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Short-Term Solar Power Prediction using Machine Learning Algorithms : A High Performing approach

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Abstract

The use of solar energy is growing in popularity across the globe as a clean and sustainable energy source. Nevertheless, integrating solar power into the grid and guaranteeing a steady supply of electricity is made more difficult by the weather patterns' tendency to cause unpredictability in solar power generation. One potential solution to these issues is the use of machine learning (ML) techniques for short-term solar photovoltaic (PV) power forecasting. This research looks into how well various machine learning algorithms work for short-term PV power forecasting. It also offers a summary of the variables that affect time-series data performance and suggests high-performance methods. Long Short-term Memory (LSTM), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) were tested on an 88,494-item dataset with 20 features at a 15-minute resolution. As accuracy metrics, root mean square error (RMSE) and mean square error (MSE) show that ANNs and LSTM perform better than SVM. The superiority of the suggested methods is demonstrated by a careful comparison with recently published results. The reason for the effectiveness of ANNs and LSTMs is their capacity to represent the complex and non-linear relationships found in the data. Short-term solar power forecasting is complex, and SVMs are better equipped to handle linear relationships. These findings will be a useful guidance for those who intend to work in the field of PV power forecasting, even though further research is required to generalize this observation.

Keywords: LSTM, ANN, SVM, principal component analysis, PV energy, renewable energy.

Highlights

- Comparison of ANN, LSTM, and SVM for short-term solar power forecasting.
- Feature selection impact on forecasting accuracy and model efficiency.
- Proposed framework for selecting machine learning models in solar power prediction.

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1 Introduction

BANGLADESH, the ninth most populous country on earth, has a finite supply of energy. This nation is dealing with serious energy issues as a result of its recent rapid development, such as a lack of power and a heavy reliance on fossil fuels [1]. Renewably sourced energy, particularly solar energy, has garnered more attention recently as a potential solution to these problems. Nevertheless, incorporating PV power into the energy mix is severely hampered by the weather patterns' tendency to vary solar power generation [2].

Using machine learning techniques for short-term solar photovoltaic power forecasting is one possible way to overcome this difficulty [3]. Machine-learning algorithms are able to estimate solar power generation with high accuracy up to several hours ahead of time by evaluating past solar and meteorological data. This makes it possible to integrate solar power into the grid more effectively and use energy resources more efficiently.

Many techniques were tried for forecasting solar power output, such as Pearson models, k-nearest neighbored, gradient boosting, and linear regression [4]. The most popular methods for short-term solar power forecasting are ANN [5], and LSTM [6], which can precisely anticipate complex, time-varying, and nonlinear PV output solar power generation. Multilayer perceptron or deep learning techniques like convolutional neural networks (CNNs) and support vector machines (SVMs) with massive datasets and feature selection are used if large area forecasting is required. Depending on the datasets, these can be single- or multivariate. Nevertheless, no single model demonstrates all the details and can be regarded as a reliable forecasting model. Multiple models need to be tested and after thorough validation, more accurate model can be selected.

Data from PV power plants has many features or data variabilities. These variables allow for the consideration of a single approach for the same parameters and feature selection, or the development of a hybrid machine learning method to forecast PV solar output power using alternative concepts. For some data, a single model may be very promising, but it may produce different results for other data. This occurs when a model that calls for long features and data is evaluated using short features and data. The right model selection can help solve this issue. ANNs require different dimensional data than Convolutional Neural Networks (CNNs), which are deep learning models. Thus, the properties and volume of the data determine which model is chosen. Support vector machine (SVM), long short-term memory, and artificial neural network (ANN) models are examined in this paper. The short-term forecasting models, such as ANN and LSTM, demonstrated more accurate and promising forecasting results than the SVM as the collected data falls into the category of short datasets and features.

A model's efficiency is strongly impacted by feature selection. Different feature selection techniques work in different ways. A well-chosen feature selection technique can increase forecasting accuracy, reduce overfitting, and increase processing efficiency. Popular techniques for short-term solar power forecasting include the correlation method and Principal Component Analysis (PCA) [7]. Every feature selection technique is data-dependent. Now that different potential models have been evaluated and compared, a suitable framework is required to identify short-term forecasting of solar PV power generation. A framework of this kind is created in this study by selecting features. With a short datasets and 15-min ahead forecasting, LSTM and ANN showed an excellent result that outperformed the deep learning methods

The following is a list of the contributions made by this work:

1. A suitable framework for various forecasting models of solar power is proposed.

2. A summary of the factors influencing the precision of machine learning-based PV power forecasting is given.

3. Appropriate feature selection criteria are described.

4. Three well-known machine learning algorithm's accuracies are thoroughly compared.

The remainder of the document is arranged as follows. The study model's core idea and relevant flowchart are presented in Section 2, along with implementation strategies. Machine learning strategies for predicting and evaluation metrics with model development are presented in Section 3. The proposed and used machine learning models for short-term forecasting are presented in Section 4. In Section 5, case studies and a comparison study with recently published methodologies are presented. Section 6 includes the conclusion and upcoming projects.

2 Procedure

This section explains the different steps of the suggested model, including the feature and data selection process, framework, and flowchart for choosing machine learning (ML) and deep learning (DL) models.

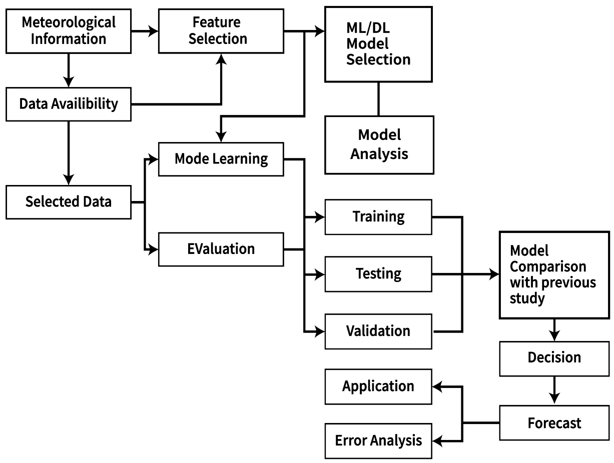

Fig 1. Machine Learning Selection Method Diagram

2.1 Model Building Method

Figure 1 shows the key steps in predicting solar power generation with machine learning algorithms. It includes (i) data collection, (ii) feature selection, (iii) ML model selection, and (iv) performance evaluation. It offers a roadmap for developing methodical forecasting models and enhancing solar power production with accuracy.

