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Original Article

Enhancing Short-Term PV Power Forecasting Using Deep Learning Models: A Comparative Study of DNN and CNN Approaches

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Abstract *- Forecasting solar power is essential for increasing solar power plants' competitiveness in the energy market and reducing reliance on fossil fuels for social and economic advancement. The novel method of forecasting solar Photovoltaic (PV) power output through the use of deep learning and machine learning techniques specifically, Deep Neural Network (DNN) and Convolutional Neural Network (CNN) models is presented in this research. To anticipate solar energy generation, our technique uses pertinent weather characteristics and historical PV power data as inputs. Although several PV power forecasting models in the literature have varying degrees of accuracy, our CNN and DNN models provide a clear benefit by obtaining important features from raw local data. With this skill, precise short-term projections of solar PV power output from a few hours to several days-can be made. In addition, the integration of naive seasonal forecasting with CNN and DNN models improves the precision of short-term power generation forecasts by identifying complex dependencies and periodic patterns in the data. All things considered, our suggested method offers a viable way to raise the accuracy and efficiency of solar energy forecasting, which will help the energy industry embrace sustainable energy sources more widely.*

Keywords *- Solar power forecasting, Machine learning, Deep learning, Short term PV power forecasting.*

1. Introduction

As a result of advancements in solar panel technologies, solar Photovoltaic (PV) power generation has become a popular and sustainable energy source. With its clean, silent, and cost-effective characteristics, PV production plays a significant role in reducing carbon footprint and cutting down costs. Nearly 3.7% of the world's power demand was met by PV in 2020; this percentage is rising quickly each year [1].

In recent years, PV production has experienced a remarkable 22% growth, positioning it as the second-largest contributor to renewable energy generation after wind power [2]. The extreme unpredictability of PV production, which is strongly correlated with meteorological factors like temperature and sun irradiation, makes controlling PV plants difficult. Grid management is made more difficult by this fluctuation, especially as solar energy penetration increases and affects power prices, energy market efficiency, and local energy systems' operating expenses [3]. Hence Predicting power generation for PV systems has evolved into a key technology crucial for enhancing scheduling accuracy and minimizing the requirement for surplus capacity reserves.

PV power forecasting systems are classified depending on a number of variables, including the time frame for which they predict, the method used, and whether or not they use numerical weather prediction. Techniques are divided into four categories according to the length of time they span extremely short-term, short-term, medium-term, and long-term forecasting. Very short-term predictions are utilized for immediate action and can be generated for a few seconds to minutes in advance and are utilized for immediate energy management in smart grids.

Short-term methods forecast from 1 hour to 1 week ahead, supporting tasks like power unit scheduling and dynamic pricing. Medium-term methods predict from one month to a year ahead and are useful for network planning, while long-term methods forecast several years ahead and aid in power infrastructure planning. By their nature and whether or not they rely on measurements, forecasting systems can also be distinguished from one another. While data-driven approaches examine weather and solar production data to anticipate power, physical methods forecast PV power using specific weather data and PV panel design factors [4]. Data-driven approaches might be machine learning-based, such as decision trees and neural networks, or they can be exclusively statistical [25].

Hybrid techniques incorporate elements of both strategies. Furthermore, while some approaches are independent of weather prediction, others rely on numerical weather prediction to increase accuracy by including weather forecasts in their predictions. To put it another way, The degree of prediction accuracy, the methodology used, and the inclusion of weather forecasts are the three categories into which solar power forecasting modes fall. These techniques use data analysis techniques or physical equations to anticipate solar power generation for various time horizons, from a few seconds to several years in the future. While some approaches do not rely on weather forecasts, others do in order to increase accuracy. Predictive modelling for PV power generation encompasses various techniques categorized as either indirect or direct forecast models [5]. Indirect methods forecast solar radiation across different time spans, which is then converted into power considering panel characteristics, while direct forecasts are derived directly from plant output. These models fall into four main classes: statistical, physical, Artificial Intelligence (AI), and hybrid approaches.

AI and Machine Learning (ML), particularly, have gained prominence due to their robust learning and regression capabilities [6-10]. Notably, algorithms like Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) have been utilized to enhance forecasting accuracy. Incorporating additional parameters like the Air Quality Index (AQI) has shown promise in improving model performance. Deep Learning has become popular for predicting PV power because it is really good at finding patterns in data, especially when things are uncertain. It has evolved to use lots of layers of neurons, which helps it understand complicated relationships between inputs and outputs, making it great for PV power forecasting. Convolutional Neural Networks (CNN), a type of deep learning model, are especially liked for PV power prediction because they are good at handling data with grid-like structures and finding important features.

