergence. However, the possibility of becoming trapped in local optima and its limited capacity for multimodal problem for PV system.

Peng *et al* [19] (2023) have proposed a Variational Mode Decomposition (VMD) with Enhanced Chaos Game Optimization (ECGO) algorithm to predict the PV power. VMD-ECGO algorithm is used to improve the accuracy of the model for prediction. In order to enhance the original Chaos Game Optimization (CGO) for PPF it improves optimization skills, ECGO makes use of chaotic maps and a unique exploration approach. Nevertheless, includes computational cost, quick convergence and local optima.

Tahir *et al* [20] (2024) have proposed a Bi-directional Long Short Term memory (Bi-LSTM) with Bayesian optimization to forecast PV power generation. Bi-LSTM with Bayesian optimization is unpredictable and volatile nature of PV generation power. However, difficulty of creating the best renewable energy system possible while balancing cost and efficiency, make it difficult to predict with any degree of accuracy.

The contribution of this work is follows

- Data cleaning based data pre-processing technique is used to the PV power forecasting for identifying and correcting the errors.
- Data transformation, the raw PV data is converted into statistical data format for analysis.
- Data exploration by univariate analyse a single variable and bivariate analyse two data's, for further engineering.
- Feature engineering using feature scaling to calculate the mini-max scalar values for further analysis.
- The proposed attention LSTM is optimized with deep SSA to improve the model prediction for PV power forecasting.

3. Proposed Work

The block diagram in proposed shown in Figure 1 for PV power forecasting by Neural Network and optimization technique with solar power generation datasets. Initially data pre-processing stages contains data cleaning to identify and correct the errors, and data transform used to transform raw data in to statistical format. Then, the Data exploration done by univariate and bivariate analyse, the univariate analysis have single variable to analysis and bivariate analysis have two variables to analysis.

