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Optimized ANN–LSTM Approach for High-Precision Day-Ahead Photovoltaic Power Forecasting

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Abstract-The growing integration of PV systems in the power grid requires an ideal forecasting approach of energy management. One of the new concepts that are presented in this research paper is the possibility to forecast photovoltaic power generation 1 day before with the assistance of long short-term memory (LSTM) algorithms which will provide the adequate possibility to predict the future photo generation of power, offer the opportunity to distribute resources much quicker and reach a better result in the utilization of the resources of the renewable energy. It discusses the limitations that relate to traditional forecasting models and presents that LSTM is a great answer to the problem because of its possibility to capture the long-term dependency of time series records. The section on methodology explains how the LSTM networks were implemented, the approach used to preprocess the data, the structure of the model and the training process. This paper has highlighted the role of appropriate selection of input features like historic solar exposure, temperature and past-historical power generation information in positive prediction. The trained LSTM-based forecasting model is validated and evaluated on actual photovoltaic power generation data. Measures of performance The following are applications of the measures of Mean AbsoluteError (MAE) Root Mean SquareError (RMSE) and Mean Absolute PercentageError (MAPE) mobilize, using, measures of HFES performance. Results show that the LSTM solution is superior to the traditional forecasting methods, which makes sense considering it should be used to identify the complex trends and improve the accuracy of day-ahead electric generation using photovoltaic panels. This article describes what the specific predicting means the stability of the grid, power trading and coherent renewable power and identifies the sense of the setting forth in practice of what has been proposed.

Keywords— Photovoltaic power forecasting, Long Short-Term Memory (LSTM) algorithm, Day-ahead prediction, Power generation data, Prediction accuracy.

I. INTRODUCTION

Qualitative enhancement of power is the first priority in The incorporation non-conventional resources such as PV power (power) into the grid has gain many significant roles in managing sustainable energy. However, the variability and intermittency of solar power pose challenges for grid operators in terms of balancing supply and demand. Accurate forecasting of PV power generation is crucial for effective grid management, especially for day-ahead predictions, to optimize resource allocation and ensure grid stability.

A day-ahead photovoltaic power prediction model based on the LSTM algorithm was developed by [1]. The study focused on improving the accuracy of forecasting solar power generation. The main finding was that the LSTM procedure showed promising results in predicting photovoltaic power generation. It only focused on day-ahead predictions and did not consider longer forecasting horizons, potentially limiting the applicability of the model in scenarios requiring longer-term predictions.[2] presented a convolutional self-attention-relied LSTM approach to forecasting day-ahead hourly solar power output. The goal of the study was to improve solar power forecasting accuracy by utilizing self-attention techniques. Since the suggested model's performance was not contrasted with that of other forecasting techniques, it was difficult to evaluate the model's efficacy in comparison to other strategies..[3] developed a model for day-ahead to week-ahead solar irradiance prediction using convolutional LSTM networks. The study focused on extending the forecasting horizon for solar irradiance predictions. It did not address the potential influence of climate inconsistency on the correctness of long-term solar irradiance predictions, which could affect the model's reliability in practical applications. By adopting an attention-based CNN-LSTM NN integrated with several relevant and desired prediction patterns, a day-ahead hourly solar power forecasting model was suggested by [4]. The study aimed to improve the accuracy of solar power predictions by considering various input variables. The study did not discuss the computational complexity of the proposed model, which could be a significant factor in real-time prediction applications where computational efficiency is crucial.[5] used an LSTM recurrent neural network to create a day-ahead PV irradiance prediction model for microgrids. The goal of the study was to increase the forecast accuracy of PV irradiation by utilizing methods based on deep

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learning. In general, the reviewed works illustrate progress in day-ahead solar power forecasting with deep-learning-based methods, but limitations on forecasting horizons, model comparisons, consideration of weather variability, model complexity, and the issue of data quality require consideration to make deep-learning-based projections in the real-life setting with limited data. [6] developed an hourly PV power forecasting methodology on three separate PV plants based on an RNN-LSTM forecasting model. The first finding was the high predictability of the forecasting model applied to different plants.The one-unit focus of the research on three specific PV plants might limit the implementation of the research in a wider range of plants or locations.

