

Hourly Solar Generation Forecasting With Feedforward Neural Networks

Tharaka Diddugoda
Department of Electrical Engineering
University of Moratuwa
Email: tharakadg.21@uom.lk

Samuditha Hettiarachchi
Department of Electrical Engineering
University of Moratuwa
Email: hettiarachchisl.21@uom.lk

Abstract—Solar PV is one of the fastest growing renewable energy sources. Solar power generation is highly variable due to the varying solar irradiance, cloud cover and due to other meteorological conditions. Therefore, solar power forecasting is one of the most critical challenges in modern renewable energy systems. Accurate forecasting can reduce uncertainty and supports efficient grid operation. This study presents a feedforward neural network-based approach for next hour solar power generation forecasting. The proposed solar power predictive model is developed utilizing historical data including temperature, cloud cover, shortwave radiation, diffuse radiation and direct nominal irradiance. The model is evaluated using several test matrices such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), coefficient of determination (R^2 score) and Mean Absolute Error (MAE). The results obtained by our study shows that feedforward neural network approach can predict solar PV power output with high accuracy which is above 97%.

I. INTRODUCTION

The global transition towards the renewable energy sources has increased in recent years and mainly solar photovoltaic (PV) system installations shows major growth. Solar energy capacity is expected to be triple as now by 2030 to meet global decarbonization targets. However, this rapid expansion introduces significant challenges to grid due to intermittency of solar generation.

Solar power output shows fluctuations throughout the day due to varying weather conditions such as irradiation, temperature and cloud cover. These variations lead to varying solar power output and results in grid instability. Since these variations occur across multiple temporal scales (from minutes to hours and days), it makes accurate forecasting difficult for traditional statistical methods as they struggle to capture complex, non-linear relationships between weather variables and solar PV output. In recent years, machine learning techniques, particularly neural networks is being using for accurate forecasting as they learn complex patterns more effectively.

This study includes the use of feedforward neural networks for short-term solar PV power output forecasting. The proposed approach uses historical weather data and solar power generation to learn underlying relationships which influence the solar power generation.

As renewable energy penetration increases, accurate forecasting becomes critical and this feedforward neural network-based forecasting model is providing reliable and efficient

information for grid stability and load balancing, economic scheduling of generating units and reducing dependency on fossil fuel backup reserves.

II. RELATED WORKS

Solar PV power forecasting initially relied on traditional statistical techniques such as support vector machines (SVM) and autoregressive integrated moving average (ARIMA) [1,4]. Because they needed low computational power. Despite their practical capability, these techniques struggled to handle non-linear behavior and time dependent nature of weather data.

This gave a motivation to use data-driven learning frameworks, particularly neural network models. Because they are capable of identifying complex relationships directly from historical data using the backpropagation algorithms [2,3,4].

Most recent studies have used different neural network methods for solar power forecasting. Among those, Feedforward neural networks (FNN) have been widely used for short-term forecasting and shows better performance compared to traditional methods [4]. In study [5], multiple methods were evaluated for power generation forecasting in grid-connected PV plants, and the FNN achieved relatively higher prediction accuracy than the other approaches.

Recurrent neural networks (RNN) and long short-term memory (LSTM) architectures [6] are designed for sequential data modelling and it makes them suitable for learning time dependant variations in weather conditions and solar power production. Therefore, they can be used to capture time related patterns in weather data and solar power output more effectively. Additionally, hybrid approaches which combined different neural network architectures such as convolutional neural networks (CNN) with LSTM networks or CNN with gated recurrent unit (GRU), have been used to enhance performance. However, these methods require large datasets, high computational resources and complex training process.

In our study, we used feedforward neural networks because of its simplicity and effectiveness in capturing non-linear complex patterns when forecasting solar power output.

III. SYSTEM DESIGN

A. Dataset Analysis

1) *Dataset Overview*: The dataset consist of approximately 70,000 hourly records of solar power generation and corre-

sponding meteorological data. To ensure robust model development and evaluation, the dataset was divided into three categories as follows:

- Training set: first 80% of the data
- Validation set: next 10% of the data
- Testing set: final 10% of the data

2) *Feature Analysis*: An exploratory data analysis (EDA) was conducted to examine the relationships among the input features and target variable. Fig. 1 illustrates a correlation heatmap showing the correlations between solar PV output and meteorological parameters.

