Short-Term Multivariate Rooftop PV Power Forecasting Using a Patching-Based Transformer Model: A Case Study

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Abstract- Rooftop solar energy constitutes a crucial component in the operation of smart grids, wherein the electrical system is managed in a decentralized and optimized approach. This energy source is characterized by its cleanliness, abundance, and cost-free nature; however, effective utilization of this resource necessitates accurate forecasting. Prior research has indicated that univariate solar energy forecasting yields superior outcomes in comparison to multivariate forecasting methodologies. Nevertheless, the accuracy of forecasting diminishes significantly in instances of the unavailability of historical target data. In the present study, a novel approach for multivariate solar energy forecasting is introduced. This approach is predicated on the transformer model and it integrates mechanisms such as patching and channel independence to attain elevated accuracy while minimizing time and computational resource requirements, ensuring compatibility with smart meters, making it a practical solution for both utilities and consumers aiming to maximize the benefits of rooftop solar energy. The efficacy of the method is demonstrated through a real-world case study conducted in Central Vietnam, revealing an enhancement of at least 6.9% in Mean Absolute Error (MAE) relative to traditional transformer models, the DLinear model, and the TSmixer model.

Keywords Multivariate solar forecasting, transformer-based model, PatchTST, smart building, rooftop solar forecasting.

1. Introduction

Utilizing renewable energy, including solar energy, is a solution to the global issues of energy and the greenhouse effect. Indeed, according to the Paris Agreement, also known as COP21 [1], nearly 190 nations have agreed on a common goal to increase the use of clean energy sources in their energy systems, aiming to reduce the greenhouse effect and transition towards sustainable energy systems. Additionally, Economic growth is inextricably linked to rising energy demand, especially in developing countries. In order to satisfy this demand, it is essential to undertake the modernization and expansion of the power grid. However, such investment initiatives necessitate considerable financial resources, thereby posing significant challenges to states. Meanwhile, the vast and free solar energy remains predominantly untapped. The elevated solar irradiance and prolonged duration of sunlight furnish a remarkable asset for solar energy advancement (for instance, in Vietnam, solar irradiance can attain up to 1700 kWh/m² and annual sunshine hours fluctuate from 1500 to 2700 [2]). Furthermore, the diminishing expenditure associated with solar panel installations, with the production cost per watt decreasing from \$100 in 1975 to \$0.26 in 2022 [3], presents a substantial prospect for solar energy proliferation. Rooftop solar energy systems are ideally aligned with the developmental paradigm of smart grids, wherein generation sources are prioritized for installation in proximity to consumption points. This arrangement enhances energy autonomy, diminishes the incidence of extensive power outages precipitated by faults, and reduces transmission losses. By harnessing local solar energy, these systems not only secure a stable power supply but also contribute to environmental protection and operational cost reductions, which ultimately alleviate pressure on the power grid and ensure energy security [4].

In Southeast Asian countries with tropical climates such as Vietnam, Cambodia, and Indonesia, installing rooftop solar energy systems faces numerous challenges. One major obstacle is the limited support from government policies. Additionally, one of the issues limiting the development of rooftop solar energy systems is that integrating a large amount of solar power into the grid reduces grid inertia, rendering the system more vulnerable to frequency fluctuations. To fully harness the potential of solar energy, rooftop solar systems need to send anticipated power generation data to dispatch centers for power regulation, ensuring the safety of the power system. In smart buildings, accurate forecasting of rooftop solar panel output is crucial for optimizing energy management algorithms. With advancements in smart meters and communication technology, interfacing with centralized data management systems (MDMS) will become increasingly streamlined in the future.

2. Related Work

Solar energy forecasting articles primarily concentrate on predicting solar irradiance, specifically global horizontal irradiance (GHI) [5], direct normal irradiance (DNI) [6], and diffuse horizontal irradiance (DHI) [7] . Theoretically, solar power output has a direct proportional relationship with solar irradiance, as defined by formula (1):

$$P = A \times G \times \eta \qquad (1)$$

P is the power output in watts (W), A is the surface area of the solar panels in square meters (m^2), G is the average solar irradiance on that area in watts per square meter ($\frac{W}{m^2}$), and η is the energy conversion efficiency of the solar panels, typically a value less than 1.