A LSTM network-based accurate solar power output prediction was introduced in [7]. The findings of the investigation revealed the quality of predicting the PV power output by the LSTM network.

It might not have taken into account all the possible factors that might influence the output of PV power, thus restricting the forecast possibilities of this model. As a follow-up, [8] proposed a convolutional-LSTM network-based PV power forecasting method. The paper demonstrated the accuracy of predicting the following day power of PV by CNN-LSTM structures. The temporal correlation as specified by 9 day-ahead PV power prediction, may be illogical and restricting in results in scenarios requiring real-time detection Because of the study was not focused on identifying short-term variations in PV power output, the overall method may not accurately represent itThe degree of temporal correlation between 900 and 1400 hours is worsening the output of the LSTM-RNN model describing the discussed day-ahead PV power predictor model. In order to compare the performance of the study with other applications of these model, emphasis on the patterns experienced on a daily basis may not accurately reflect the variability within an hour of production in the solar power and thus, it may not effectively help to predict the occurrence of the short run changes[10] in the study proposed an LSTMNN to predict the short term solar power. The authors have focused on the application of the LSTM networks towards efficient future prediction of PV power. In some cases, the short-term forecasting structure of the research would not be applicable to long-term planning or forecasting, which restricts the applicability of the model in practice. Wr promote [11] proposed a simplified version of LSTM neural network prediction model to make one day-ahead prediction of PV. The model was promising in terms of accurately predicting the amount of PV that will be generated tomorrow. The study focused on a single day-ahead forecast and may not capture changes or trends in solar energy generation over a longer period of time. Moreover, the simpler form of LSTM model might not be as viable and precise as more sophisticated models under specific conditions An LSTM model to project solar power one hour in advance was developed by [12].

For real-time power administration, the model performed well in predicting the generation of solar electricity one hour ahead of schedule.

Fig.1 Block Diagram of Proposed system.

Its applicability could be restricted to long-term planning or forecasting since it is based on hour-ahead forecasting. Along with this, quality and quantity of input records can influence the LSTM model performance and hence the performance of the forecasts. In this context, the LSTM process has been shown to be a useful tool when it comes to time series prediction, particularly due to the ability of the underlying algorithm to detect complex patterns and associations among data.

In this research paper, emphasis is given to using an LSTM-based method that is specially designed to predict PV power generation as presented in Fig.1. This solution can aim to improve the precision of day-ahead predictions leveraging historical PV power data, weather conditions, and other factors of interest to support more effective decision-making by grid operators and enhance efficient use of solar energy sources..

II. DEEP LEARNING AND FORECASTING OF PV POWER PRODUCTION

Many studies in recent years have been done to predict problems in various fields of application. Recurrent neural networks (RNNs) have been applied successfully to machine learning issues. These methods have been proposed to solve time-dependent learning problems. The basic concept of RNNs is observed in Figure 1 in which a part of a neural network, A, analyzes a section of some input and generates an outcome. Note that RNNs are ideal to extract and learn temporal RNNs..

$$h_t = \begin{cases} 0, t = 0 \\ \varphi(W_{x_t}, x_t), otherwise \end{cases} \quad (1)$$

where the function ϕ is non-linear. The recurrent concealed state update manifests as:

$$h_t = g(W_{x_t} + uh_{t-1}) \quad (2)$$

The hyperbolic tangent curve is represented as g (tanh). When it comes to capturing long-term temporal relationships in time series, RNN are frequently not the best option. LSTM models were developed to overcome this limitation. An enhanced RNN variant called LSTM is

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V1I102

capable of handling data temporal dependence rather well. These models have shown success in a number of applications and are adaptable and effective at describing time-dependent data. For time-series information prediction, LSTM is one of the most widely used RNN models, and it works well for problems requiring PV forecasting.We then go over the fundamentals of LSTM and its design and implementation processes.