Gathering historical weather data is the first step. It consists of sun irradiance, wind speed, temperature, and humidity. Due to their direct impact on solar energy production, these climatic elements are essential for accurate projections. Choosing the dominant features or parameters is another essential stage. This lowers processing requirements, improves model precision, and decreases the dimensionality of the problem. The most significant meteorological factors that have an effect on solar power production are identified as part of the feature selection process. The next stage is to choose the suitable deep learning or machine learning algorithm. Choice of this algorithm depends on the issue at hand, the quantity and caliber of data accessibility, and the degree of accuracy desired. Several deep learning and machine learning methods can be evaluated with relevance. Model study is the final stage where the efficacy of the chosen model is assessed using various metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE).

A training-testing-validation method is used to increase the forecasting model's accuracy. The data is divided into three sections, with 70%, 80%, 10% used for training, 30%, 20%, 10% for testing, and 5%, 10% validation. On the validation set, the model's performance is assessed. If it's not up to par, the model can be updated using different parameters or an alternative approach. The outcomes of the old and new forecasting models are compared in order to determine which is the better model. A systematic method for forecasting solar output is presented in the flowchart in Figure 1, which enables the development of accurate and reliable models for optimizing the generation and distribution of solar power. Through comparison, appropriate models are determined, which can be applicable for the application and the error analysis.

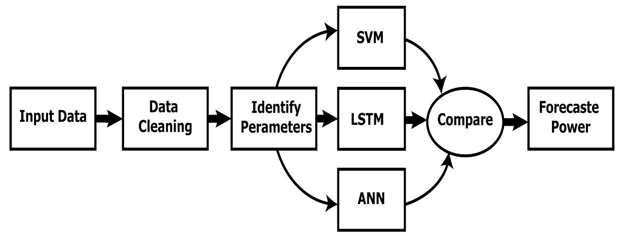

Fig 2. Proposed Method

2.2 The Framework

Figure 2 shows the framework of the proposed method. First the input datasets are cleaned and pre-processed. It is then divided into training, testing with proper regularization and cross validation. Using ANN, LSTM, and SVM to train the datasets. For regularization, the ANN employed the Bayesian technique, the LSTM took the Pearson, and the fine Gaussian for the SVM. During the training stage, the algorithm dynamically learns and adjusts its settings to maximize efficiency. Two hyper-parameters in SVM, ANN, and LSTM are the hidden neuron layer length and the coefficient of regularization term, which are modified based on validation.

The testing is used to assess the trained models. This framework enables the continuous comparison of different machine learning and deep learning strategies, data scaling and feature selection techniques, required for the determination of the most effective strategy.

2.3 The Study Data

This research makes use of Australian meteorological and solar data gathered from Kaggle database, an open-source. It was collected for a period of over one year with 15-minute resolution. There are total 88,494 counts with a total of 20 features including irradiance, temperature, radiation, relative humidity, cloud cover, wind direction, pressure, precipitation, azimuth angle, incidence angle, zenith, and other meteorological factors those affects the performance of PV power generation. The generated PV output power varies from 5-3100 KW. This relatively short dataset is frequently used in academic and research purposes for solar energy forecasting. As part of the preprocessing, the data is closely examined, and any missing data is corrected.

2.4 Feature Selection and Correlation

Feature selection is the process of choosing and modifying the characteristics that are most pertinent to the predicting model. The forecasting algorithm performs better if the characteristics are carefully chosen and transformed. In this work, Principal Component Analysis (PCA) is performed that uses an orthogonal transform to convert a set of possibly correlated variables into linearly uncorrelated variables [8].

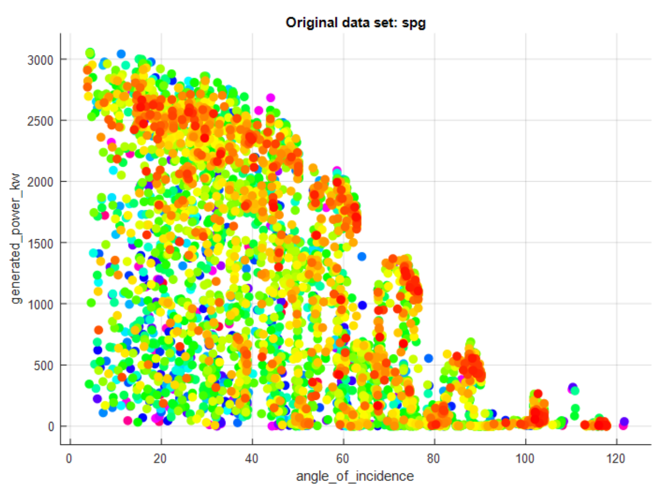

Fig 3. Plot of power generated versus incidence angle

The right choice of pre-processing methods raises the accuracy level, which has a bigger effect on accuracy. And PCA is the most performed methods for solar power forecasting. PCA converts the set of input levels of each output from the variable into a collection of new levels known as principal components (PCs), in order to look into potential methods to minimize the number of inputs. With this configuration, the correlation between the inputs and outputs is chosen, and the data is cleaned. Additionally, each component's amplitude shows how much deviation from the original set it has. The PCs are generated so that they are uncorrelated and are just combinations of the original input levels. This only to take the original component from the dataset and void the null components or reduce the component size of frequency features for the better precision of the results.