Studies have shown that models like ResNet and DenseNet work well for forecasting PV production, confirming that deep learning is the best choice for this task [11-16]. Deep Learning models are gaining popularity in PV power forecasting because they are really good at understanding complex data patterns, much better than traditional methods. H.Z. Wang et al. [8] introduced Deep Neural Networks (DNN) for time series prediction, leveraging their ability to capture temporal and nonlinear characteristics of data. DNN-based predictive models can effectively identify complex data associations from large datasets. In theory, predictive models based on DNNs should exhibit better performance and robustness compared to traditional shallow network models. Overall, deep learning-based predictive models have shown significant advancements and promise in handling complex data and improving forecasting accuracy.

This indicates that because of their capacity to manage massive volumes of data and identify crucial correlations, they are emerging as the go-to choice for precisely estimating PV power output [7, 18-20]. This paper aims to improve PV production forecasting by introducing a new method that combines different forecasts. While individual deep learning models have shown promise, they do not always give the best predictions for every solar plant. Our approach uses a mix of advanced deep learning models like DNN and CNN with naïve seasoning.

Naive seasonal forecasting is often used alongside CNN and DNN for short-term PV prediction to complement the capabilities of these advanced machine learning models. While CNN and DNN are powerful for capturing complex patterns and relationships in the data, they may struggle with certain types of periodic or seasonal patterns present in solar energy generation data. Naive seasonal forecasting, on the other hand, relies on simple methods like averaging historical data from the same season or time period to make predictions.

By combining naive seasonal forecasting with CNN and DNN models, it is possible to leverage the strengths of both approaches. Naive seasonal forecasting can capture recurring patterns in solar energy generation data that CNN and DNN may overlook, particularly in short-term predictions where these patterns are more prominent. Meanwhile, CNN and DNN can handle the nonlinear relationships and complex features in the data that naive seasonal methods cannot capture. Overall, using naive seasonal forecasting alongside CNN and DNN models allows for a more complete and accurate prediction of short-term power generation by incorporating both the periodic patterns and complex dependencies present in the data to overcome this issue.

2. Methodology

The forecasting process of the proposed framework is shown in Figure 1. The dataset utilized in this work is publicly available and comprises two distinct sets: solar power generation data and weather data. The integration of two essential datasets significantly enhances the understanding and optimization of solar power generation dynamics. The first dataset, consisting of 69,000 records, focuses on power generation and includes timestamps, plant and inverter identifiers, as well as metrics for DC and AC power output daily yield and total yield.