Considering an individual rooftop solar system in a short timeframe, the surface area and efficiency of the panels are generally assumed to be fixed. In such cases, the power output (P) is directly proportional to the solar irradiance (G). Thereby the predictions for solar irradiance or output power forecasts adhere to the same pattern. Nevertheless, power output forecasting provides a more comprehensive perspective by incorporating factors influencing the panels' energy conversion efficiency, such as temperature coefficients, soiling, and technical degradation. Solar power generation is highly susceptible to weather fluctuations. Factors like cloud cover and precipitation can dramatically reduce output. Accurately forecasting solar power is challenging due to these variables. Data from meteorological stations, satellites, and on-site sensors are collected to make predictions. This data includes historical output, weather parameters, and satellite imagery [8].

The forecast horizon varies significantly depending on the specific objectives of the forecast, and the required accuracy level differs accordingly. Forecasts are generally categorized into long-term (1-10 years), medium-term (1 month-1 year), short-term (1 hour-several days), and very short-term (less than 1 hour) [9]. Long-term forecasts are typically used for project planning and solar farm development, while medium-term and short-term forecasts are essential for the effective operation of power grid. The forecasting techniques employed can vary greatly depending on the specific forecasting requirements. Short-term forecasts, especially those with a horizon of one hour or less, are essential for grid operators to effectively integrate solar power. By providing timely and accurate predictions of solar generation, these forecasts facilitate grid operators to adjust their operations to balance supply and demand [10].

Numerous techniques have been proposed to enhance the accuracy of solar power generation forecasts, including historical data-driven approaches, operational structure-based methods, and satellite image-based models [11]. Structure-based methods, often relying on physical models, have shown promise for long-term forecasts. These models typically involve a set of equations representing the relationship between observed variables and target values. Key parameters include geographic coordinates, azimuth and elevation angles, atmospheric conditions, and meteorological data. Prominent models include Numerical Weather Prediction (NWP), Markov chains, empirical models, and regression models using ARIMAX, ANN, or deep learning [12]. However, the development of such models is often time-consuming and requires extensive data. Additionally, the performance of these models can be sensitive to changes in environmental conditions and system configurations, limiting their generalizability. Paper [13] has explored extracting attributes from reconstructed sky images as exogenous inputs for machine learning algorithms in short-term forecasting. This method utilizes direct information from high dynamic range (HDR) cameras. However, image processing and labelling are computationally expensive and time-consuming, requiring significant computational resources and high installation costs. These factors make this approach less suitable for forecasting rooftop solar power generation.

In such cases, forecasts utilizing historical data have proven to be more effective. Data can be categorized into three components: time-series data, which includes only forecasted values over time; structure data, which encompasses relevant parameters like geographic location and weather conditions; and hybrid data, which combines both time-series and structure data. Forecasts based solely on time-series data are referred to as univariate forecasting, while forecasts using structure or hybrid data are considered multivariate forecasting [14]. Although univariate forecasting is often preferred due to its simplicity and effectiveness, multivariate forecasting can be beneficial when there is a lack of historical target data. In fact, introducing irrelevant or weakly correlated variables into the training process can increase training time and reduce accuracy. Post-processing techniques have been developed such as Principal Component Analysis (PCA) [15], K-means clustering [16], and Pearson's correlation [17] to select the most relevant features before training.

Data-driven forecasting methods commonly employ regression models. Among the most popular are ARIMAX and SARIMAX, which are extensions of the AutoRegressive (AR) and Moving Average (MA) models. These models are designed using straightforward statistical techniques. Support Vector Machines (SVM) is another machine learning method that utilizes statistical learning to map dependent variables to forecast data [18]. Artificial neural networks, capable of handling nonlinear problems, can employ various algorithms like scaled conjugate gradient, Levenberg-Marquadt (LM), and Polak-Ribiere. However, LM is the most widely adopted by researchers due to its superior performance [11].