A dataset can be transformed into a different dimension using the PCA approach [9]. This transformation is linear in nature and is accomplished via a variety of statistical measurements. Principle components are obtained by computing statistical computational measures such as the standard deviation, covariance matrix, eigen values, and eigen vectors of the data set in a methodical way. Proposed method uses the supervised learning with the back propagation to suppress the unnecessary feature component backed with PCA. This PCA contains the standardization of the datasets, compute the covariance matrixes, singular value decomposition (SVD) Also, in Figure 3, the generated power against the angle of incidence is displayed as a symbol of two features in a single frame along with an initial PCA layout example. The measures' magnitudes are indicated by colored dot bars.

These color bars showed the incidence according to the output of the PV as generated. Other features also been considered to provide the best use of the system.

2.5 Training and Testing of Datasets

Training and testing for forecasting are shown step-by-step in Figure 4. This case skips validation, but it is taken into account in the main model. For the ANN, LSTM, and SVM models, here, 70%, 80%, and 10% of the data are set aside for training and 30%, 20%, and 10% for testing each. For the model, 10-15% validation was conducted.

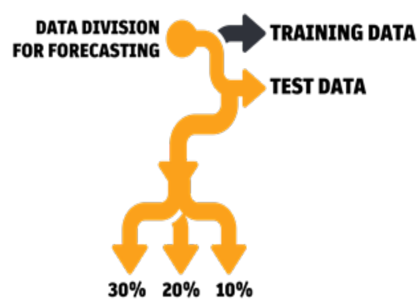

Fig 4. Diagram for model training and testing

3 Forecasting and Model Development Issues

This section describes the model development problem in forecasting.

3.1 Obtained model development issues

In machine learning, model development depends on input and output parameters. Thus it is very much subjective to the problem in hand. So one model will not fit for all. Among the dominant factors affecting accurate prediction of solar power forecasting are:

1. Weather variables: For accurate predictions of solar output power temperature, humidity and cloud cover are important.
2. Solar irradiance: Accurate measurement and forecasting of solar irradiance are essential for predicting solar output power.
3. Historical data: Historical solar output power data are required to train and validate forecasting models.
4. Benchmarking against less capable models.
5. Performance metrics: Different performance metrics are used to evaluate the accuracy of the solar output power forecasting models.

3.2 Model Development for PV Systems

Careful data collection, pre-processing, feature selection, and model development are necessary when building a PV system model for solar output power projection using machine learning approaches. The forecasts' accuracy can be increased by periodically feeding the models with real-time data and evaluating how well they perform. Testing and training the system continuously until the intended result is achieved. Table 1 displays the input combinations used in the creation of the PV system model. On occasion, it could produce corrosive results. This article sets the required scheme for the PV system window to execute.

Table 1. Input features for PV forecast model development

Feature type	Input feature
Climatic feature	Cloud cover, power, temperature, humidity, wind direction, speed, and air pressure, among other factors.
Window type	15-min resolution Window Size.
Output	PV Power (KW)

3.3 Model Evaluation Metrics

As mentioned earlier, the efficacy of the chosen model is assessed using various metrics, including Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE).
These can be described through mathematical equations (1 - 4).

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|M_j - t_j\right| \tag{1}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|M_j - t_j\right|}{M_j} \times 100\% \tag{2}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(M_j - t_j\right)^2 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(M_j - t_j\right)^2} \tag{4}$$

where N is the number of time series point, i is the i^{th} element of the projected power of M_j and measured power t_j output values.
MAE measures the average absolute difference between the predicted and actual values. It's commonly used in regression tasks and provides an intuitive understanding of the average prediction error.
MAPE measures the average percentage difference between the predicted and actual values. It's commonly used in forecasting tasks and provides a measure of the relative accuracy of predictions.
MSE measures the average squared difference between predicted and actual value. It penalizes larger errors more heavily than smaller errors, making it sensitive to outliers.
RMSE is the square root of MSE and represents the standard deviation of the prediction errors. It's often used in regression tasks and provides a measure of the average magnitude of errors in the same units as the target variable.
The forecasting model's objectives and the particular application determine which assessment metrics should be used. It is recommended to use a variety of evaluation measures to obtain a thorough assessment of the model's success.
Overall, RMSE and MSE provide a simple yet effective way to assess the accuracy of regression models, making them popular choices in machine learning. This choice stems from their combination of mathematical properties, interpretability, and widespread adoption in the field. Both metrics have a clear statistical interpretation that

lends credibility to the assessment of model accuracy. Models with lower RMSE or MSE values are generally considered better at predicting the target variable.
Other metrics such as the linear connection between the expected and real numbers is measured by the correlation coefficient (CC), ranging between -1 and 1, with 1 denoting a perfect positive correlation, -1 a perfect negative correlation, and 0 denoting no correlation at all. In many ML/DL uses the volume and organization of the training data which have a greater impact on accuracy than the model's design. Modern machine learning-based techniques frequently have millions of matched parameters, making them adequately flexible. Finding the appropriate material with the primitive purpose to teach them is essential. In this study, short parameter datasets are taken into consideration and tried to obtain the best output with adequate research.
The raw data were normalized from 0 to 1 using the equation 5:

$$x_{tr} = \frac{x_{te} - x_{min}}{x_{max} - x_{min}} \tag{5}$$

where, x_{tr} and x_{te} are the training, and testing data, respectively, x_{max}, and $x_{min}$are the maximum and minimum number of testing and training, respectively.

4 Machine Learning Common Models

For design purposes, several machine learning models, including ANN, LSTM, and SVM are considered in this section. The basics of each model are described below.