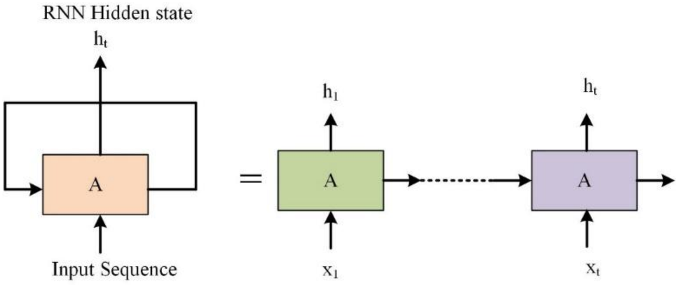

Fig.2 Basic illustration of RNN.

A. LSTM Networks

RNNs of the LSTM are especially good at managing long-range relationships and identifying temporal patterns in sequential input. To solve diverse issues and enhance performance in a range of jobs, LSTM networks have been built in several versions or designs. The following are a few varieties of LSTM architectures:

1. Vanilla LSTM: The basic building blocks of an LSTM network are an input, output & forget gate, and a memory cell. The forget gate chooses which data to erase from the memory cell, the input gate controls the information reaching the cell, and the gate that outputs the data adjusts the output in accordance to the cell's state.

Bidirectional LSTM or Bi-LSTM: A Bi-LSTM feeds the response series the forward and reverse track. This allows the network to extract information of both the past and into the future in activities such as speech recognition, and natural language processing, where both sides of the context play a vital role.

Stacked LSTM: A stacked LSTM is an LSTM layer that is stacked above a LSTM layer. Having handled the input sequence, every layer of the stack gives its output to the immediate upper layer. With LSTMs stacked, a model can pick up detailed shapes and structures within the input and perform better on tasks that have multi-level relationships.

Peephole LSTM: Peephole LSTMs extend the design of original LSTMs by providing the gates with direct access to whatever was fed into the cell last time step. This additional relation that helps the gates to obtain a better determination by considering the record of the cell and so therefore makes modeling long-term interdependence more accurate.

5. Gated Recurrent Unit (GRU): GRUs are closely linked to LSTM architectures, however not exactly the same. They provide a more straightforward version with less parameters. By merging the input and forget gates into one,
"update gate," GRUs are able to capture temporal relationships more effectively while also being computationally more economical.

Based on the particular needs of the application and the complexity of the data, each of these LSTM architectures offers benefits and is appropriate for a certain set of jobs.

B. LSTM principles and applications

Hochreiter was the first to suggest LSTM. In 2000, Schmidhuber enhanced the LSTM system by introducing the forget gate technique, which may be used to anticipate continuousness. After that, Grave's book enhanced and expanded upon the LSTM. LSTM has been applied extensively and successfully in a variety of problems. RNN are the forerunners of LSTM neural networks.

Neural networks called RNNs use internal loops to learn sequential patterns. Many recurrent loops in an RNN network have the potential to broadcast data continuously. The weight learning and modification procedures employ the chain rule replication technique. When the value is communicated back to the activation activity, such as the Sigmoid and Tanh functions, the gradient vanishing issue occurs. The slope will now become incredibly little (or enormous).

These issues were avoided in the development of the LSTM model. Memory cells and gates were postulated by Hochreiter et al. A structure like this may retain information for a very long period without losing track of unneeded information.

LSTM networks do not employ neurons, but memory cells. One memory cell (ct) and 3 gate assemblies—an input gate (it), a forget gate (ft), and an output gate (ot)—make up an LSTM cell. The input data is currently represented by t,xt, t, while the hidden layer state is represented by ht.