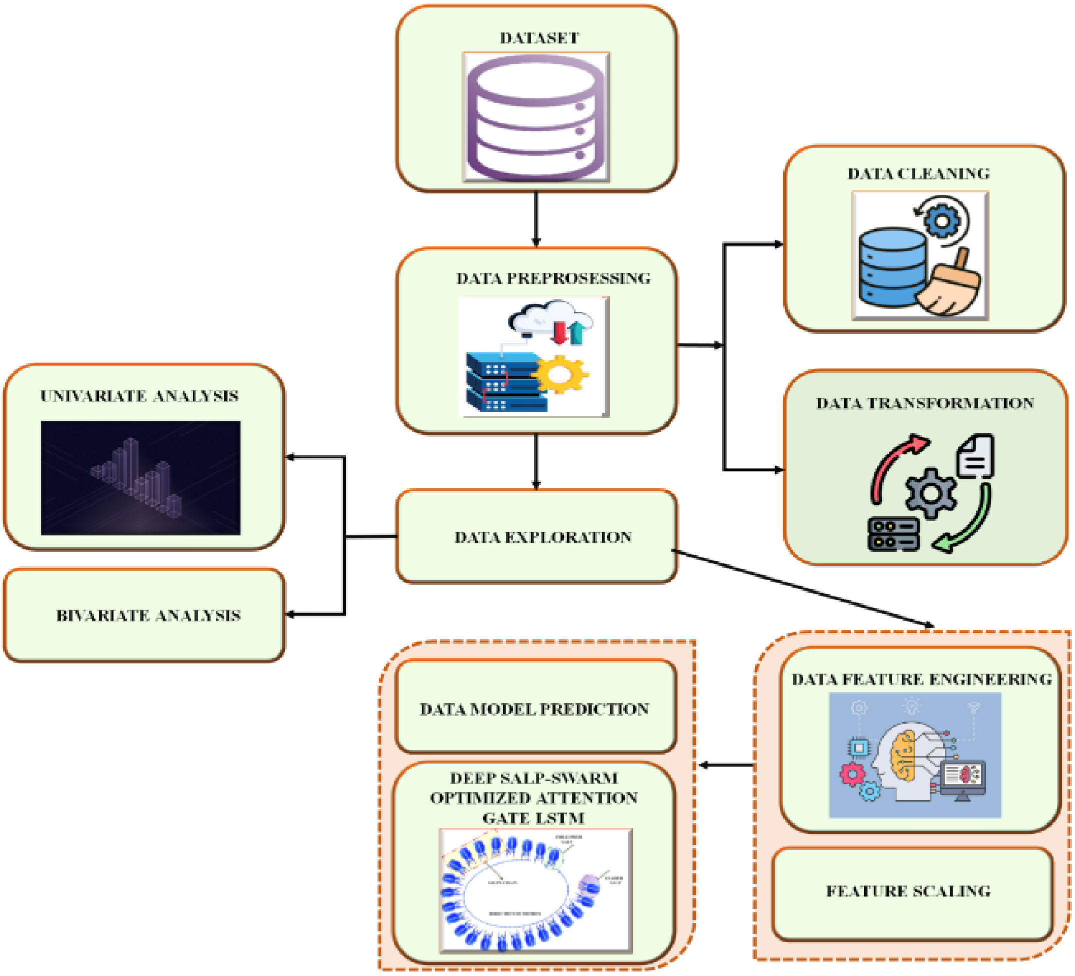

Figure 1: *Block Diagram of proposed work*

Next by feature engineering the PV power data is captured by the mini-max- scalar using feature scaling technique. Finally featured value is given as input to the model prediction technique as DS^2-ALSTM. The DS^2-ALSTM to find the collective behaviour of particles in a swarm for PV power forecasting.

3.1 Data Pre-Processing for PV Power Forecasting

In data pre-processing for PV power forecasting, it have two methods such as data cleaning and data transformation.

3.1.1 Data cleaning

Data cleaning in PV power forecasting is the process of identifying, correcting errors, variations, and inaccuracies in solar power generation datasets. It involves identifying and resolving problems like as inaccurate values, duplication, insufficient data, or incorrect formats in order to secure data quality and dependability for analysis.

3.1.2 Data transformation

In PV power forecasting the process of changing data formats is referred to as data transformation. The process of data transformation in PV power forecasting is converting raw data in to statistical form. There are two categories in data transformation they are syntactic and semantic data transformation. Syntactic transformations process is to change a table's syntactic format, frequently without the reference data. Semantic transformation allows data sources to convert into a common data model by mapping rules. Following to data pre-processing the data's are set to data exploration for PV power forecasting.

3.2 Data Exploration

In data exploration for PV power forecasting, calculated a univariate and bivariate analysis.

3.2.1 Univariate Analysis

In PV power forecasting the purpose of univariate analysis is to calculate single variable from the solar power generation dataset. A single variable in dataset discusses the variable quantity and the number. Univariate analysis's process is to characterize the data in order to identify the pattern. The mean, mode, median, standard deviation, dispersion, etc. are all observed in the univariate analysis.

3.2.2 Bivariate Analysis

Bivariate analysis in PV power forecasting is to analyse two variables from the solar power generation dataset. The purpose of bivariate analyse is to determine the link between two set of value and potentially predict one from the others. The rank correlation coefficient is calculated if both the independent and dependent variables as ordinal, meaning they have a ranking or position. Following univariate and bivariate analysis the data's are set to feature engineering for PV power forecasting.

3.3 Feature Engineering

Feature Engineering is done by using a feature scaling method for PV power forecasting.

3.3.1 Feature Scaling by Min-max Scalar

The min-max scalars have two stages of normalization techniques; the preliminary step in the normalizing process is to minimize the excessive variation in the same feature's data values. In this stage, the logarithmic function is applied to the various feature values when there is a significant discrepancy between the feature's maximum and minimum values.

$$\text{If } (X_{Max} - X_{Min} > threshold$$

Then

$$X_{normalize} = \log(x) \tag{1}$$

Where,

X represents the value of feature trying to normalize

The Min/Max Scalar approach, which involves determining the maximum and minimum of every data feature and then relating the subsequent function, is used in the second normalization step,

$$X_{normalize} = x - X_{Min}/X_{Max} - X_{Min} \tag{2}$$

Where x is the value of the feature we are attempting to normalize, X_{Min} is the smallest value the feature x observed, and $X_{Max}$is the highest value the feature observed. To get a better update of weights during the learning phase, the goal of this phase is to acquire all values between 0 and 1. Followed by feature engineering, the featured output is given as input to model selection as proposed DS^2-ALSTM.

3.4 Model selection for PV power forecasting

In the proposed work DS²-ALSTM is to enhance the model prediction for PV power forecasting.

3.4.1 Attention LSTM

For PV power forecasting long-term dependency issues are resolved with attention LSTM neural networks. LSTM contains a unique neuron structure termed a memory cell that stores information over an arbitrary time, as different to networks that make advantage of the input data's temporal information. A attention LSTM architecture contains a memory cell connected by subsequent gates. The forget gate determines which data is securely deleted from the memory cell. After deciding which values from the input to update the memory state, the input gate then uses the input and memory cell to construct the output for the current time-step. Figure 2 shows the basic LSTM model.