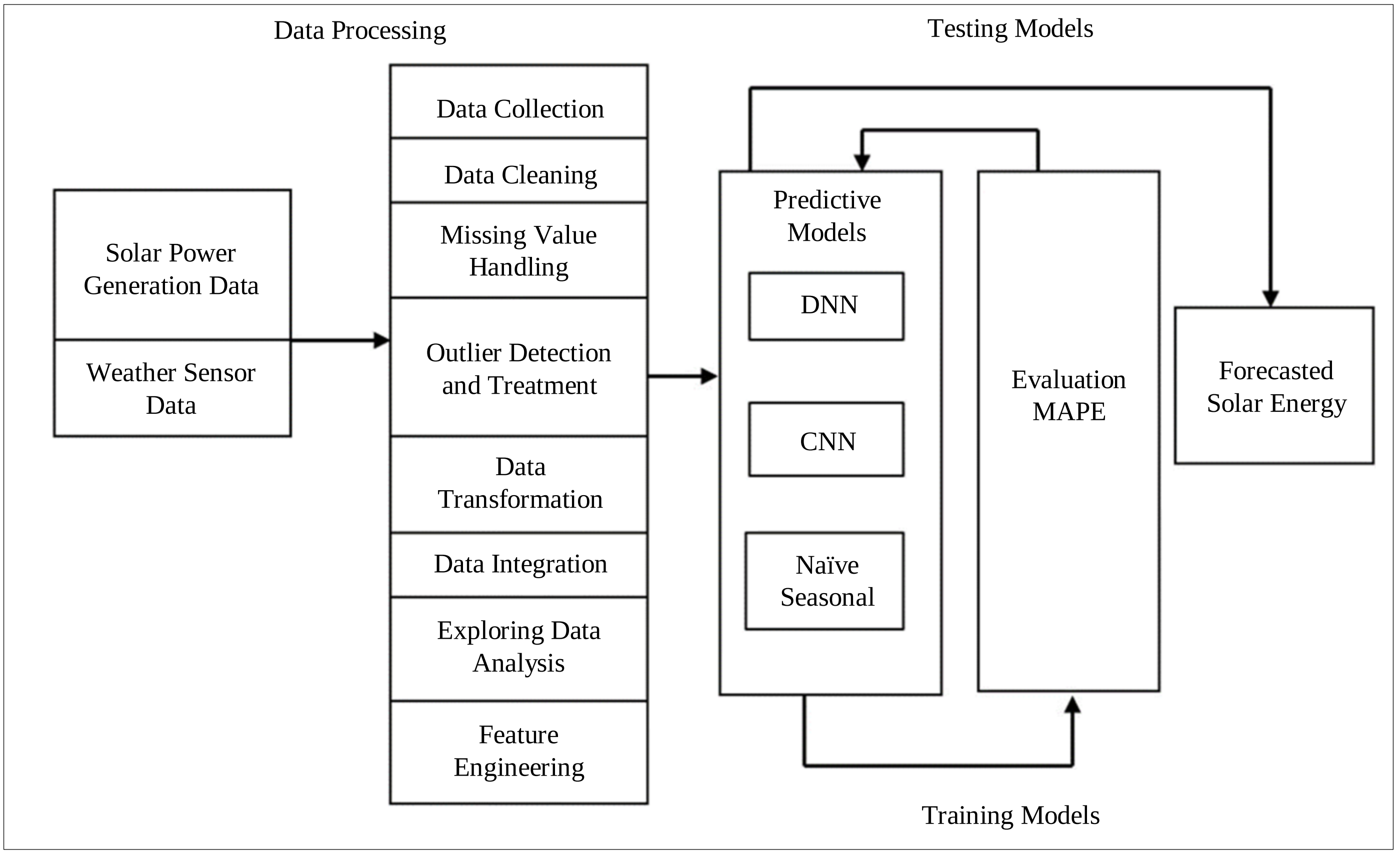

Fig. 1 Architecture of the proposed framework

This dataset provides detailed insights into individual inverter performance and overall plant productivity. Complementing this, the Weather Sensor Data offers environmental context with ambient and module temperatures, irradiation levels, and matching timestamps. By combining these datasets, a comprehensive understanding of how environmental conditions influence solar panel performance is achieved. This integration facilitates efficiency optimization, prediction of generation patterns, and informed decision-making in the field of solar energy production.

3. Data Preprocessing and Manipulation

Currently, the data is structured with rows corresponding to each inverter, resulting in multiple rows for the same timestamp if data is available for multiple inverters at that time as shown in. However, we aim to organize our data at the plant level, aggregated by day and timestamp, with columns representing the sum of values for all inverters at each timestamp. To achieve this, we will group our data by inverter and merge each group sequentially using an outer join on the DATE_TIME column. Ensuring to generate a single, cohesive dataset, we will also combine this dataset on power generation with our weather dataset. The DATE_TIME column will then be divided into separate columns for DATE and TIME. Finally, we will use the Pandas data range function to generate a new column named "BLOCK" that will represent 15-minute intervals and be stored in a dictionary. Each day will then have 96 time blocks, allowing for stratified training splitting. With our dataset structured accordingly, we will proceed with analysis and imputation, followed by splitting it into train and test sets, keeping the test dataset separate for evaluation.

Currently, the data is organized with rows for each inverter, meaning each timestamp is repeated for the number of inverters present at that time. However, it is desired for our predictions to be at the plant level, with rows representing each day divided into 15-minute intervals. Thus, the data needs to be rearranged. Firstly, the data will be grouped by inverter, and each group will be stored in a list. Then, each group will be merged using the outer join method based on the DATE_TIME column. This will result in the introduction of a lot of null values for timestamps that are not common across all inverters. Subsequently, this power generation dataset will be merged with our weather dataset to create a single dataset.

Next, the DATE and TIME columns will be separated, and a new column called "BLOCK" will be created to represent each 15-minute interval using the Pandas date range function, as shown in Figure 2. This will facilitate the splitting of the data during training. Each day will be comprised of 96 time blocks, from 00:00 as the 1st block to 23:45 as the 96th block.