4.1 Artificial Neural Network (ANN) models

ANN is a powerful computing tool for difficult tasks, as it exhibits adaptive behavior for complicated and noisy information. It is capable of handling nonlinear connections. The working diagram of an ANN is shown in Figure 5.
The basic input/output diagram of an ANN is shown in Figure 6. Parameters and hyper-parameters affecting the performance of ANN include: batch size, learning rate, biases, weights, and other factors. The weight of each node in the ANN are updated as the learning stage progresses. Node layers in ANNs consist of input layer with elements $a_1, a_2, \ldots a_n$; one or more hidden layers; and an output layer. Each node, or artificial neuron, is interconnected to the other with weights $\omega_1, \omega_2, \ldots \omega_n$ and bias. The output of a node is enabled and information is delivered to the network's upper tier when it reaches a certain bias. If this isn't the case, then no data is sent to the network's next layer.

Table 2. ANN Parameters [10]

Data					No. of Observation	MSE	R
Predictors	Responses	Algorithm type	Layer size	Training	2949	0.0053	1
4213	Power in KW	Levenberg-Marquardt	30	Validation	843	0.0248	1
				Test	421	0.0138	1
				Epoch	1000(Best in 43)		
				Optimizer	Adam		

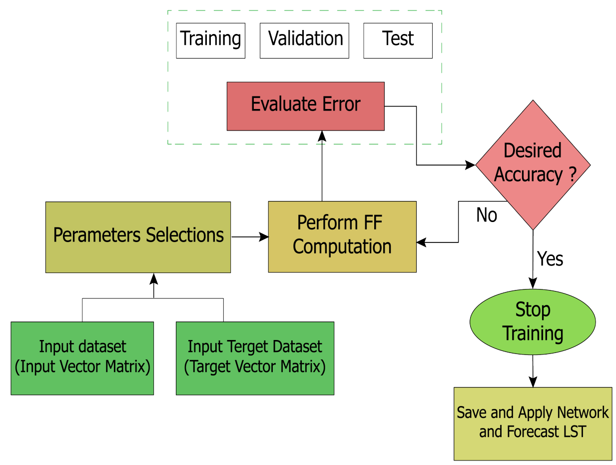

Fig 5. Artificial neural network working diagram

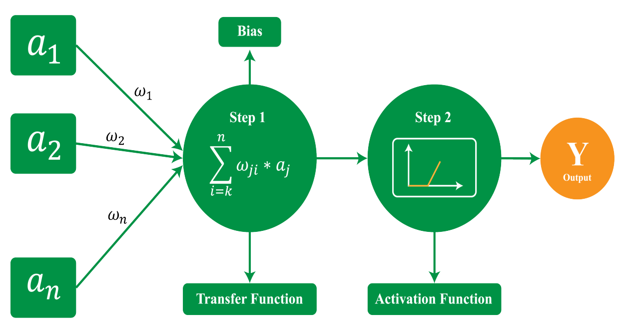

Fig 6. Basic ANN diagram with Activation factor

The algorithm modifies the weights of the hidden and output nodes when the output approaches the true data within the parameters of the given threshold [11]. The input-output relation is defined by equation 6.

$$Y = g(\sum_{I=0}^{n} w_{JI} * aJ) \tag{6}$$

where Y and aJ are the output and input of the neuron, respectively, and w_{JI} is the weight connecting the Jth and Ith neuron. This suggested model makes use of the multilayer perceptron and Adam optimizer. The hidden and output layers use a sigmoid (σ) activation function. In Table 2, every pertinent ANN parameter is displayed.

4.2 Long Short-term Memory (LSTM)

A Recurrent neural networks (RNNs) variant LSTM is commonly employed for forecasting time-series data, particularly solar power forecasting [12], [13]. Because LSTMs can keep past data in memory, they are particularly well adapted for this task, which allows them to predict future values in time-series data. Seasonality, historical solar power output, weather patterns, and other factors are only a few of the elements that LSTMs take into account when estimating future solar power generation.

Numerous applications, including grid management, energy trading, and the design of renewable energy sources, can make use of these projections. Organizations may maximize their use of solar energy and make better energy-use decisions by utilizing the potential of LSTM.

4.2.1 LSTM models

The LSTM is comprised of many cells stacked both horizontally and vertically. A structure of each cell is shown in Figure 7.

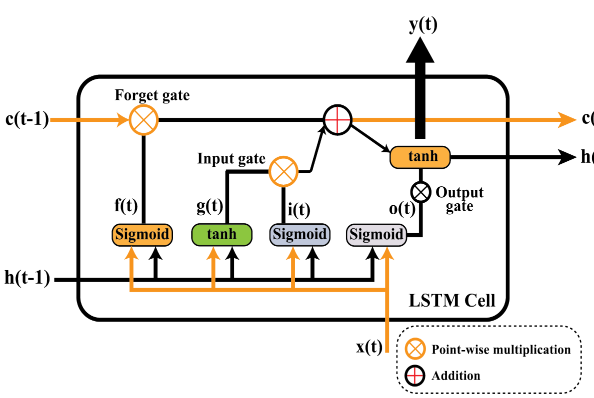

Fig 7. LSTM diagram with the activation function

4.2.2 LSTM Operation

LSTM cell operations are governed by the following equations [14]:

$$i_t = \sigma(x_t W_{xi} + h_{t-1} W_{hi} + b_i) \tag{7}$$

$$f_t = \sigma(x_t W_{xf} + h_{t-1} W_{hf} + b_f) \tag{8}$$

$$o_t = \sigma(x_t W_{xo} + h_{t-1} W_{ho} + b_o) \tag{9}$$

$$\tilde{c}_t = tanh(x_t W_{xc} + h_{t-1} W_{hc} + b_c) \tag{10}$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{c}_t \tag{11}$$

$$h_t = o_t \otimes \tanh(c_t) \tag{12}$$

Table 3. Parameters of LSTM Model [15]

PARAMETERS	VALUE
No. of layers	2
Initial learning rate	0.005
Type of Loss function	Cross-entropy
Hidden unit size	200
Optimizer	Adam
Drop factor	0.2
Training epoch size	250