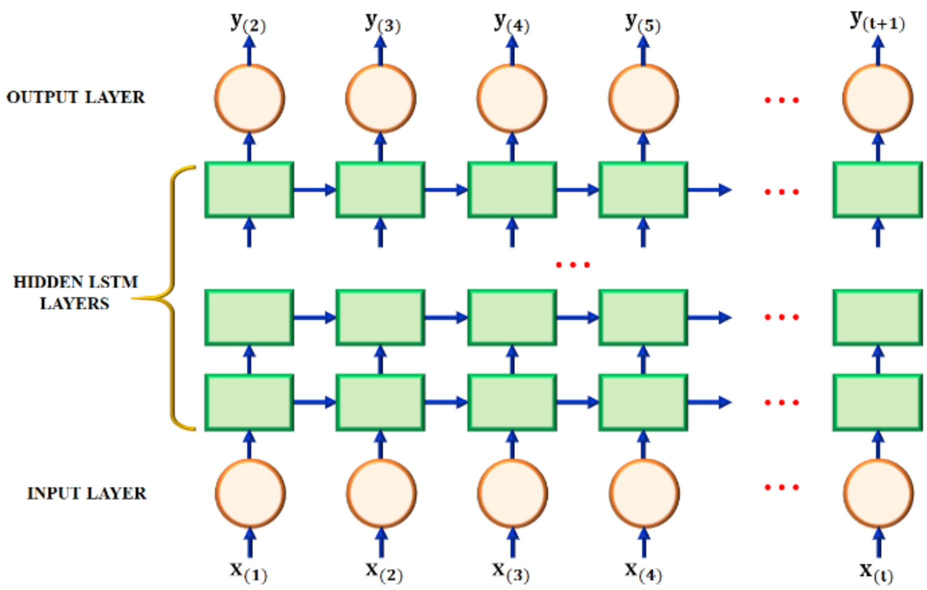

Figure 2: *Basic LSTM model*

With multiple stacked hidden layers, the attention LSTM model is an extension of the LSTM that offers the benefit of allowing the model to learn near the raw temporal input at every time period. Furthermore, because the parameters of attention LSTM models are dispersed throughout space, they accelerate convergence and enhance the non-linear processes of raw data.

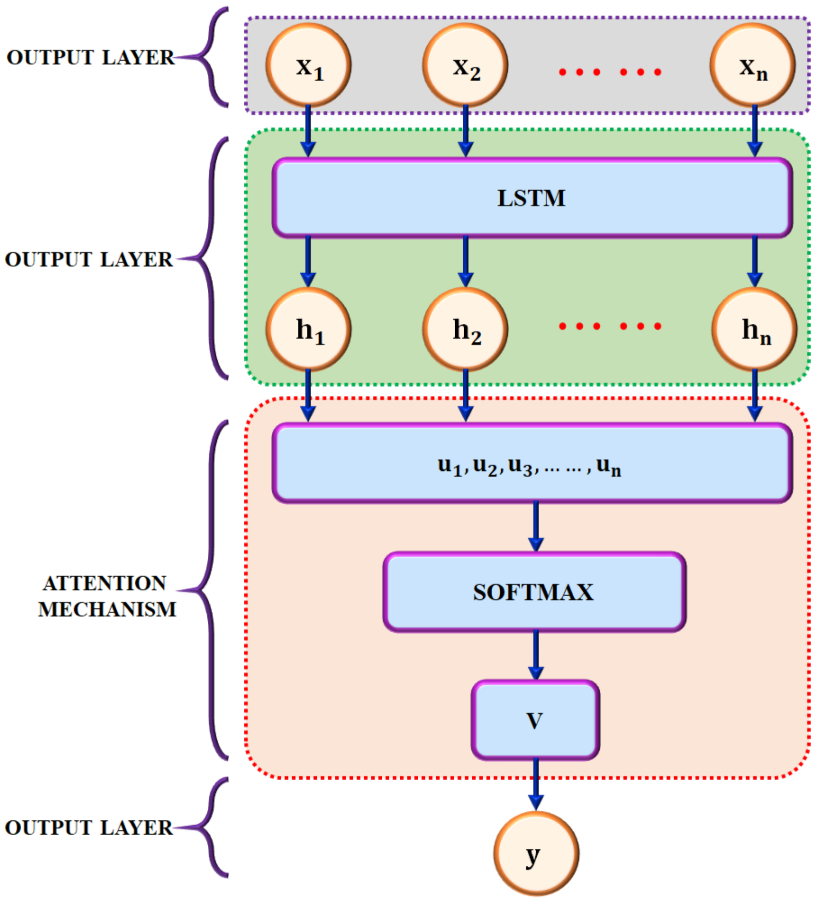

Figure 3: *Attention LSTM*

An attention LSTM with several hidden layers, each of which have a number of memory cells, shown in figure 3. This stacking of numerous LSTM layers for a deep LSTM-based neural network is important because hierarchically feature learning uses multiple non-linear mapping layers between inputs and outputs. Before the last layer produces the output, each layer processes a portion of the work to enhance by using SSA. To improve the PV power forecasting system performance Deep salp swarm optimization is utilized.