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD
0	15-05-2020 00:00	4135001	1BY6WEcLGh8j5v7	0.0	0.0	0.000	6259559.0
1	15-05-2020 00:00	4135001	1IF53ai7Xc0U56Y	0.0	0.0	0.000	6183645.0
2	15-05-2020 00:00	4135001	3PZuoBAID5Wc2HD	0.0	0.0	0.000	6987759.0
3	15-05-2020 00:00	4135001	7JYdWkrLSPkdwr4	0.0	0.0	0.000	7602960.0
4	15-05-2020 00:00	4135001	McdE0feGgRqW7Ca	0.0	0.0	0.000	7158964.0
...	…	…	…	…	…	…	…
68773	17-06-2020 23:45	4135001	uHbuxQJI8IW7ozc	0.0	0.0	5967.000	7287002.0
68774	17-06-2020 23:45	4135001	wCURE6d3bPkepu2	0.0	0.0	5147.625	7028601.0
68775	17-06-2020 23:45	4135001	z9Y9gH1T5YWrNuG	0.0	0.0	5819.000	7251204.0
68776	17-06-2020 23:45	4135001	zBIq5rxdHJRwDNY	0.0	0.0	5817.000	6583369.0
68777	17-06-2020 23:45	4135001	zVJPv84UY57bAof	0.0	0.0	5910.000	7363272.0

68778 rows x 7 columns

Fig. 2 Data after grouping by inverter wise

	BLOCK	DATE	TIME	AMBIENT_TEMERATURE	MODULE_TEMERATURE	IRRADIATION	Inverter_No_1	DC_Power_1	AC_Power_1	Inverter_No_2	-	AC_Power_19	Inverter_No_20
0	1	2020-05-15	00:00	25.184316	22.857507	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
1	2	2020-05-15	00:15	25.084589	22.761668	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
2	3	2020-05-15	00:30	24.935753	22.592306	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
3	4	2020-05-15	00:45	24.846130	22.360852	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
4	5	2020-05-15	01:00	24.621525	22.165423	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
...	...	…	…	…	…	…	…	…	…	…	…	…	…
3259	92	2020-06-17	22:45	22.150570	21.480377	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
3260	93	2020-06-17	23:00	22.129316	21.389024	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
3261	94	2020-06-17	23:15	22.008275	20.709211	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
3262	95	2020-06-17	23:30	21.969495	20.734963	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0
3263	96	2020-06-17	23:45	21.909258	20.427972	0.0	1.0	0.0	0.0	2.0	-	0.0	20.0

3264 rows x 72 columns

Fig. 3 Data represented as block

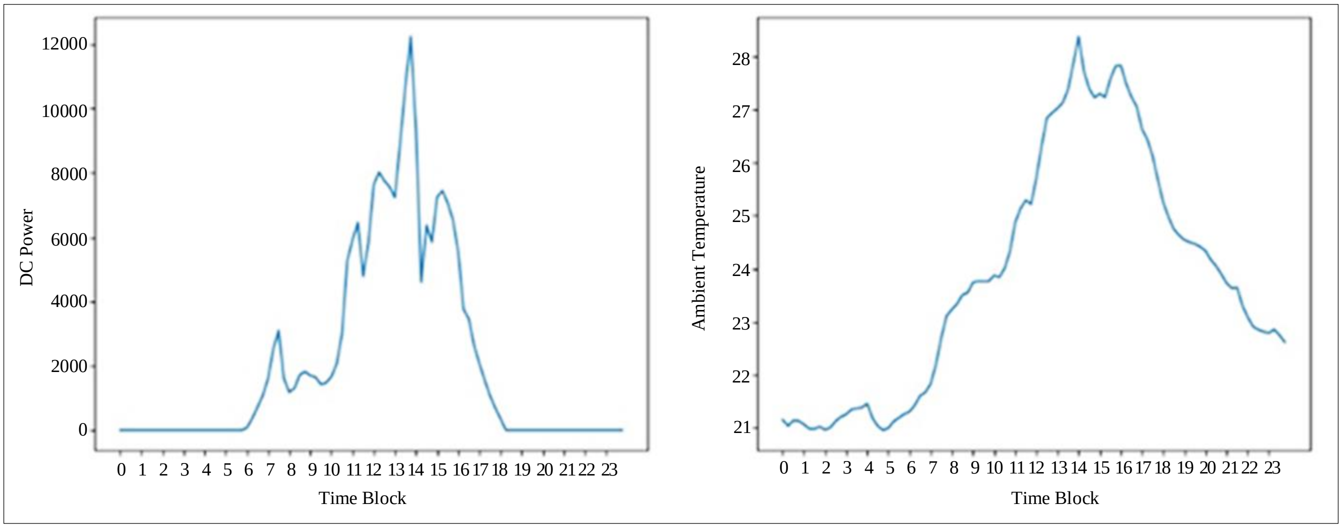

Fig. 4 Understanding patterns in PV power generation on a random date

For the sake of continuity, a deliberate splitting approach will be employed instead of random selection. Specifically, the last three days of data will be designated for testing purposes, while the remaining data will be utilized for training. Consequently, the training dataset will consist of 2971 rows, and the test dataset will be comprised of 288 rows. With a significant number of missing values present in the training dataset, the next step will involve addressing the imputation of these missing values.