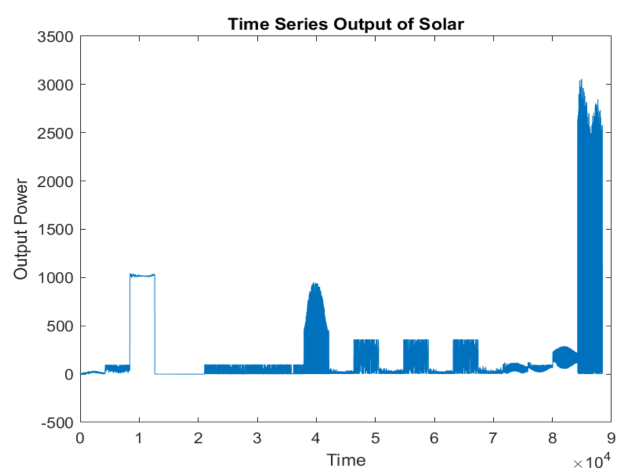

Fig 8. Time Series Output Data for LSTM method

Various weights $(W_{xi},\ W_{xf}, W_{xo}, W_{hi}, W_{hf}, W_{ho})$ and bias parameters $(b_i, b_f, b_o,\ b_c)$of the entire networks are tuned dynamically by the learning algorithm. The LSTM network is trained by providing it with a time-series data $x(t)$. Two activation functions $(i) sigmoid \sigma(x) = (1 + e^{-x})^{-1}$ and $(ii) tanh$, operating on it produce different states of internal nodes - input gate (i_t), forget gate

(f_t) output gate (o_t), input node $(\tilde{c}_t)$. These temporary states interacts each other and produces other two states c_t and h_t those can capture the time dynamics of the data. Finally, the model outputs the same time-series $x\,(t+T)$ but at a later time, where T is the forecast horizon. i.e.

$$x(t+T) = \mathcal{L}_t\,(x\,(t)) \tag{13}$$

The activation function determines whether a neuron should be stimulated or not, and adds non-linearity to the network.

Other essential parameters are shown in the Table 3. Typical output of the LSTM with time-series data weather data is shown in Figure 8.

4.3 Support Vector Machine (SVM)

Support vector machines are a type of supervised learning technique basically used for regression and classification issues. SVM also widely used in PV power forecasting. Depending on historical data and a host of other pertinent factors, it can be used to predict future solar power generation.

4.3.1 SVM Model

Figure 9 shows the basic architecture of SVM, where $x_1,\ x_2, \ldots . x_n$ represent the input variables for the support vector machine, $K(x, x_1), K(x, x_2), \ldots K(x, x_n)$represents the kernel function, $\omega_1,\ \omega_2,\ \ldots .\omega_n$ is the weights, and B is the threshold or the bias.

In a nonlinear regression method like SVM, a nonlinear mapping of the input time series data samples into a wider function space, which is followed by the execution of a linear regression in this space.

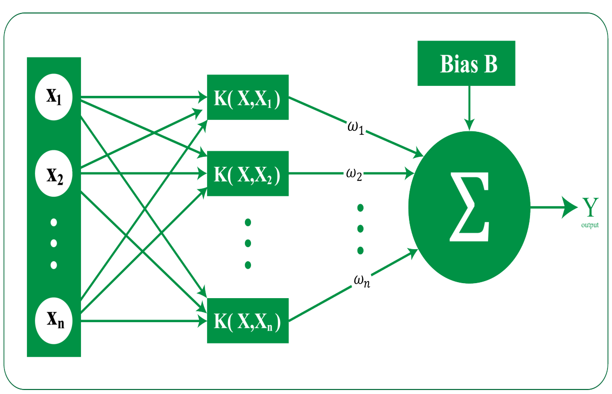

Fig 9. Basic SVM architecture diagram

It considers the $(x_i,\ y_i)_{i=1}^{N}$ training set where $x_i \in\ R^n$ is the input vector and an associated output value is $y_i \in\ R^n$ [16] A generalized form of output equation is given by 14 [17].

$$Y = f\,(x) = \omega \times \varphi\,(x) + B \tag{14}$$

where, $\varphi(x)$ is the feature inputs of x, and $\omega \in R^n$ is a weight vector, and B is bias. This can be reformulated as equation 15.

$$R\,(c) = c\frac{1}{n}\sum_{i=1}^{n} L\,(d_i y_i) + \frac{1}{2}||\omega||^2 \tag{15}$$

Here, c is the variable error, n is the observation number, d_i is the chosen value, and $c\frac{1}{n}\sum_{i=1}^{n} L\,(d_i, y_i)$ is the experimental error for the function $f(x)$, and $\frac{1}{2}||\omega||^2$ is the regularization value [17].

Table 4. Parameters of SVM [18]

PARAMETERS	VALUE
No. of feature	20
Initial learning rate	0.005
Cross validation	5%
Kernel function	Gaussian
Best perform	Fine Gaussian
Kernel scale	1.1
Epsilon	Automatic
Data dimension	4213
Power	KW

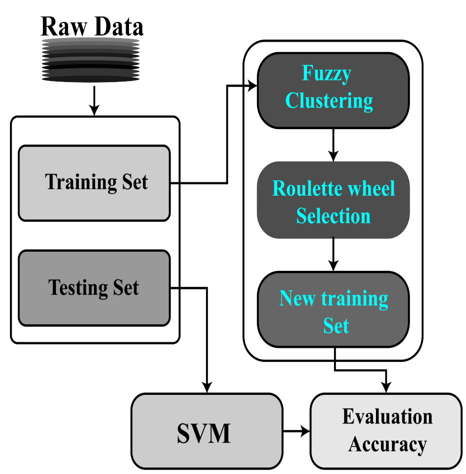

Fig 10. SVM working diagram

4.3.2 SVM working diagram

Figure 10 shows the working diagram used in this study. Unlike previous other complex ML models used for short-