3.4.2 Deep Salp Swarm optimization

For PV power forecasting the behaviour of salps in a chain formation with reference to their hunting strategies is used to construct the DSSA. By helping the DSSA escape from local optima and avoid the issue of stagnation, these chains have a major impact on the SSA's ability to balance the exploration and exploitation impulses. Leaders and followers are the two sorts of salps that are used to form the population in DSSA. Other salps are categorized as followers, while the agent in the lead is categorized as the leader. The leader salp is responsible for directing and guiding the population's next course of action, while the follower salps observe their peers in Figure 4.

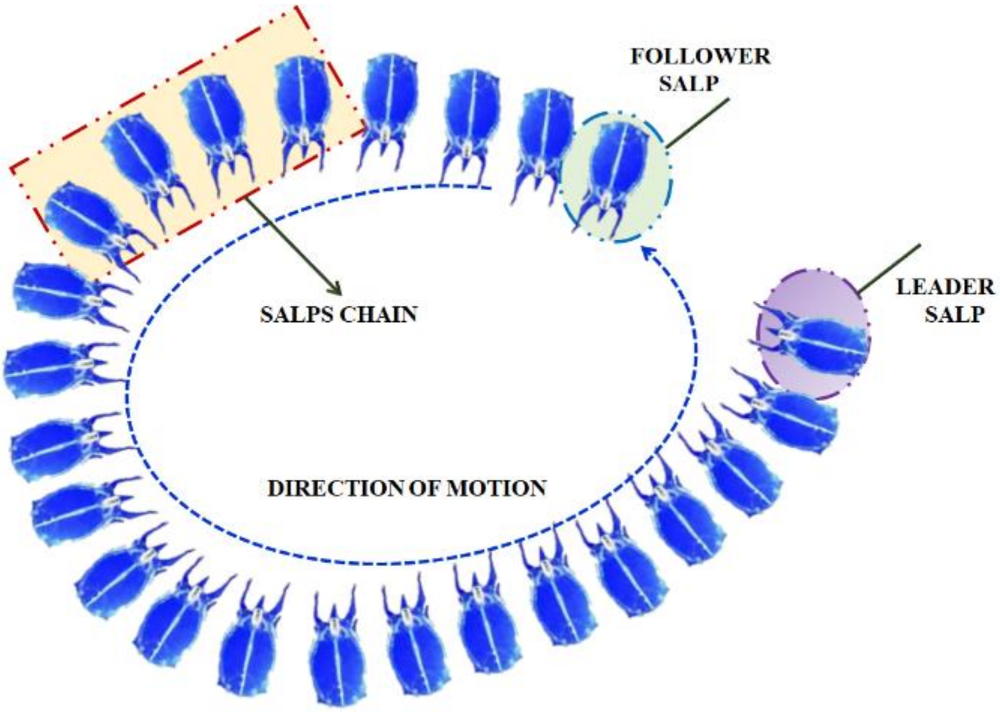

Figure 4: *Architecture of SSA*

Where n is the total number of variables, the positions of the salps during the exploration and exploitation stages are defined as an n-dimensional space, as seen in Figure 5. A DSSA population is recorded in a $(N \times d)$ dimensional matrix for a set of salps X, which consists of N salps with d dimensions. Following that, leader and followers are the two divisions of the salp population. The salp at the head of the chain is the leader and the other salps are followers.