In solar energy forecasting research, deep learning methods have shown promising results. Commonly used deep learning algorithms include Recurrent Neural Networks

(RNNs) [19], Long Short-Term Memory (LSTM) networks [20], Convolutional Neural Networks (CNNs) [21], and Gated Recurrent Units (GRUs) [22]. These studies have demonstrated that deep learning methods outperform traditional regression models and simple ANNs on specific datasets. These deep learning models process batches of data sequentially, sample by sample, and optimize unknown model parameters using the well-known gradient descent algorithm. The gradient information for updating model parameters is computed through backpropagation through time (BPTT). However, they face limitations due to sequential data processing and challenges related to BPTT, especially when handling datasets with long-term dependencies. Moreover, training deep learning models also encounters issues with vanishing and exploding gradients [23]. When processing long sequences, the gradient descent algorithm (using BPTT) may fail to update model parameters because the gradient information can diminish (approaching zero) or become excessively large (exploding). Additionally, these models often do not benefit from parallel computations provided by modern hardware such as Graphics Processing Units (GPUs), Tensor Processing Units (TPUs), and other hardware accelerators. Though modifications and advanced training techniques can help alleviate these issues, RNNs' limitations in handling long sequences and using parallel computing remain hurdles for scalability.

To improve the accuracy of solar irradiance forecasts, researchers have turned to hybrid methods. These approaches combine various techniques, such as pre-processing, post-processing, and optimization, to enhance the overall performance. Examples of hybrid models include k-means+Fuzzy+ANNx [24], DFT+PCA+Alman [25], ANFIS+ANN [26], LSTM+CNN [27], PSO+CNN [28], LM-ANN [29], and SVM+RBF+WT [30], etc,. By combining the strengths of different techniques [31], hybrid models can often achieve better results than individual models.

Transformers, with their self-attention mechanism, have achieved remarkable success in various domains, including natural language processing (NLP) [32], computer vision (CV) [33], speech recognition [34], and recently, time series forecasting [35]. Unlike RNNs, Transformers can parallelize computations and avoid vanishing gradient problems, making them well-suited for sequential modeling tasks. Recent studies have demonstrated that Transformer-based models (such as Informer [36], Autoformer [37], FEDformer [38], etc) outperform traditional RNNs (LSTM) in time-series forecasting, as evidenced by lower MAE and RMSE values. Moreover, variants like TSMixer [39]introduced by Google in 2023, which replace the attention mechanism with MLP-based mixing, have shown promising results in time series domain.

While Transformer models have demonstrated superior performance in various domains, to the best of our knowledge, their application to short-term solar energy forecasting remains relatively unexplored. In this study, a novel Transformer architecture is proposed, termed the Patching-based Transformer model, to enhance the accuracy of forecasts. This model will be compared to traditional linear model, previous Transformer versions, and the TSmixer (MLP-based model) to evaluate its effectiveness.

The main contribution of the paper: (i)The application of a novel patching-based Transformer technique to the problem of short-term rooftop solar energy forecasting. (ii) A comparison of the proposed model with state-of-the-art deep learning models for time series prediction is conducted. (iii)Evaluation of single-step and multi-step forecasting methods, as well as weather effects.

The paper is structured as follows: Section 1 provides an introduction to the topic, Section 2 reviews state of the art, Section 3 details the Patching-based transformer model, Section 4 outlines the experimental setup, Section 5 presents the results and discussion, and Section 6 concludes the paper.

3. Methodology

Considering a time series sample with H dependent variables and a look-back window L denoted by $x_1, \dots, x_L$, which x_t is a vector of dimension H at time step t, $x_t = x_t^1, \dots x_t^H$. This sample will predict T future values $(x_{L+1}, \dots, x_{L+T})$. In the following section, a description of the operating mechanism of the patching-based Transformer model is provided. *Structure of Patching-based Transformer Model*

Each sample $x \in R^{H \times L}$ with look-back window length L is split into H univariable time series denoted by $x^{(i)} \in R^{1 \times L}$, and fed independently into the Transformer backbone according to the Channel-independently setting as present in Fig. 1.

As depicted in Fig.1(b), the transformer backbone comprises four main steps:

(i) Patching: Each univariate time series $x^{(i)} \in R^{1 \times L}$ is divided into overlapping or non-overlapping patches. Denoting the patch length as P and the stride (non-overlapping region) between two consecutive patches as S, the patching process generates a sequence of patches $x_p^{(i)} \in R^{P \times N}$. The number of patches is computed as $N = \frac{L-P}{S} + 2$.