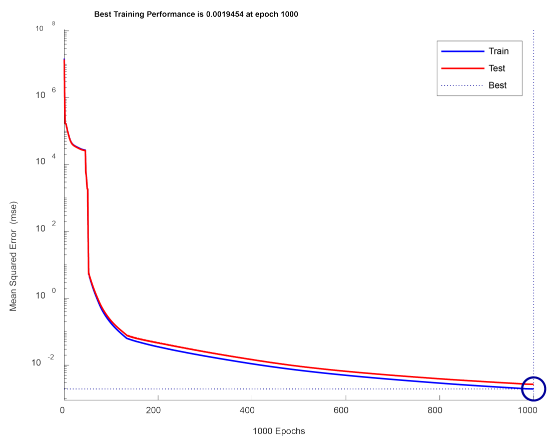

Fig 11. ANN without validation at 1000 epoch

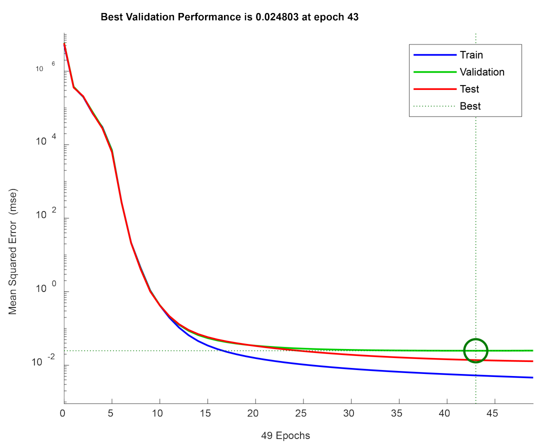

Fig 12. ANN with validation

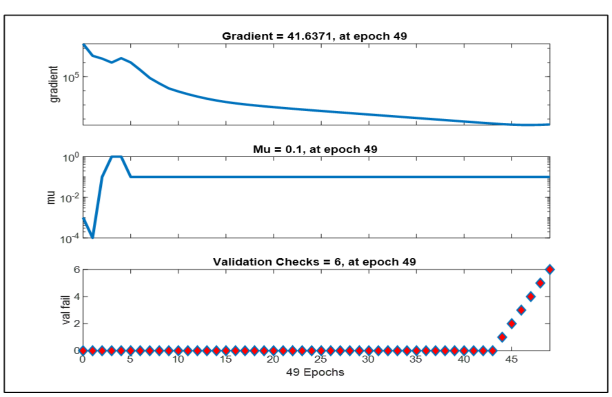

Fig 13. Training Status of ANN

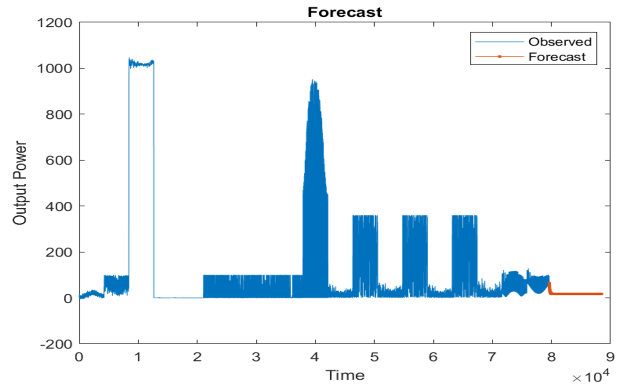

Fig 14. LSTM output data

term PV power prediction, SVM model here acts as a supporting comparison model. Machine learning model selection for forecasting can have some limitations relating the nature of data. Table 4 shows working parameters used in this study with SVM. As the implementation of SVM is the direct technique computing of kernel function, the main procedure is Identifying the best division hyperplane that optimizes the distance between the points of each category by mapping learning points by a non-linear function to a large-dimensional space in which the points are linearly divided. In addition, Table 4 represents the state parameters that are required to obtain the RMSE as referred in the model evaluation metrices section as in the earlier mentioned LSTM and ANN method. Activation functions are not used in SVM. The hyperplane that maximizes the margin between the classes is found in SVMs in order to establish the decision boundary. SVM is renowned for its flexibility and capacity to handle non-linear data connections when compared to ANNs and LSTMs. But failed to handle time series linear data. This could be problematic for solar power forecasting as weather patterns and other relevant factors can have long-term impact on solar power generation. SVM can handle high-dimensional data, which is helpful for solar power forecasting since a variety of variables, including the weather and previous production data, which might affect the prediction.
Finally, even though support vector machines (SVM) are strong algorithms with their own advantages and disadvantages, the best technique to utilize for PV power prediction ultimately depends on the data being used.

5 Case Studies and Simulation Results

The simulation was performed on Core-i51035G1 @1.19GHz, with 24GB RAM. MATLAB 2022a was used to run all the required simulations. Even though the datasets used for