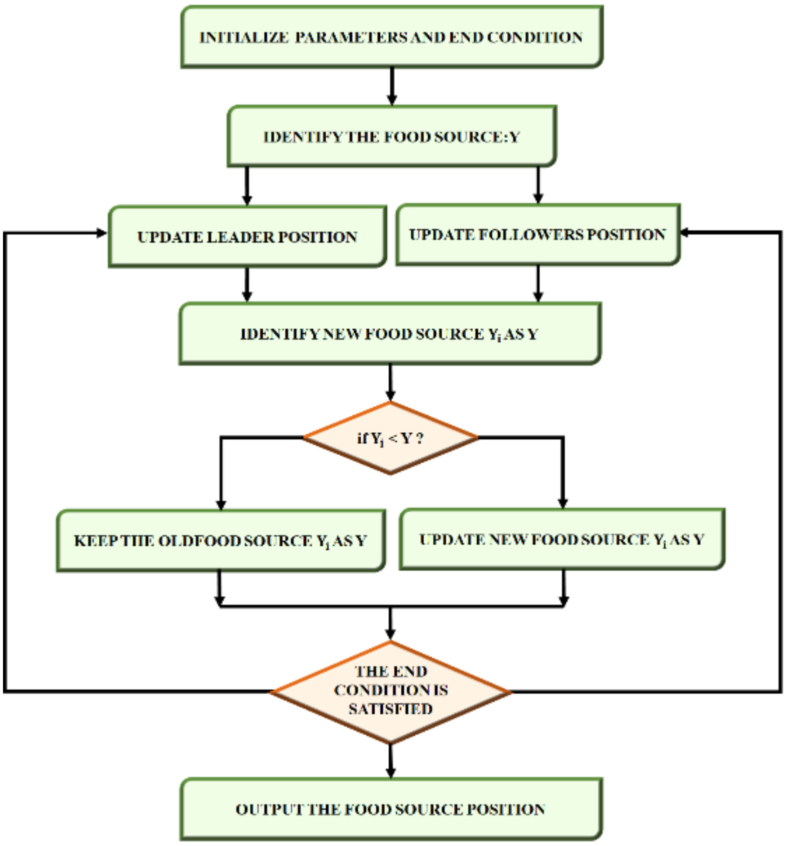

Figure 5: *Algorithm for SS Optimization*

The leader and follower salps' positions are updated to calculate the salp chains. The food source has an impact on the leader salp position is updated. Within the upper and lower boundaries of ub_j and lb_j,, respectively, the food source location F_j, is used to update the leader position x_j^1 in the jth dimension of the search space. Equation (3) additionally updates the leader position based on the coefficients c_1, c_2 and c_3.

$$x_j^1 = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right), c_3 \geq 0 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right), c_3 < 0 \end{cases} \quad (3)$$

Where the uniform random values between [0, 1] are the coefficients c_2 and c_3. This coefficient, specifically for c_1, stands for the balance aspect of exploration and exploitation, which is described as follows:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \quad (4)$$

Where L is the maximum number of iterations and l is the current iteration. The addition of indicates c_1, c_2 and c_3.that the step size and the subsequent position in the jth dimension should both go in the direction of positive or negative infinity. The following model therefore be used to represent the process of updating the positions of the follower salps:

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right) \quad (5)$$

The location of the ith follower salp in the jth measurement is denoted by x_j^i. DSSA is employed in this work to determine the ideal parameters for the benchmark algorithms and suggested approach with good performances. The model performance metrics MSE, RMSE and MAE is calculated, where the MSE value is 0.28, RMSE value is 0.53 and MAE is 0.4 for PV power forecasting by proposed DS²-ALSTM method.

4. Result and discussion

In the result and discussion the PV power forecasting is predicted using the proposed DS²-ALSTM. For identifying and forecasting power the solar power generation dataset is taken from the kaggle.com, which is implemented using Python software.

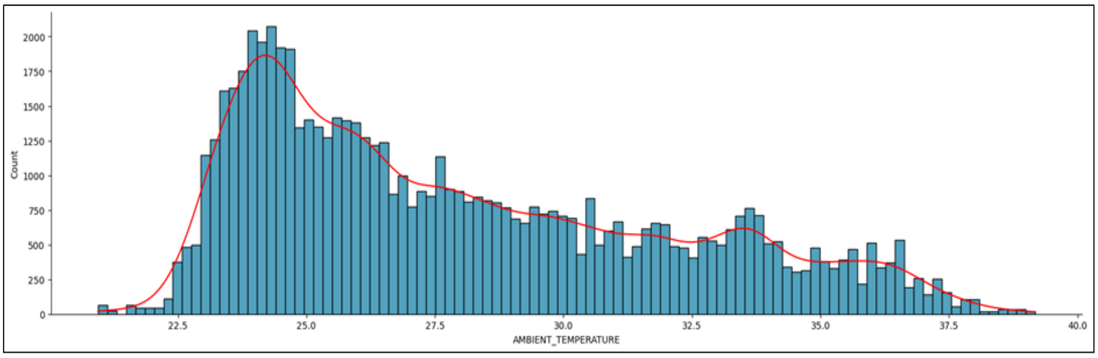

Figure 6: *ambient temperature vs count*

The ambient temperature vs count for PV power forecasting is shown in figure 6. The X-axis indicates the ambient temperature and Y-axis indicates the count. Y-axis varies up to 2000 counts it is going on increasing and decreasing, the ambient temperature is up to 39 it is going on increasing and decreasing. Ambient temperature is peak in the count 2000 in between 22.5 to 25 and then going on decreasing.