By employing patches, the number of input tokens can be reduced from L to approximately $\frac{L}{S}$. This leads to a quadratic decrease in the memory usage and computational complexity of the attention map by a factor of S. With the same hardware constraints, the patching process allows the model to process longer historical sequences, thereby improving forecasting performance [40].

(ii) Projection and Position Embedding: Each patch is projected into a D-dimensional latent space within the transformer using a trainable linear transformation $W_p \in R^{D \times P}$. To capture the sequential order of these patches, a learnable positional encoding $W_{pos} \in R^{D \times N}$ is added. The resulting representation $x_d^{(i)} \in R^{D \times N}$, which combines the projected patch and its corresponding positional encoding, is then fed into the transformer encoder. This technique helps the input can be processed in parallel.

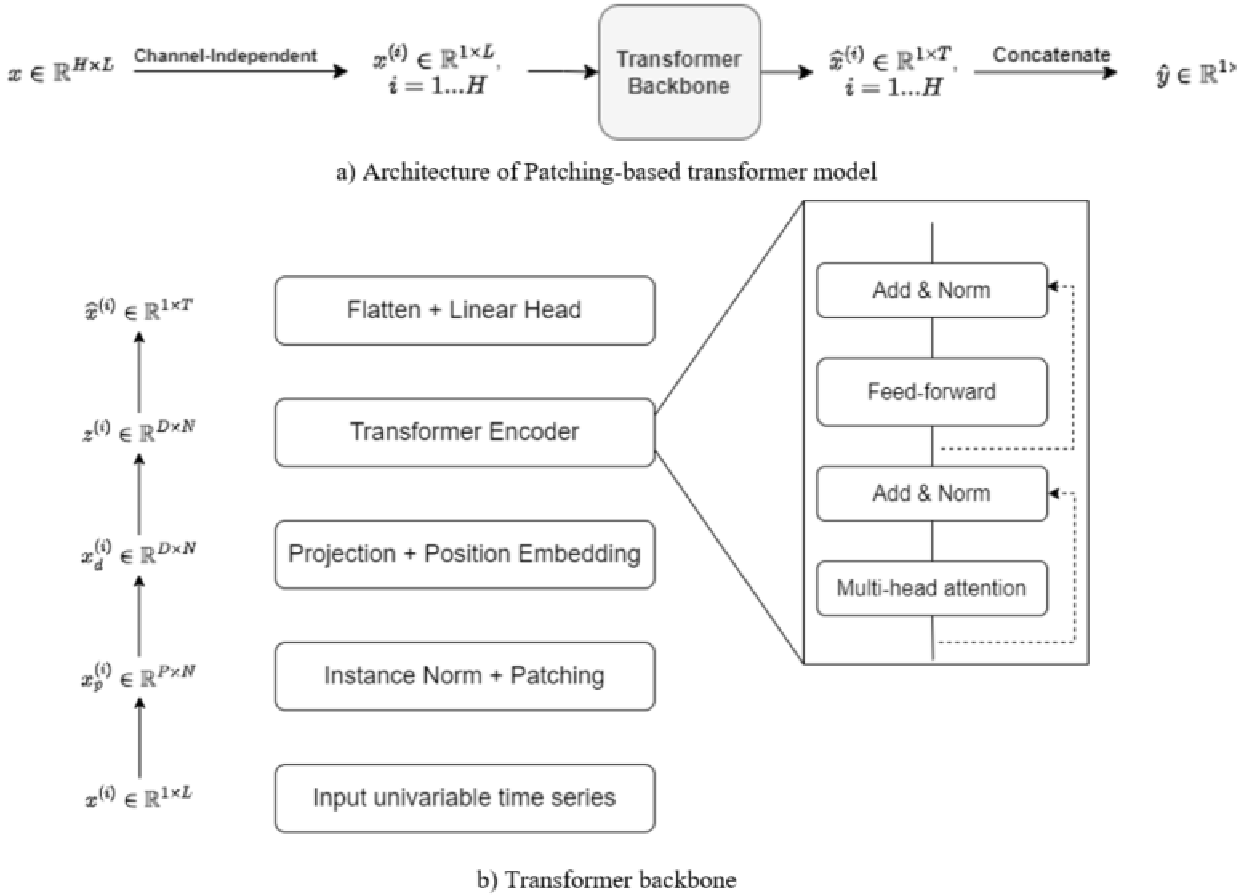


Fig. 1. Structure of Patching-based transformer model.