The vector outer product is represented by the character ×, while the superposition operation is represented by the sign. Equations (3)–(8) display the LSTM operation formula. In this case, b stands for offset, σ is the sigmoid function, and the sign * denotes vector outer product. Additionally, U and W indicate matrix weights.

$$f_t = \sigma(U_f x_t + W_f H_{t-1} + b_f) \quad (3)$$

$$i_t = \sigma(U_i x_t + W_i H_{t-1} + b_i) \quad (4)$$

$$u_t = \tanh\,(U_u x_t + W_u H_{t-1} + b_i) \quad (5)$$

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V1I102

$$c_t = f_t \times C_{t-1} + i_t \times u_t \quad (6)$$

$$o_t = \sigma(U_o x_t + W_o\, H_{t-1} + b_u) \quad (7)$$

$$h_t = o_t \times \tanh(c_t) \quad (8)$$

As seen in Eq. (3), the forget gate computes the biased sum of t, ht-1, and bf and yields ft ($ft\in(0,1)$) via the sigmoid function. In the final memory cell (Ct-1), ft stands for the mass of the data that must be ignored. Put differently, as indicated by Eq. (6), the forget gate regulates the quantity of data stored in the preceding memory cell.

The input gate (according to Eq. (3)) chooses how much fresh data is sent to the memory cell (Ct). The memory cell storage weight, or Ct, may be found in Eq. (5). The forget gate and input gate, individually, regulate the original and new information, and the current memory cell (Ct) is taken (see formula (6)). Lastly, use formula (7)'s output gate to filter the memory cells (Ct). Equation (8) is used by the updated memory cell to determine the present hidden layer state, ht. These storage blocks are then combined to create the LSTM model through the process of back-propagation. By avoiding gradient dispersion and utilizing multi-gate cooperation, LSTM strengthens LSTM training. The configuration of LSTM is represented in the Fig.2.

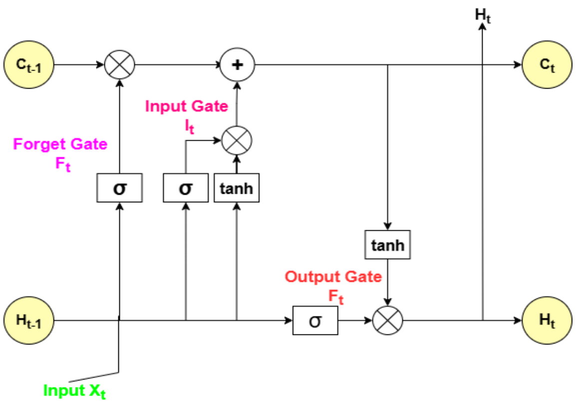

Fig.3 LSTM structure

Measures to assess the forecasting models Many statistical metrics, such as RMSE, MAE, coefficient of purpose (R2), and MAPE, have been presented in the literature to evaluate the forecasting effectiveness. In this investigation, we assessed the forecasting accuracy using R2 and MAPE, which are often utilized.

Evaluation metrics for the forecasting models Many arithmetic pointers presented in the works to evaluate the forecasting effectiveness, Fig.3 shows the flowdiagram for PV forecasting.

$$MAE = \frac{1}{n}\sum|\hat{x} - x| \quad (9)$$

$$RMSE = \sqrt{\frac{\sum|\hat{x}-x|^2}{n}} \quad (10)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_i-\hat{x}_i)^2}{\sum_{i=1}^{N}(x_i-\bar{x})^2} \quad (11)$$