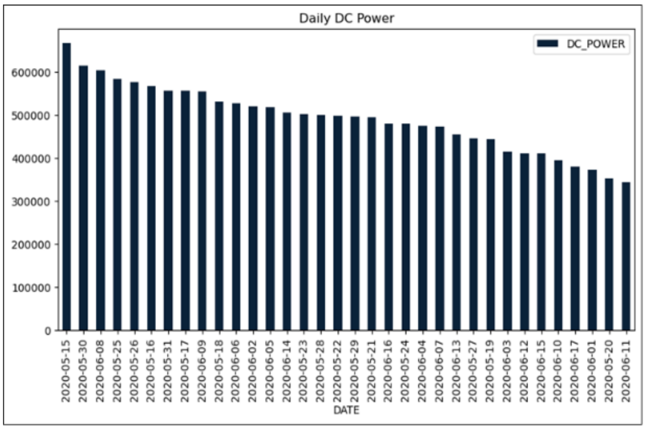

Figure 7: *Daily DC power*

Figure 7 shows the daily DC power for PV power forecasting. The X-axis indicates the date and Y-axis indicates the power. The DC power is calculated for May 2020 to June 2020 it is high in 15th May 2020 and low in 11th June 2020. The power is low up to 400000 and high up to 700000.

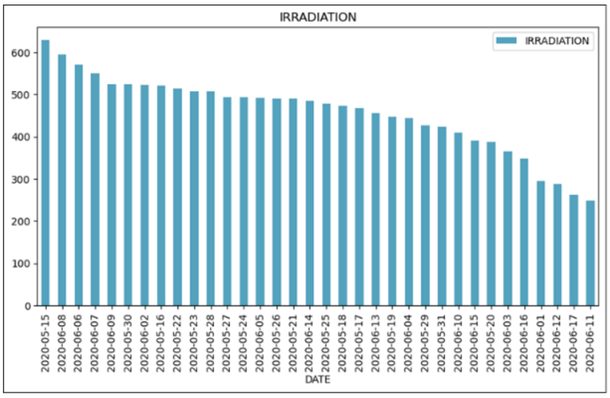

Figure 8: *Irradiation for PV power forecasting*

Figure 8 shows the irradiation for PV power forecasting. The X-axis indicates the date and Y-axis indicates the irradiance. The irradiation is calculated for May 2020 to June 2020 it is high in 15th May 2020 and low in 11th June 2020. The irradiation is low up to 250 and high up to 650.

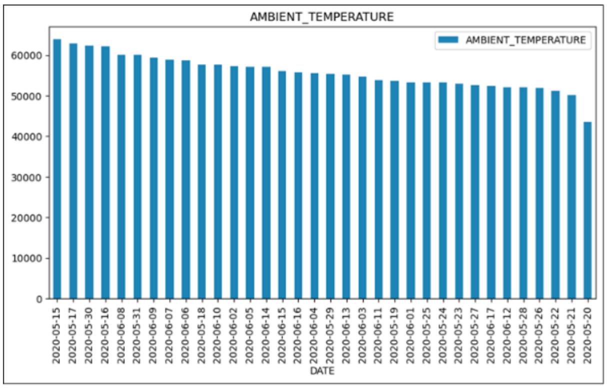

Figure 9: *Ambient temperature for PV power forecasting*

Figure 9 shows the ambient temperature for power forecasting. The X-axis indicates the ambient temperature and Y-axis indicates the count. The ambient temperature is calculated for May 2020 to June 2020 it is high in 15th May 2020 and low in 20th May 2020. The ambient temperature is low up to 48000 and high up to 63000.

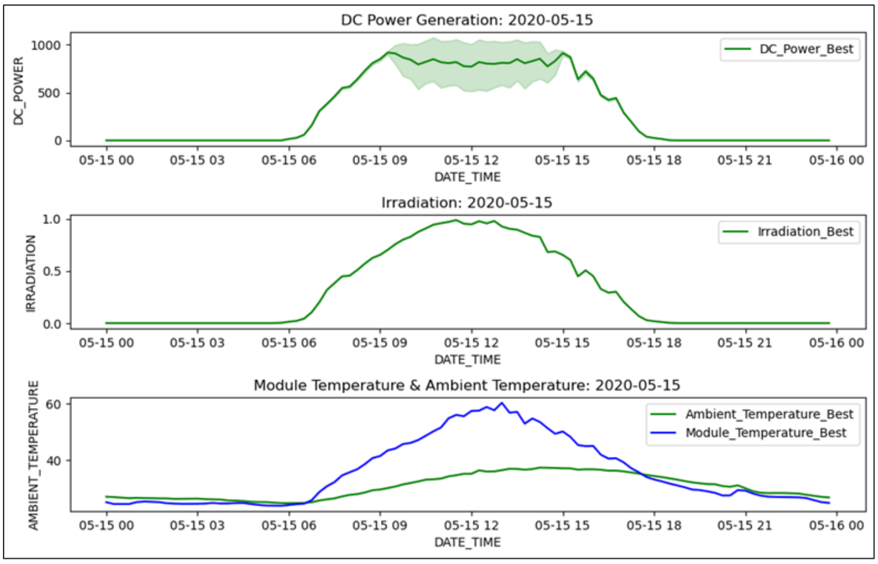

Figure 10: *DC power generation, irradiation and module temperature & ambient temperature for 15th May 2020*

Figure 10 shows the DC power generation, irradiation and module temperature & ambient temperature for 15th May 2020. DC power generation is best on 800 watts which produces high power. Irradiation is best on which is peak at 0.9 and decreased for PV power forecasting. The ambient temperature is best when it is increased to 40 and then decreased, the module temperature is best when it is increased to 60 for the PV power forecasting.