(iii) Transformer Encoder: The data is fed into the multi-head attention mechanism, which employs distinct weight matrices W_q, W_k, and W_v to extract various levels of correlation between the input data. Assuming there are r heads, there are r sets of weight matrices. For each head l, query matrices Q_l , key matrices K_l , and value matrices V_l are generated by multiplying the weight matrices with the input matrix. The attention output is then computed using the scaled dot-product formula (2):

$$Z_l^{(i)} = Softmax\left(\frac{Q_l^{(i)}.K_l^{(i)}}{\sqrt{(d_k)}}\right)V_l^{(i)} \quad (2)$$

The outputs $Z_l^{(i)}$ from all r heads are concatenated and linearly combined using a learnable weight matrix $W_o \in R^{d\times rs}$. The result of multi-head attention will be passed through BatchNorm blocks and a feed-forward network to generate the representation $Z^{(i)} \in R^{D\times N}$.

(iv) Flatten and linear head: used to obtain the prediction result $\hat{x}(i) = \left(\hat{x}_{L+1}^{(i)}, \dots, \hat{x}_{L+T}^{(i)}\right)$

4. Experiment

The proposed method is applied in dataset as described below:

4.1. Dataset

A dataset containing hourly measurements of solar power generation from a residential rooftop system in Da Nang City, Vietnam, was collected over a period of 1 year and 11 months, spanning from January 1, 2022, to November 25, 2023. The data includes precise timestamps, local temperature readings, weather conditions, and the corresponding power output at each hour. This hourly resolution is well-suited for analyzing the performance of the solar system and integrating it into current power grid systems. Given that the rooftop solar system is fixed, the azimuth and elevation angles, along with the system's latitude and longitude, are considered constant and therefore are not included as variables in this dataset.

As seen in Fig.2, the generated power energy of rooftop PV has a distinct pattern according to the hours of the day, the generating power peaks at noon and decreases in the afternoon, according to the increase or decrease of solar radiation. When considering the daily and weekly patterns, the chart fluctuates widely and the trend is unclear. Radiation capacity increases in the summer months from March, and decreases from September as the weather gradually shifts to autumn. Solar power dropped suddenly in October, as the weather recorded a lot of rain in these months. The dataset is split into three parts: Data from 01/2022 - 12/2019 used for training, data from 05/2023 – 06/2023 used for validation, and data from 07/2023 – 11/2023 used for testing.