Before proceeding with imputation, it is essential to understand the underlying patterns in the weather and generation data. Let us visualize a plot for a random date to gain insights. From the plot, as shown in Figure 4, it is evident that the columns exhibit a continuous, ordered nature with some sequential properties. Therefore, for imputing missing values, leveraging the values from the previous and next timestamps can be beneficial. This is why we opted not to split the dataset randomly for train and testing, as doing so helps preserve the sequential nature of the data. To handle missing values in our data, we have a few strategies. One approach is to find the mean, median, or mode for each time block in the training data and use these values to fill in missing data in the test data. Another method involves training a model only on the non-missing values and using it to predict the missing values. However, this second strategy can be computationally expensive and time-consuming, so it is not usually recommended for production. Instead, we can use spline interpolation. This method generates a smooth curve between the two nearest non-zero values to estimate the missing values, as shown in Figure 5. However, we need to consider the nature of the data columns. For example, irradiation and AC/DC power generation are zero during non-solar hours (e.g., nighttime), so we will fill in missing values with zeros during these times.

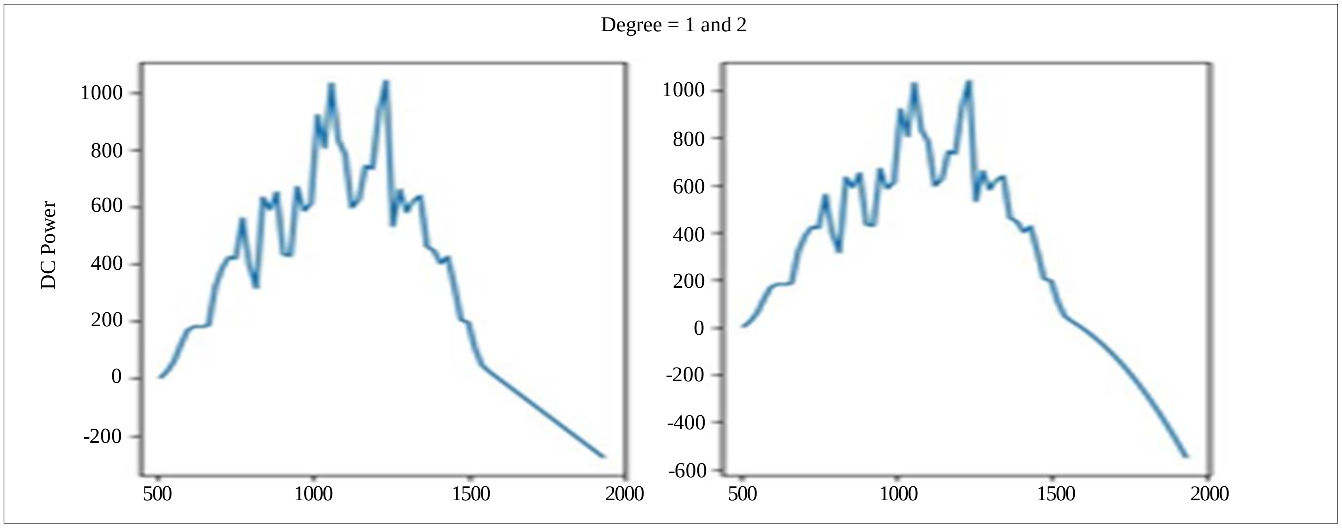

Fig. 5 Smoothing PV power data with spline interpolation

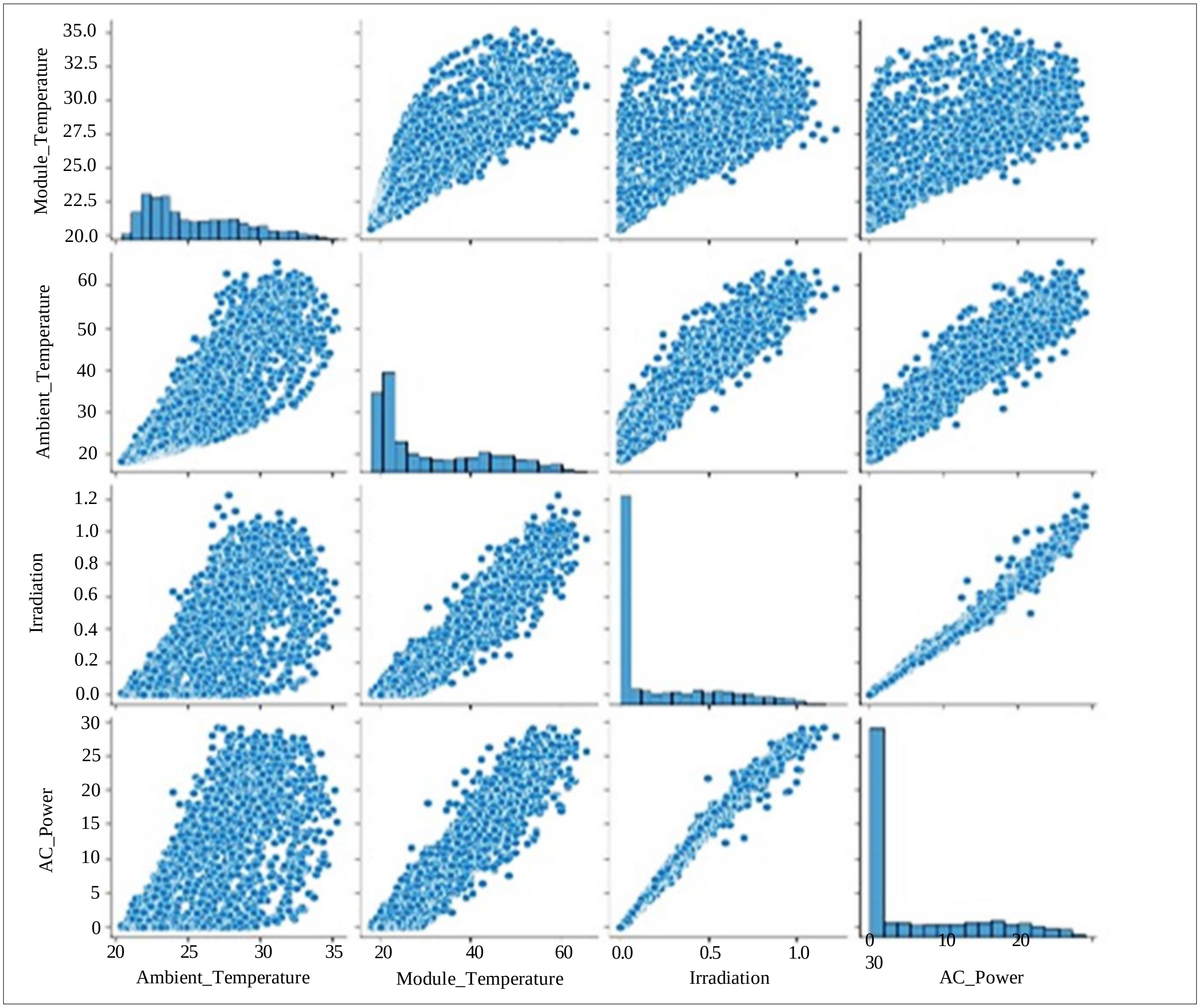

Fig. 6 Expletory data analysis