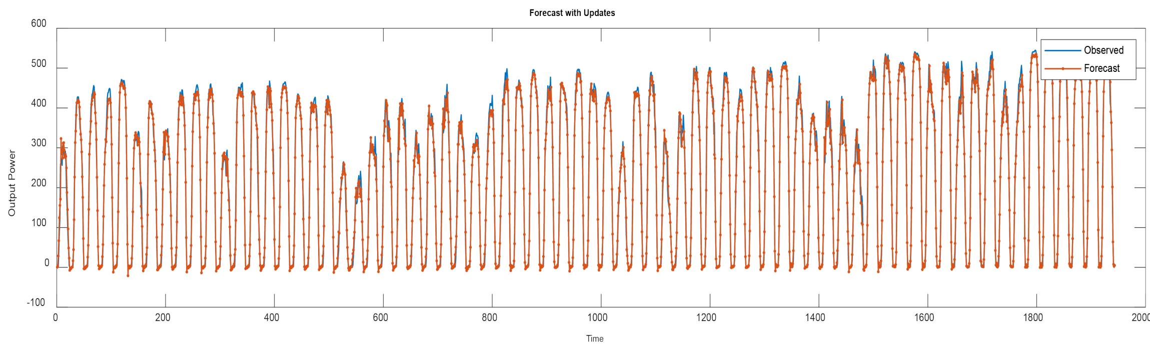

Fig 15. with 30 % test data

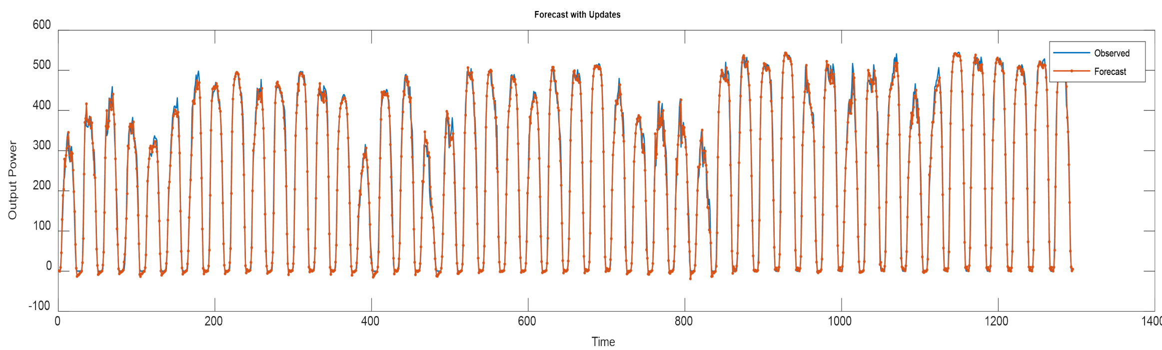

Fig 16. with 20 % test data

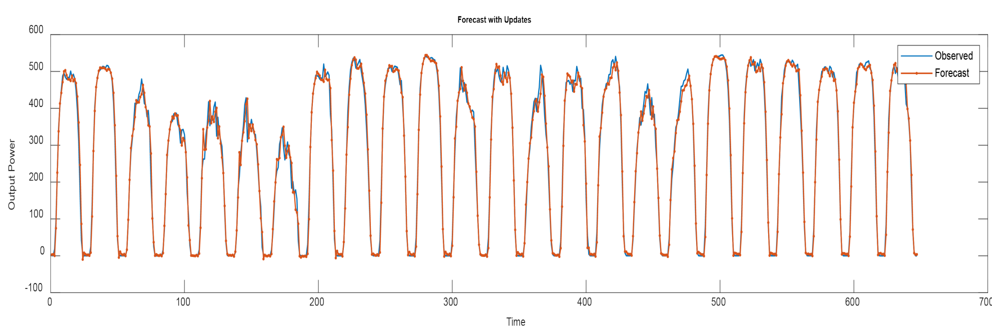

Fig 17. with 10 % test data

training, validation, and testing are the same, each example displays unique findings. Azimuth angle, incidence angle, zenith, temperature, radiation, irradiance, humidity, wind direction, pressure, cloud cover, SFC precipitation, generated power in KW, and meteorological factors are all taken into consideration. Artificial Neural Networks (ANN) are the first case scenario, followed by Long Short-Term Memory (LSTM). The training duration was 5 min 23 sec (approx.), and whole computational cost was around 12 min. These two models showed considerable root mean square error (MSE). Together, they can accurately forecast the solar PV power generation. Next, the effectiveness of Support Vector Machine (SVM) in handling small datasets within a regression context was tested. Unfortunately, it

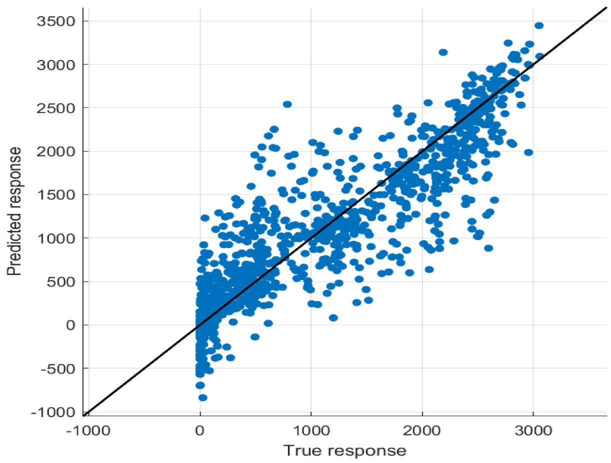

Fig 18. Support Vector Machine Linear Responses

was unable to demonstrate accuracy matching with the two other models that were run.

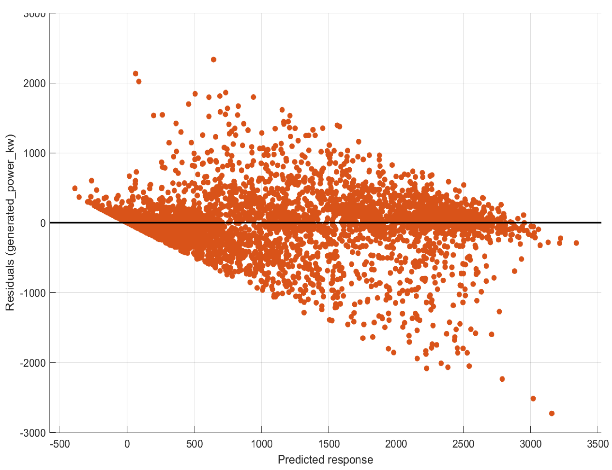

Fig 19. SVM Fine Gaussian residual diagram

5.1 Case #1 : Artificial Neural Network

In this case the ANN model observations presented where coefficient, maximum iterations, regularization, hidden layer size are tuned accordingly and evaluated. Figure 11 shows the prediction without validation where MSE is 0.0019%.
The same ANN model performed much better while equipped with Adam optimizer and Levenberg Marquardt regularization algorithm. It produces MSE of 0.024803% at 43 epochs instead of 1000 as shown in Figure 12. This low MSE suggests that the model can accurately predict the solar power output for the validation data.
Figure 13 presents the training status of ANN which shows at epoch 49 of the training stage the gradient is where Mu = 0.1 indicates that a relatively low momentum value was used. This may slow down the convergence of the training process but can help prevent the model from getting stuck in a local minimum. The valid failure 6 indicates that the validation error did not improve for 6 consecutive epochs. This suggests that the model is overfitting to the training set and has hit its performance limit.