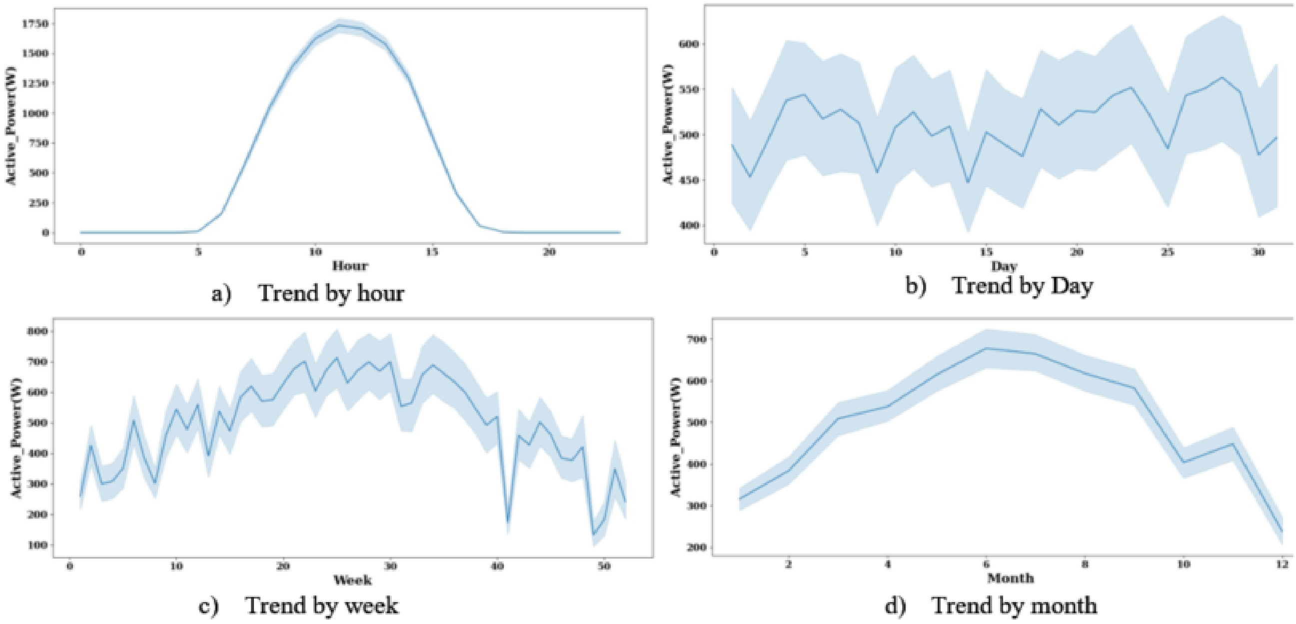


Fig. 2. Data analysis by trends.

4.2. Model's Parameters

Utilizing transformer models outlined in the literature review section - namely *Informer, Autoformer*, *FedFormer*, and *Transformer* as baseline models. To ensure a fair valuation, the look-back window length across all models.is fixed in the multivariate implementation, the target variable is excluded. The multivariate forecasting model uses three input parameters: date time, temperature, and weather conditions. The quantity of input parameters corresponds to the number of input encoders. Specifically, the encoder input, number of encoder layers, number of heads, stride, and patch size are designated as 3, 3, 8, 8, and 16, respectively. In the recent paper [41] shown that a simple linear model can outperform all of the transformer models on a variety of time-series forecasting. Thus, this linear model is included in the comparison as well.

4.3. Metric Performances

There exist numerous metrics to appraise the accuracy of models in time series forecasting. Unlike load forecasting, solar power forecasting poses particular difficulties wherein there are intervals with zero output. Using metrics that are sensitive to division by zero in such cases can lead to inaccurate evaluations. In this paper, we focus on assessing the forecasting methods using the following metrics: MAE, RMSE, and R^2. These metrics are formulated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

with y_i is the real value, $\hat{y}_i$ is the predicted value, n is the number of observations, $\bar{y}$ is the mean of the real values.

Smaller MAE and RMSE values indicate that the predicted values are closer to the real values, while an R^2 value closer to 1 indicates that the model captures the pattern of the graph well.

5. Results and Discussion

Multivariate forecasting models are implemented with the dataset described above. To evaluate the effectiveness of the proposed model, assessing various aspects such as the accuracy of the forecasting method, the impacts of the look-back window, the effects of weather factors, and the complexity of the algorithm are suggested.

5.1. Accuracy

The accuracy of the models is compared by three metrics MAE, $RMSE$, and R^2. The models utilize the same look-back window of 72 previous steps to forecast one future point. The results are presented in Table 1.

As shown, the proposed model yields better results, with lower MAE and $RMSE$ values than other models. The R^2 value is closer to 1. The proposed model improves the MAE metric by more than 6.9% compared to the Informer model,

Table 1. MAE, RMSE and R^2 index of different models

Metrics	Multivariate Models						
	Proposed model	**DLinear**	**Informer**	**Transformer**	**Autoformer**	**FEDformer**	**TSMixer**
MAE	<u>**0.158**</u>	0.282	0.170	0.172	0.210	0.295	0.185
RMSE	<u>**0.314**</u>	0.422	0.323	0.321	0.336	0.412	0.324
R^2	<u>**0.925**</u>	0.866	0.903	0.920	0.913	0.888	0.917
Proposed model MAE imp.		<u>43.97%</u>	<u>6.95%</u>	<u>8.39%</u>	<u>24.9%</u>	<u>46.4%</u>	<u>14.6%</u>

14.6% compared to the TSMixer model, and 43.9% compared to simple linear model. Although the MAE index of Informer is smaller than Transformer, the $RMSE$ and R^2 index of Transformer is better than Informer. Among the transformer-based models, FEDformer has the worst accuracy.