For solar hours, we will use linear spline interpolation for irradiation and a polynomial spline with degree 2 for AC/DC power, as the generation does not vary linearly during solar hours. This approach helps maintain the smoothness of the curve and ensures accurate imputation of missing values, as shown in Figure 5. Degree 2 spline imputation is employed to achieve smoother results, resembling the parabolic nature of the data. The dataset is aggregated on the plant level, combining values from all 22 inverters and scaled to megawatts from kilowatts. With the training and test data prepared, Exploratory data analysis is initiated to extract insights, as shown in Figure 6. Starting with pair plots, strong linear relationships are observed between AC Power and Irradiation, as well as between Module Temperature and Irradiation. The distributions of Irradiation and AC/DC Power are heavily skewed to the right due to non-generating periods (6 pm-6 am), while Ambient and Module Temperatures are slightly less skewed. Module Temperature demonstrates increasing variation with each degree rise in Ambient temperature, suggesting potential influence from other weather parameters like humidity and wind speed, which are not included in the dataset. Additionally, the presence of outliers in AC Power is noted.

The process involves splitting the DataFrame into train, validation, and test datasets based on unique dates, with the train set encompassing 80% of the data and the validation set containing 20%. After filtering and sorting the datasets by date and time block, they are saved to CSV files with no missing values present. The process involves building a neural network model (`model1`) with three dense layers using the sequential API, followed by compiling the model with Mean Squared Error loss and Adam optimizer. ModelCheckpoint is employed to save the best-performing model during training.