5.2 Case #2 : Long Short-Term Memory

The Adam optimizer with tanh, sigmoid activation function was taken into consideration when the LSTM model was running. Table 3 shows that there were 200 hidden units and that the testing and training epochs were both 250. The study was conducted using the same criteria in order to ensure a genuine comparison. The output for the LSTM along with the forecast is seen in Figure 14. The goal of the procedure was to train the system to provide better outcomes. In order to get more precise results that may be correlated, the system was evaluated after being trained for multiple rounds.
Figures 15, 16, 17 show the training part of the LSTM models where 30% test shows the RMSE=3.48%, 20% test shows the RMSE = 5.54% and last 10% test shows the RMSE=0.27%. The 3rd round training result as shown in Figure 17 shows is quite promising. To maintain a similarity with the whole work, after evaluation of this model, three steps of training and testing was performed. And 10% test results are shown in this section.

5.3 Case #3 : Support Vector Machine (SVM)

Solar output power was predicted using an complex Gaussian regression model in the SVM simulation. Using the same data as used for the other two models, and going through same modeling building, training, and testing processes, SVM produced an RMSE of 136%. The high values of RMSE could be attributed to lower datasets and the result is consistent with the one reported in [19]. The model was trained using a box constraint, an automatic epsilon, and a kernel scale of 1.1. With 5% of the data, a cross-validation was carried out to evaluate the model's performance and prevent overfitting. Even though the RMSE was high, the SVM model with a fine Gaussian regression performed well overall in predicting solar output power. There may need to be more model parameter adjustment in order to improve the forecasts' accuracy.
Figure 18 shows the observations as a blue dot and the predicted response as a black dot based on all of the data.

Orange dot in Figure 19 indicates the generated power in KW, whereas the black dots indicate the predicted responses. A residual fine gaussian validation result and the linear responses of the SVM in Figure 18 are shown in Figure 10 to negate the assertion that a complex model such as the support vector machine could not achieve better accuracy than the ANN, LSTM, or other short-term techniques.

Table 5. Reference and Proposed Forecast

Published Ref.	Year	Method used	Accuracy (Average Value)
[20]	2017	SVM	RMSE: 3.08%
[21]	2017	ANN	MAPE: 46.3%
[22]	2019	LSTM	RMSE: 1.816%
[19]	2019	CNN SVM LSTM	RMSE: 163.15% RMSE: 167.52% RMSE: 164.19%
[23]	2020	LSTM	RMSE: 1.0382%
[24]	2021	LSTM	RMSE: 9.81%
Proposed Method			LSTM (RMSE): 0.27%
			ANN (MSE): 0.248%
			SVM (RMSE): 136%

5.4 Comparison with Published Results

The contribution of the proposed approach is evaluated through a comparative analysis among similar works reported in the recent past. The comparison is based on the performance of different parameters as shown in Table 5.

Regression-based model SVM examined in [20] where RMSE obtained was 3.08%. But in this study the obtained RMSE was 136% which is attributed to the low dataset value. Another low data-set based study in [19] produces 163.15% of RMSE with CNN, 167.52% with SVM, and 164.19% with LSTM respectively. ANN is used to forecast solar power in [21] obtained MAPE was 46.3%. More recently LSTM was used in [23], [24] and produced forecasting accuracy was 1.038% and 9.81% RMSE respectively. Now with the proposed methods shown in this paper, the short-term forecasting result produced 0.27% of RMSE with LSTM and 0.24% MSE with ANN which is more accurate and easier to forecast short-term solar power output. And like complex SVM machine learning models can be avoided for the short-term forecasting setup.

6 Conclusion

For the solar power forecast, three machine learning models — ANN, LSTM, and SVM—are investigated. The study's findings demonstrate how important it is to select an algorithm using 15-minute interval data for short-term solar PV power output forecasts.

Based on the study's analysis, it can be concluded that ANNs and LSTM networks are more appropriate than SVMs for short-term solar power forecasting. The effectiveness of ANNs and LSTMs can be attributed to their capacity to represent the complex and non-linear correlations found in the data, accounting for variables like temperature, humidity, irradiance and radiance, and historical data. The hidden layers in ANNs and the cell state in LSTMs act as a 'memory' of previous computations, which contributes to their ability to recognize patterns over time and space. Thus, both ANNs and LSTMs can adapt their weights during training through backpropagation, which allows them to fine-tune their understanding of the data patterns. SVMs, on the other hand, may find it difficult to handle the complexity of short-term solar power forecasts, as they are more suited to managing linear correlations. SVM is a type of machine learning technique that uses a hyperplane to split data points into many classes. In the forecasting of solar power, SVMs might be unable to capture the non-linear relationships between the input variables and output power, which could result in inaccurate forecasts. This is a serious shortcoming for SVMs in this situation because precise scheduling and grid management depend on it.

Finally, for short-term solar power forecasting in an acceptable range, ANNs and LSTMs provide a reliable and adaptable solution. These results can help engineers and researchers choose the best optimizer, forecasting structure, and short-term forecasting method for a range of application scenarios, including solar and wind.

In the future, large data can be used to investigate deep learning techniques like SVM for long-term forecasting.

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