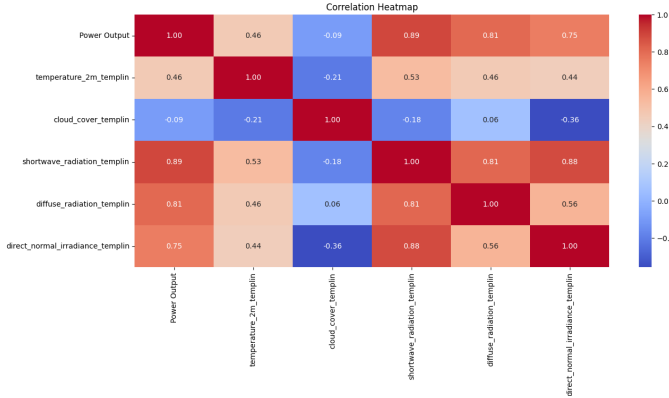


Fig. 1: Correlation heatmap showing relationships between solar PV power output and meteorological features.

B. Data Preprocessing and Preparation

Data preprocessing steps were applied to handle missing data and remove outliers before feeding data into the neural network.

Missing values were filled using median imputation. For each feature, the median is calculated from the training dataset and used to replace missing values in the training, validation, and test sets. This method is less sensitive to unusual values and helps keep the data pattern realistic.

C. Feature Engineering

Feature engineering is used to improve the forecasting performance of our feedforward neural network (FNN). Since FNNs do not have built-in memory to capture time dependencies, creating additional input features such as time-based variables (hour, day, month), cyclical encodings to represent daily and seasonal cycles, lag features that provide past power values, and rolling statistics to capture short-term trends and variability is important. These engineered features help the model understand temporal patterns and seasonal effects by making time-series behaviors clearer and improving prediction accuracy.

1) Temporal Feature Engineering:

a) *Cyclic Encoding*: Cyclic encoding was used to map time and date variables onto a circular representation where the start and end points connect smoothly. By having cyclic encoding, model can smoothly understand transition in time. They are computed as:

$$\sin_component = \sin\left(2\pi \frac{\text{value}}{\text{period}}\right) \quad (1)$$

$$\cos_component = \cos\left(2\pi \frac{\text{value}}{\text{period}}\right) \quad (2)$$

where

- value = current time value
- period = length of the cycle

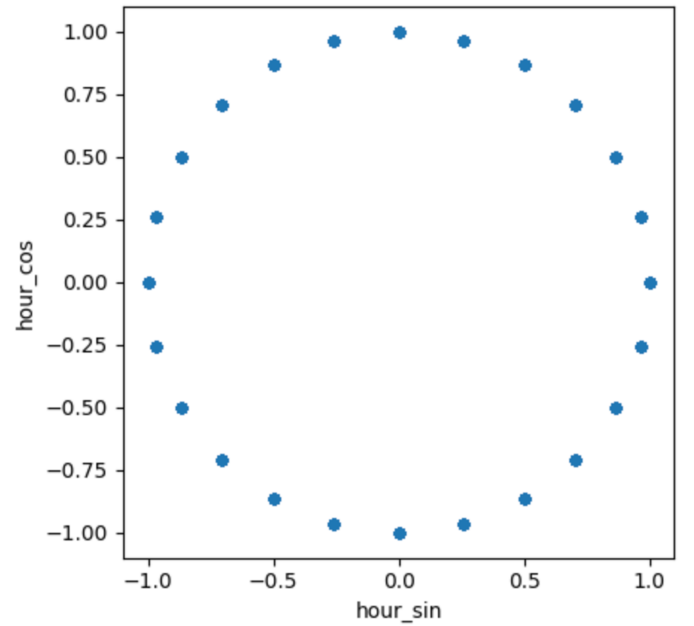


Fig. 2: Circular representation of time variables using cyclic encoding

b) *Solar-Specific Sine Curve*: The solar-specific sine curve shows how solar irradiance changes throughout the day. It creates a bell-shaped curve that shows peaks at noon when maximum solar intensity is available, drops to zero at sunrise or sunset and stays zero during the nighttime hours.

This helps the neural network learn that solar power generation follows a predictable daily pattern, rather than just using raw hour values.

The daily sunlight pattern is modeled as:

$$\text{solar_hour} = \begin{cases} \sin\left(\pi \frac{\text{hour}-6}{12}\right), & 6 \leq \text{hour} \leq 18 \\ 0, & \text{otherwise (night hours)} \end{cases} \quad (3)$$

Characteristics:

- Zero at sunrise (6 AM) and sunset (6 PM)
- Peaks at solar noon (12 PM)