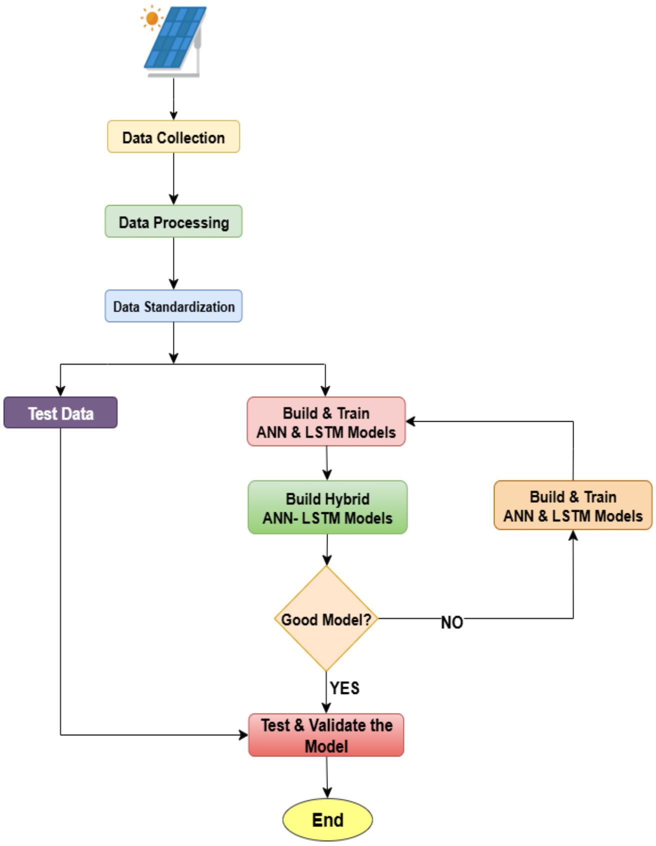

Fig.4 PV Forecasting Flow defines LSTM Flow chart

n is the measurements or measurements assumed in the experiment, x are the measurable standards, and x are the following values expected by the LSTM structure.
There are many crucial factors affecting the accuracy of an LSTM model:
Data Quality: The accuracy of the model is seriously affected by the standard and quality of the guiding set. High quality information that contains fewer noise, outliers, and missing data contribute to the power of the LSTM model when uncovering meaningful patterns and associations that can be better predictive.
Data Quantity: Critical is The amount of training data that is available. With greater volumes of data, model performance can be higher due to its exposure to more instances, which is particularly advantageous to complex phenomena and those exhibiting longer term correlations.

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Selection of Features: This is one other important aspect of model correctness where relevant characteristic features are selected. The introduction of functions, which are unnecessary or redundant can result in noise and deteriorate the performance. Precision could be improved by suitable feature engineering including dimensionality reduction algorithms and finding meaningful features.

Model Architecture: The network structure of the LSTM model, such as the count of hidden units, the activation function and the count of layers could influence accuracy. Deep architecture, multiple-layered architectures can identify more complicated patterns, and capture hierarchical relationships, making them more accurate in difficult jobs.

Tuning hyperparameters: To achieve optimal model performance, we need to pay attention to choosing various hyperparameters, such as the learning rate, batch size, dropout percentage, or the optimization algorithm. In a massive way, these values can be checked by trial and error to augment accuracy significantly.Training Duration: The other factor that affects accuracy is the duration of training and the caliber of the model being used. Long training times also support acquisition more complex patterns along with optimization of the model solution; too many training processes can lead to overfitting. Basic to Accuracy- It is based on training length.Regularization Techniques: Under regularization, such as batch normalization, L2 regularization, and dropout, generalization is possible and suppression of overfitting can take place, therefore, resulting in higher accuracy even for data not yet seen.Preprocessing of Data: Model accuracy can be increased by ensuring consistency of data and its suitability to be used in training through proper preprocessing techniques such as normalization and scaling, encoding of categorical data, management of missing data and outliers.It can be stated that one can significantly enhance the accuracy of an LSTM model by systematically addressing these key factors and tuning them based on the issue domain and shape of the data.

III. Simulation Results & Discussions

In simulation, the forecasting is done in MATLAB/Simulink. The 12 months Forecasted data is in the Fig.4. Here PV power and time step in hours are to be supplied..