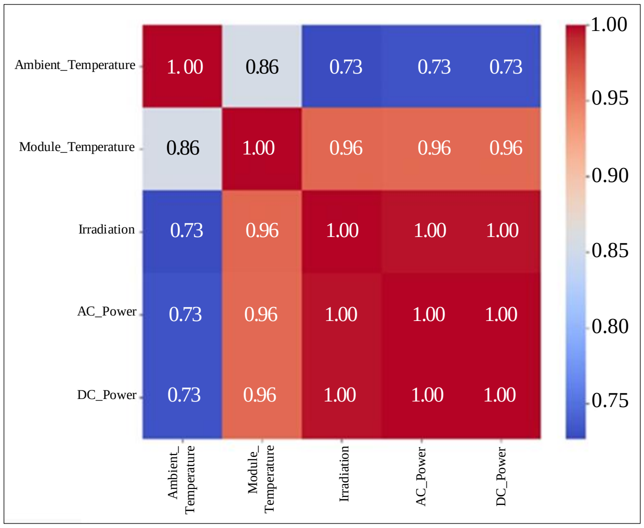

Fig. 7 Correlation heat map

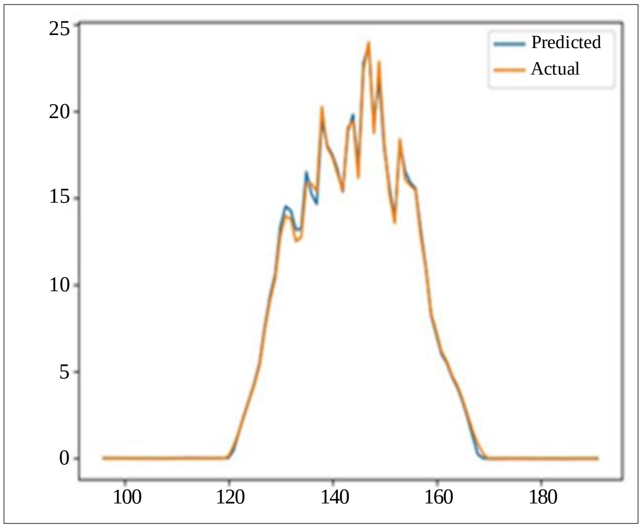

Fig. 8(c) Validation

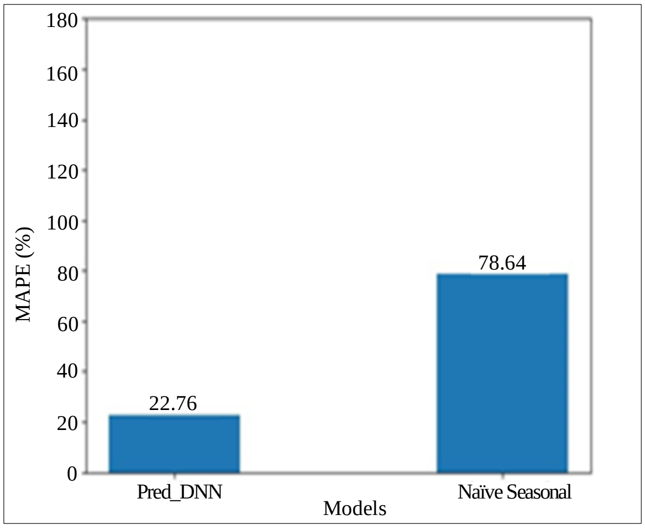

Fig. 8(a) Yielding MAPE

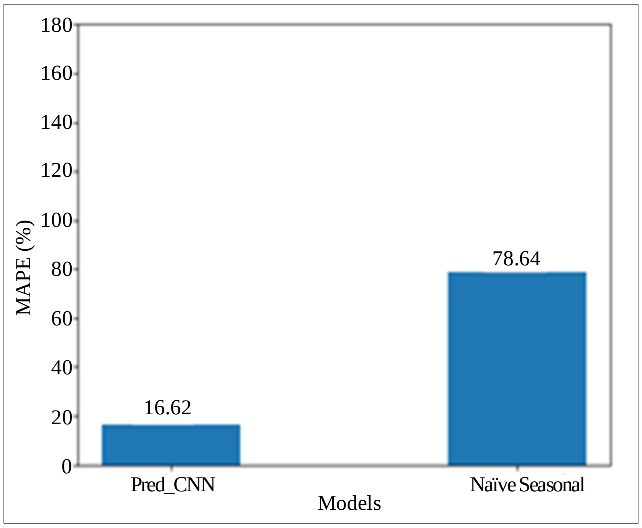

Fig. 8(d) Comparision

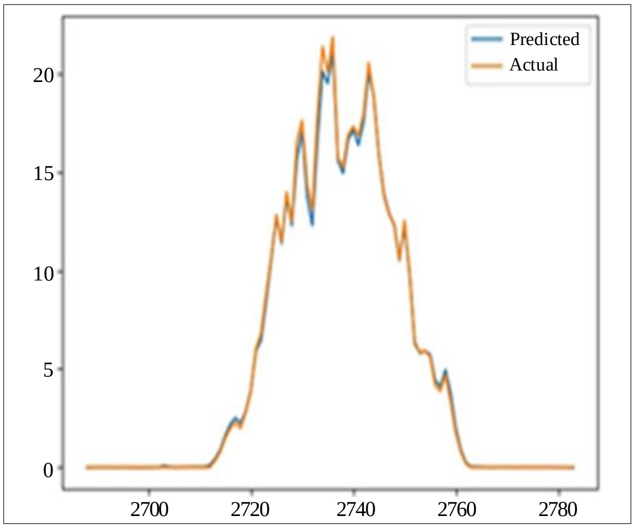

Fig. 8(b) Training

The model is trained on various features such as ambient temperature, Pv array temperature, and irradiation, with training predictions generated and compared against actual values using pandas DataFrame. The process involves making predictions on the training, validation, and test datasets using the trained neural network model (`model1`). For the training set, the predictions are compared with the actual values, and a DataFrame (`train_results`) is created to store these results.

Similar steps are followed for the validation and test sets, resulting in DataFrames (`val_results` and `test results`, respectively). Additionally, for the test set, the Root Mean Squared Error (RMSE) is calculated and printed as a measure of model performance. Finally, line plots are created to visualize the predicted values against the actual values for the training, validation, and test sets. The process involves comparing the predictions generated by the Deep Neural

Network (DNN) model (`Test Predictions`) with the actual values (`Actuals`) and a naive seasonal baseline (`naive_seasonal`) for the test dataset. Afterwards, a bar plot is created to visualize the Mean Absolute Percentage Error (MAPE) for both models, which is calculated using the function `calculate mape` for the DNN model and the naive seasonal baseline. Finally, the MAPE values for both models are printed, with the DNN model achieving a MAPE of approximately 22.76% and the naive seasonal model yielding a MAPE of around 78.76%, in Figure 8.

4. CNN Convolutional Neural Network