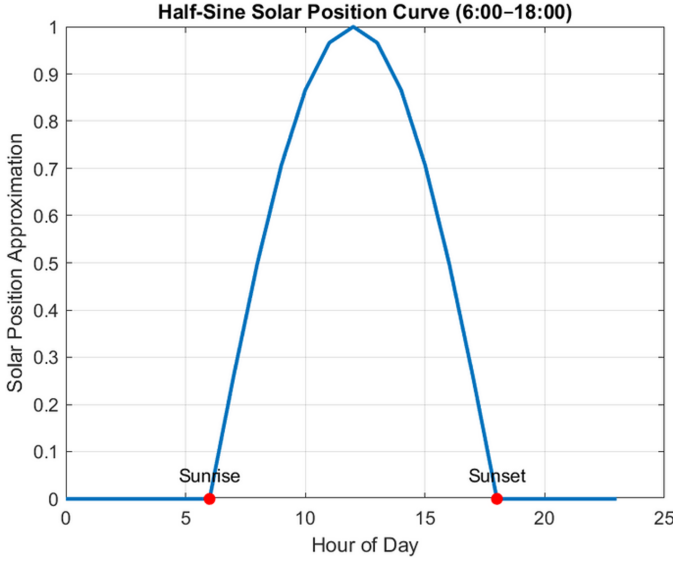


Fig. 3: Daily solar irradiance pattern modeled as a sine curve between 6 AM and 6 PM

2) Historical Memory Features Engineering:

In historical feature engineering part mainly lags, rolling features and exponential moving average(EMA) are created. A lag feature represents the previous value of the target variable, and it allows the model to recall past information. This feedforward neural network creates 72 lag features. Hence this model uses past three days solar power output when it forecasts the next hour solar power output. Rolling features are also created by using the past solar power output data. This helps model to understand the recent behavior of solar power output with environmental conditions. Rolling features are the values calculated over a moving time window that summarize recent data and helps the model to capture short-term trends and patterns. Mainly rolling average, minimum, maximum and the median are calculated, and these features help feed forward neural network to make better predictions by adding the recent trend information.

Exponential moving average (EMA) is a method that we used to smooth out the time series data by giving more weight to recent values and the less importance to the older values. Different smoothing factors ($\alpha = 0.1, 0.3, \text{ and } 0.5$) are used to help the feedforward neural network to capture recent trends in solar power output in a smooth and stable manner.

$$\text{EMA}_t = \alpha x_t + (1 - \alpha)\text{EMA}_{t-1} \quad (4)$$

- x_t is the value at time t
- α is the smoothing factor ($0 < \alpha < 1$)
- EMA_{t-1} is the EMA at the previous time step

D. Neural Network Architecture Design

In this study, feedforward neural network (FNN) is used as the solar power prediction model due to its relative simplicity and ability to model complex non-linear relationships between input features and solar power output.

This Feedforward Neural Network consists with one input layer, six hidden layers, and an output layer. In here all layers are dense layers except the input layer. Dense layer means, every neuron of the layer connect with every neuron in the previous layer. The input layer consists of 137 input features consisting of weather data, time information, and additional engineering features. The output layer consists of a single neuron because it only provides the solar energy output. But the hidden layers consist of several neurons. Number of neurons and the drop out rates of each hidden layer as follows,

Hidden Layer	Number of Neurons	Dropout Rate
1st hidden layer	1024	0.30
2nd hidden layer	514	0.25
3rd hidden layer	256	0.20
4th hidden layer	128	0.15
5th hidden layer	64	0.10
6th hidden layer	32	0.05

Table 1: Hidden layer configuration and corresponding dropout rates

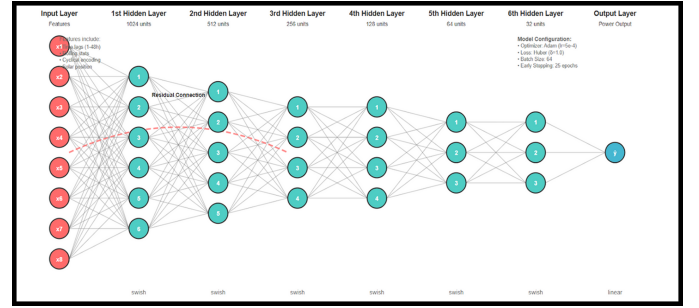


Fig. 4: FNN Model Architecture

The Swish activation function is used for all hidden layers to capture non-linear relationships between solar power generation data. A residual connection is added at the 3rd hidden layer to enhance training stability. The main path processes features through 1st, 2nd and 3rd layer with Swish activation, while a skip connection makes connection between input layer and third layer directly and it use linear activation function.

E. Training Process

In the training processes 150 epochs are used, which means the number of times the model goes through the entire training dataset to learn patterns. At the each epoch, model was trained by using the Mean Absolute Error(MAE) and the Root Mean Squared Error (RMSE). In training Adam optimizer is used to update the weights and the Huber function is used as loss function.