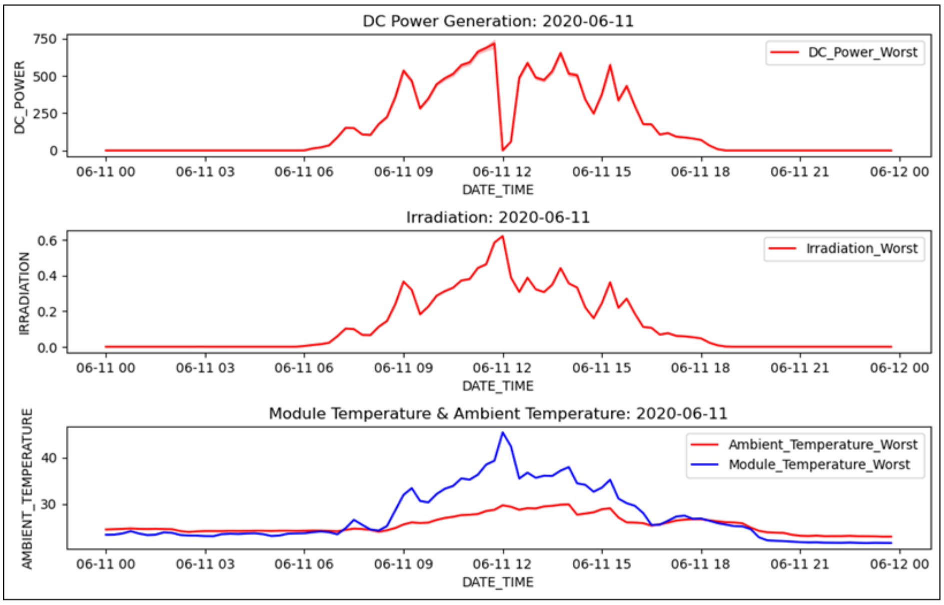

Figure 11: *DC power generation, irradiation and module temperature & ambient temperature for 11th June 2020*

Figure 11 shows the DC power generation, irradiation and module temperature & ambient temperature for 11th June 2020. DC power generation is worst on 11th June 2020 in PV power forecasting. The power is suddenly decreased to 1 and there is a vibration in the power. The irradiance is worst because there is a vibration or distortion in the PV power forecasting. Whereas, the ambient temperature is worst since there is a distortion in the forecasting, the module temperature is work because the temperature is going on increasing and decreasing and there is a distortion in the PV power forecasting.

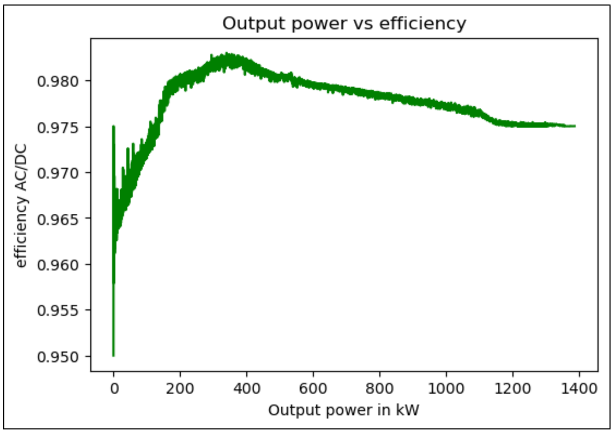

Figure 12: *Output power vs efficiency for PV power forecasting*

Figure 12 shows the output power vs efficiency for PV power forecasting. The X-axis indicates the output power in kW and Y-axis indicates the efficiency DC/AC. The output power is peak in 400 kW at the efficiency is 0.99. Then the output power is decreased up to 1300 kW in the efficiency of 0.97.