The Convolutional Neural Network (CNN) model is constructed using Keras' Sequential API. The architecture begins with a Conv1D layer containing 64 filters and a kernel size of 2, followed by a Flatten layer to transform the output into a one-dimensional array. This is followed by two dense layers with 32 and 16 neurons, respectively, both utilizing the ReLU activation function. Finally, a dense layer with a single neuron and a linear. The activation function is added to produce the output. The summary of the model displays the layers, their types, and the output shapes at each layer. Additionally, it provides information about the total number of parameters in the model, including trainable and non-trainable parameters. Comparing the results of the CNN and DNN models with the naive seasonal approach, both the CNN and DNN models outperform the naive seasonal approach in terms of predictive accuracy, with the CNN model showing superior performance with a lower MAPE compared to the DNN model.

5. Conclusion

This paper introduces an innovative method for short-term Photovoltaic (PV) power forecasting by employing Deep Neural Network (DNN) and Convolutional Neural Network (CNN) models. The study evaluates the prediction accuracy of both models and reveals that the CNN model surpasses the DNN model. Technological advancements, particularly in earth and atmospheric sciences, have increased the availability of meteorological data for predicting PV power generation. Despite these advancements, predictive modelling continues to face challenges, with traditional neural networks struggling to handle complex input variables.

To overcome these challenges, future research should concentrate on refining predictive models through deep learning techniques and PV power generation systems. Enhanced data integration strategies, ultimately improving the accuracy and reliability of PV power generation systems reforms the DNN model. Advancements in technology, particularly in earth and atmospheric sciences, have increased the availability of meteorological data for PV power generation prediction. Despite these advancements, challenges remain in predictive modelling, with traditional neural networks struggling with complex input variables. To address these challenges, future research should focus on refining predictive models using deep learning techniques and improved data integration strategies, ultimately enhancing accuracy and reliability.

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