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i|$$

$$\text{Mean Squared Error (MSE)} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\text{MSE}}$$

- n = number of data samples
- Y_i = actual value of the i^{th} observation
- \hat{Y}_i = predicted value of the i^{th} observation

The Mean Absolute Error is used to measure the average difference between predicted solar power and actual value of solar power output. Root Mean Square Error is used to measure the square root of the mean square error of solar power output. Neural network predicts solar power output more accurately when the RMSE and MAE errors getting lower values. During the training process data is given to the model as batches. In there each batch size is 64. Initial learning rate of the model is 0.0005. The “seed” hyperparameter of this feed forward neural network model is equal to 42, and the patience is equal to 25. Patience refers to the number of consecutive epochs with no improvement after which the training process is terminated. In this model, training is stopped if the monitored performance metric does not improve for 25 consecutive epochs.

Mean Absolute Error (MAE), Mean Squared Error (MSE), Coefficient of Determination (R^2), and the Root Mean Squared Error (RMSE) are used as evaluation metrics in the model testing. R^2 is used to measure how well neural network’s predictions explain the variance with the actual data. R^2 value varies between 0 and 1 and if the R^2 value closer to the 1, it indicates that model accuracy is better. Model accuracy is considered as low when R^2 value closer to the 0.

IV. RESULTS AND DISCUSSION

The obtained results from the FNN model indicate a high predictive capability, with an R^2 value of 0.999166 for the primary test dataset. This implies that 99.91% of the variance in the power output is explained by the model and demonstrates a strong correlation between the predicted and actual values.

The MAE and RMSE values are 697.803 and 1225.925 respectively and it indicates relatively low values compared to the test data. The MAE and RMSE correspond to 2.3256% and 4.0857%, respectively when expressed as percentages relative to the mean power output. These low normalized error values imply that the model shows good accuracy. The normalized MSE value of 0.055606% indicates the model’s ability to minimize large prediction errors.

```
===== TEST METRICS (Target: Power Output) =====
R2      : 0.999166
MSE      : 1502893.125000
RMSE     : 1225.925416
MAE      : 697.803162

----- Percentage (normalized) -----
MAE%     : 2.325644% (denom = mean(|Power Output|) = 30004.730469)
RMSE%    : 4.085774% (denom = mean(|Power Output|) = 30004.730469)
MSE%     : 0.055606% (denom = mean((Power Output)2) = 2702774782.122605)
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Fig. 5: Evaluation metrics

Figure 6 illustrates the comparison between the true and predicted power output values for the test dataset. It can be

observed that the predicted output closely follows the actual power output profile over time.

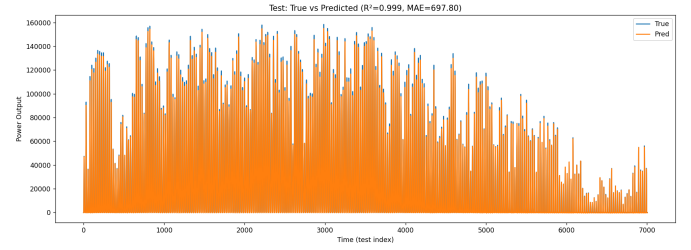


Fig. 6: True vs predicted plot

Figure 7 shows the True vs. Predicted Parity Plot, where the relationship between the predicted and actual power output values is visually assessed. The data points are tightly clustered along the diagonal line, which represents perfect prediction. This narrow distribution confirms the model’s accuracy and low bias across the operational range of the power output.

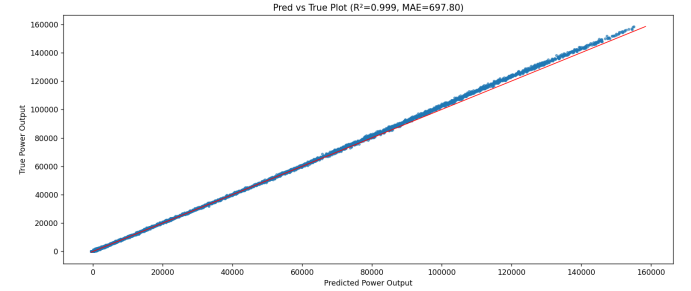


Fig. 7: Parity plot

The figure 8 shows the training and validation Mean Absolute Error (MAE) across epochs during model training. Both curves show a rapid initial decline where training MAE dropping sharply from approximately 0.15 to below 0.02 within the first 10 epochs. The validation MAE follows a similar pattern, stabilizing around 0.01-0 after epoch 20. The small gap between training and validation errors, along with their parallel convergence indicates good generalization without overfitting. The model achieves stable performance after approximately 40 epochs and it suggests that training could be terminated early without substantial loss in accuracy.

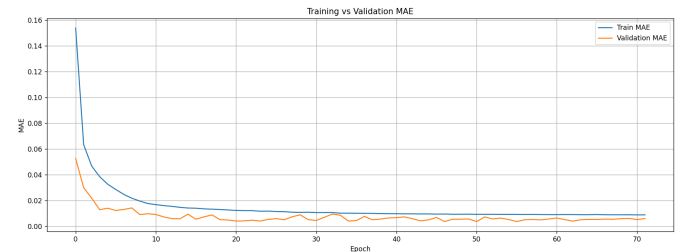


Fig. 8: Training vs validation MAE

The trained model was further used for inference on a separate dataset which has over 8500 samples to represent a real-world testing scenario.

Metric	Inference Dataset
R^2	0.99924
MSE	0.053452%
RMSE	4.246882%
MAE	2.385652%

Table 2: Performance metrics obtained on the unseen dataset during inference

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===== INFERENCE METRICS (Target: Power Output) =====
R2      : 0.999240
MSE      : 1370535.625000
RMSE     : 1170.698776
MAE      : 657.630676

----- Percentage (normalized) -----
MAE%     : 2.385652% (denom = mean(|Power Output|) = 27566.074219)
RMSE%    : 4.246882% (denom = mean(|Power Output|) = 27566.074219)
MSE%     : 0.053452% (denom = mean((Power Output)^2) = 2564064982.814751)