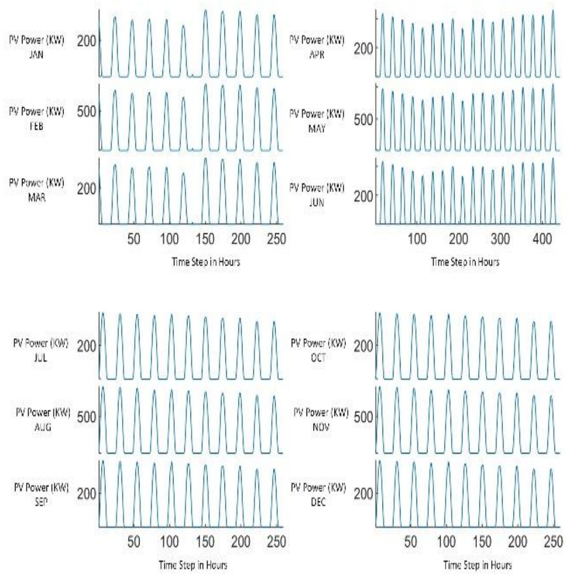

Fig.5 Monthly data for the PV Power

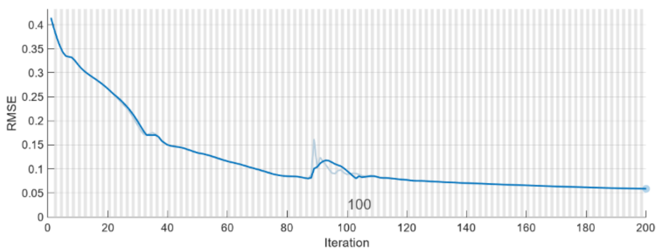

Fig.6 Training progress vs weighted RMSE vs Iteration.

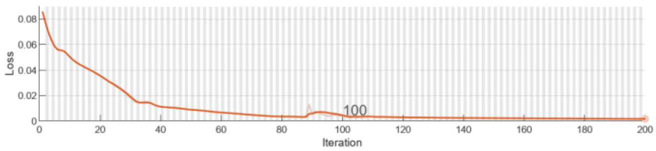

Fig.7 Training progress Loss vs Iteration

The training dynamics at 200 iterations are plotted in Figures 5 and 6: namely, the plots of RMSE and Loss. These are the key metrics used to determine the performance and accuracy of the forecasted data. RMSE plot helps us to understand the level of conformity between the variables in the forecast and in the actual case and the low RMSE will mean that the forecast is more accurate. As with the Loss plot, the process of the model learning is being drawn where the model is reducing errors and increasing its ability to predict more and more accurately over iterations. By taking a closer look at these progress plots of training, one would have a better understanding of the reliability and quality of the forecasted data so that, with some degree of informed choice, he/she could make an improvement in the PV-power forecasting model..

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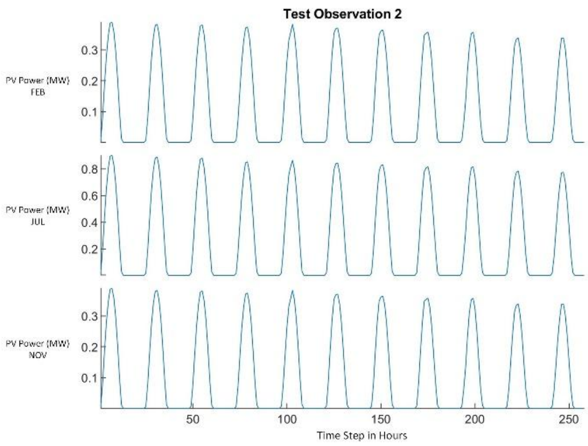

Fig.8 Test observation for the months Feb,Jul & Nov

IThe results of evaluation of the tests of three random months, namely, February, July, and November, are represented in n Fig. 7. Cases were sampled into these months to give a wide range of coverage of season changes, as well as varied solar conditions across the year. We are able to also predict the PV power of these particular months and therefore learn a lot about the behavior of the model under different ecofriendly conditions, including PV irradiance levels, and temperature variations. To confirm its dependability, the model predictive can be subjected to the analysis to justify its validity and power and establish its consistency in different seasonal and climatic scenarios.
The forecasting on the open loop of the months made in the test is shown in the Fig.8.Here also the data of input and the forecasted one were represented clearly.

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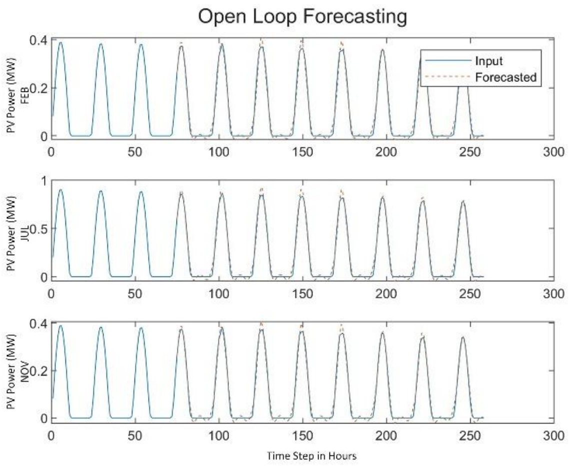

Fig.9 Open loop Forecasting

The open loop forecasting for the months taken for the test is represented in the Fig.8.Here the Input data & the forecasted one was clearly represented.