4.1 Performance Criteria

The model performance is measured using a statistical evaluation for PV power forecasting, including coefficient of determination (R^2), RMSE, MAE, and MSE. The PV power forecasting criterion formulas are shown below.

$$MSE = \frac{\sum_{i=1}^{m}[x_i - \widehat{x_i}]}{m} \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}[x_i - \widehat{x_i}]2}{m}} \tag{7}$$

$$R^2 = [\frac{1}{M}\frac{\sum_{j=1}^{M}[(Y_j - \bar{Y})(X_j - \bar{X})]}{\sigma_y \sigma_x}]^2 \tag{8}$$

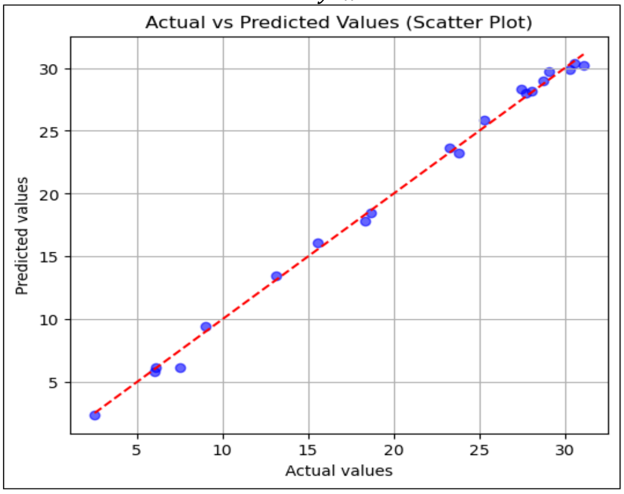

Figure 13: *Actual vs predicted value (scatter plot)*

Figure 13 shows the predicted value vs actual value for PV power forecasting. Actual as well as predicted value is calculated to find the perfect predicted line using the solar power generation data.

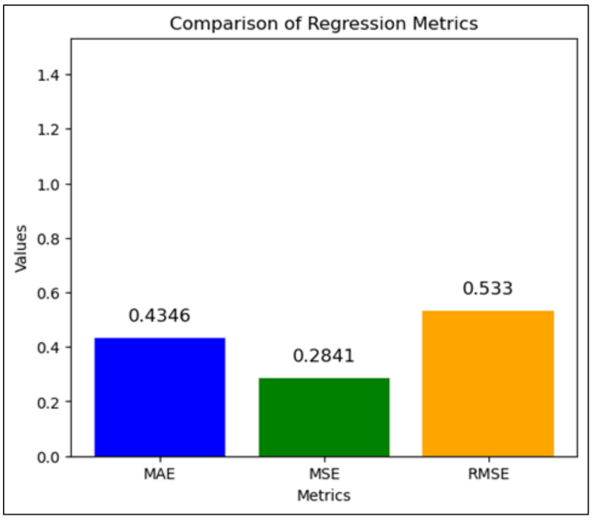

Figure 14: *Comparison for regression metrics*

Figure 14 shows the comparison for regression metrics. The model performance metrics comparison the MSE, RMSE and MAE is calculated, where the MSE value is 0.28, RMSE value is 0.53 and MAE is 0.4 for PV power forecasting.

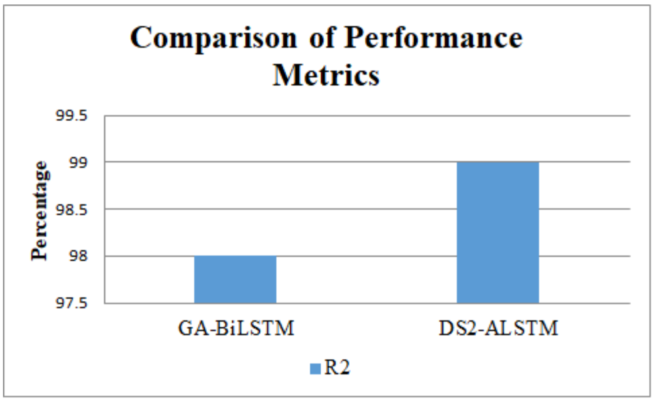

Figure 15: *Comparison of performance metrics for R2*

Figure 15 shows the comparison of performance metrics for R2. The proposed DS^2-ALSTM have the higher value of 99% and the GA-BiLSTM [15] have the value of 98%. GA-BiLSTM R2 value is low compared to the propose DS^2-DLSTM method.

5. Conclusion

In this paper, DS^2-DLSTM is proposed for the forecasting of PV power. The data pre-processing stage effectively find the missing values using data cleaning and transforms the raw data using data transformation. Next, Univariate and bivariate based data exploration finds the variables in the solar power generation dataset. Furthermore, Feature scaling-based feature engineering calculates the mini-max scalar values for forecasting the PV power. Finally, the proposed DS^2-ALSTM forecast the PV power with better performance and achieves higher coefficient. The performance evaluation, conducted on the solar power generation dataset, demonstrates the superior capabilities of the DS^2-ALSTM method. The improved MSE of 0.2, MAE value of 0.4, RMSE value of 0.5 and R2 value of 99% is achieved as a greater performance in contrast to the surviving methods.

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