```

Fig. 9: Evaluation metrics - Inference Dataset

The dataset used during inference showed R^2 as 0.99924 and it demonstrates consistent predictive accuracy. For this dataset, the model achieved an RMSE of 4.246%, an MAE of 2.385%, and an MSE of 0.0534% confirming the robustness of the model.

Figures 9 and 10 represents the comparison between the true vs predicted power output values and parity plot respectively for the inference dataset. The predicted power output closely follows the actual power output. Therefore, it further validates the strong prediction performance of the FNN model.

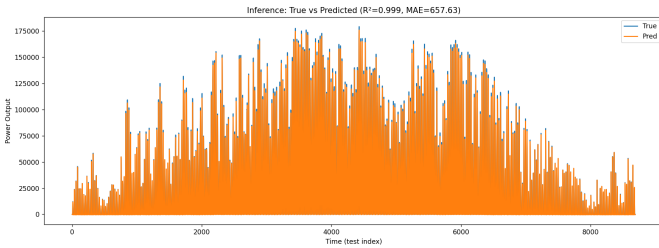


Fig. 10: True vs predicted plot - Inference Dataset

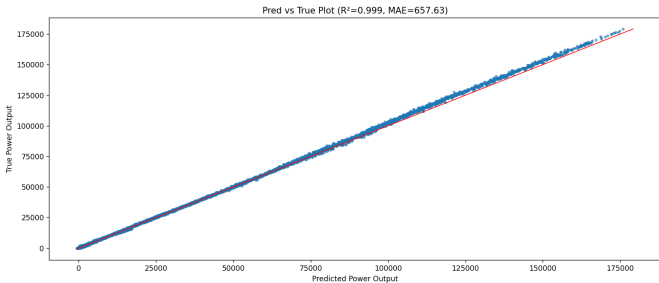


Fig. 11: Parity plot - Inference Dataset

V. CONCLUSION

Solar power forecasting is important to manage energy efficiently when renewable energy resources are being increasingly used as power sources. Our study explored the use of feedforward neural network model in forecasting solar PV power output. This feedforward neural network model used weather data and historical data in training. The model demonstrates high accuracy level in predicting hourly solar power generation according to the results obtained. The results shows that feedforward neural network model can predict hourly solar power generation with an accuracy over 97%.

Since feedforward neural network models lack inherent memory to store and process sequential data, memory was provided through feature engineering. Specifically, lag features and rolling statistics were used for this purpose. Therefore, FNN models are particularly well-suited for short-term forecasting tasks.

However, FNN models face limitations in long-term prediction scenarios due to the absence of temporal dependencies. Moreover, performance of the model is highly sensitive to quality of the input data and preprocessing. Despite these limitations, the FNN model shows competitive performance with relatively low computational complexity compared to recurrent models such as LSTM and GRU, which typically require high computational power.

Our proposed model achieves high prediction accuracy while maintaining computational efficiency, thus it is reliable for grid management applications such as more precise load balancing, reduces dependence on spinning reserves, and supports optimal scheduling of energy storage systems. Additionally, this helps in enhancing grid stability by facilitating a more seamless integration of solar power into modern smart grids.

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