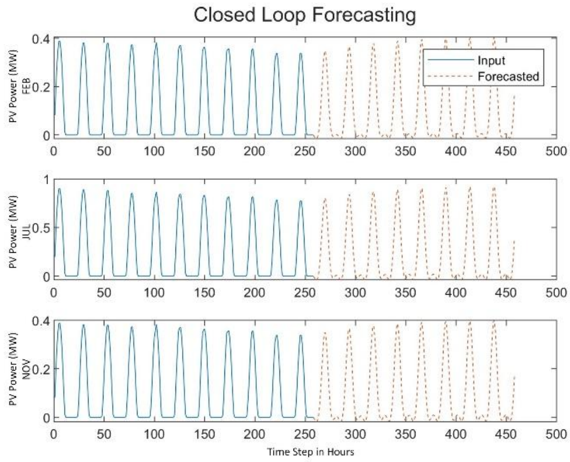

Fig.10 Closed loop Forecasting

Table 1. The Perfomance of the LSTM for PV power prediction

Method	RMSE	MAE	Accuracy (%)	Correlation Coefficient (COR) (%)
ANN	0.15	0.17	95	92.3
LSTM	0.05	0.08	98	96.7

The closed-loop forecasting outputs concerning the chosen test months are depicted in Fig. 9, where the actual input data and the forecast data are compared with each other. The impact of this loop-based approach is that the actual system feedback is calculated and the prediction errors and agreement between the predictions is enhanced. As soon as we organize the input information and compare it with the predicted values, the visual analysis of the changes will help us verify whether the model can achieve and adjust to the technical and physical changes in the PV generation records. This discussion provides insight information on the performance of the model in the aspect of predicting of models predictively as far as operational anticipations escalate as well as provide how the model probably can be effectively implemented in development of corrective projections on the PV power while using the model in practice. Table 1 reports the PV power prediction performance of the LSTM. The outcomes of the simulation to forecast PV power with (LSTM in MATLAB/Simulink) are discussed. The 12 months of PV power data is presented monthly and therefore represents the time step in hours. Root Mean Square Error (RMSE) and Loss versus iteration training until 200 iteration are the training developments that help in the analysis of the data accuracy. The February, July and November test observations give an idea on predictive capabilities. In open-loop forecasting, data is compared to the predicted values and, in closed-loop forecasting,

Doi: https://doi.org/10.XXXXX/IJDTSC.2025.V1I102

an explicit comparison is presented between the actual and predicted PV power data. Generally, the power prediction provided in the LSTM model is extremely reasonable and can be used reliably as demonstrated in these results and it is extremely needed in optimization in PV systems energy.

IV. CONCLUSION

In summary, it is possible to state that this study describes the efficiency of using the (LSTM) algorithms to forecast the production of power of photovoltaic a day ago. The paper clarifies why proper prediction of power is critical in performing a comparison and maximisation of the grid functions and maximisation of the use of renewable energy. The proposed approach provides meaningful gains in prediction accuracy by mitigating the issue of traditional forecasting models and the benefits of LSTM networks are additional to ensure that long-term dependencies of their time series data are limited and reduced. The validation and analysis of the LSTM forecasting model with the real-world photovoltaic power generation data demonstrates that this model can be trusted and outperforms the traditional approaches with indicators like MAE, RMSE. The approximate performance of prognosis of a specific nature demonstrating ingenuity in essence of grid comfort, in respect to either viable energy capital or even incorporation within non conventional into the power grid, emerges in such outcomes. Overall, the results demonstrate the possibilities of LSTM-based methods to perform day-ahead forecasting of PV load and its use in the organization of the sustainable energies strategy..

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