5.2. Look-back Window

In this case study, examining the appropriate look-back lengths for the solar power forecasting problem is focused on. The length of the window will vary from 24 (1 day), 72(3 days), 168(1 week), 336(2 weeks), to 720 (1 month), the metric performances are shown in Fig. 3. As the window length L increases, $RMSE$ index of proposed model gradually decreases meanwhile other models lightly increase. At $L = 72$, the MAE and $RMSE$ metrics of the models are better compared to $L = 24$. However, if L is further increased to 168, 336, or 720, the MAE index is not improved. Across various time steps for each window length, the proposed method shows better results compared to the other methods.

5.3. Multisteps Prediction

Multi-step forecasting provides information essential for optimizing energy planning. Considering the effectiveness of the method when performing multistep forecasting. The look-back window is fixed to 72 to predict 1, 24, 48, and 72 hours ahead. Two metrics MAE and RMSE are illustrated in Fig. 4.

Multistep forecasting typically yields less accurate results compared to single-step forecasting. This is understandable because solar energy varies significantly over time, so the further the forecast extends into the future, the greater the potential error. However, for a given number of forecast steps, the proposed method results in lower errors than other methods.

5.4. Weather Impact

Weather variability is a crucial factor affecting the power output of solar energy. In this section, the accuracy of the forecasting method is examinated under two specific contexts: sunny vs. cloudy days, and observations by month.

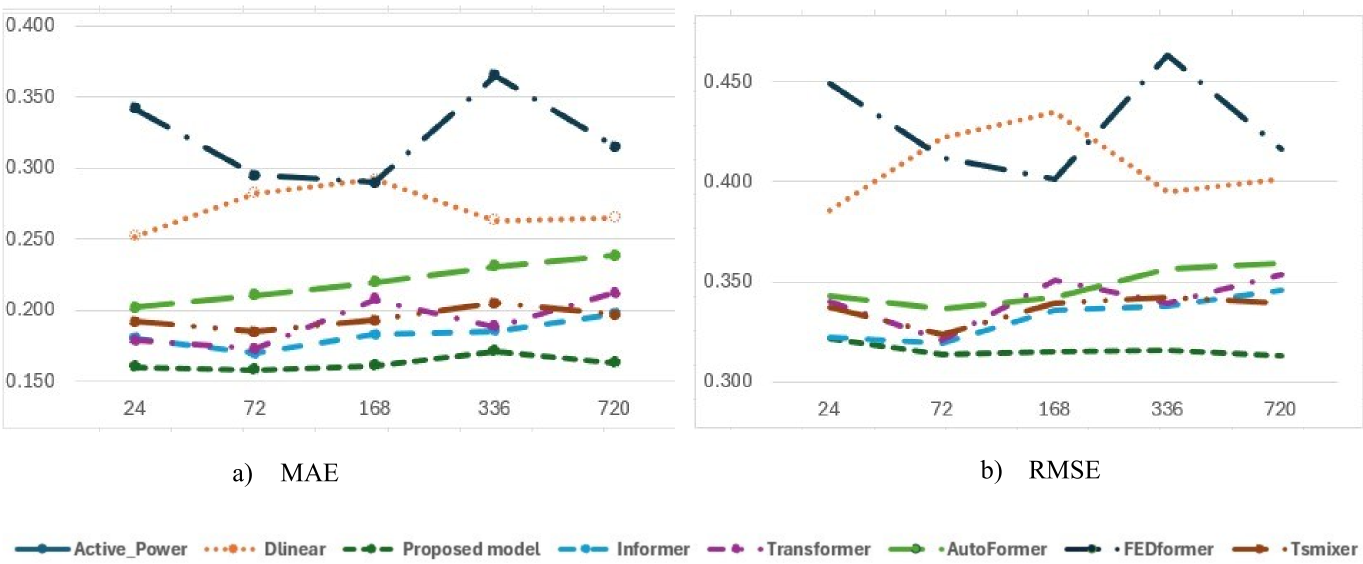
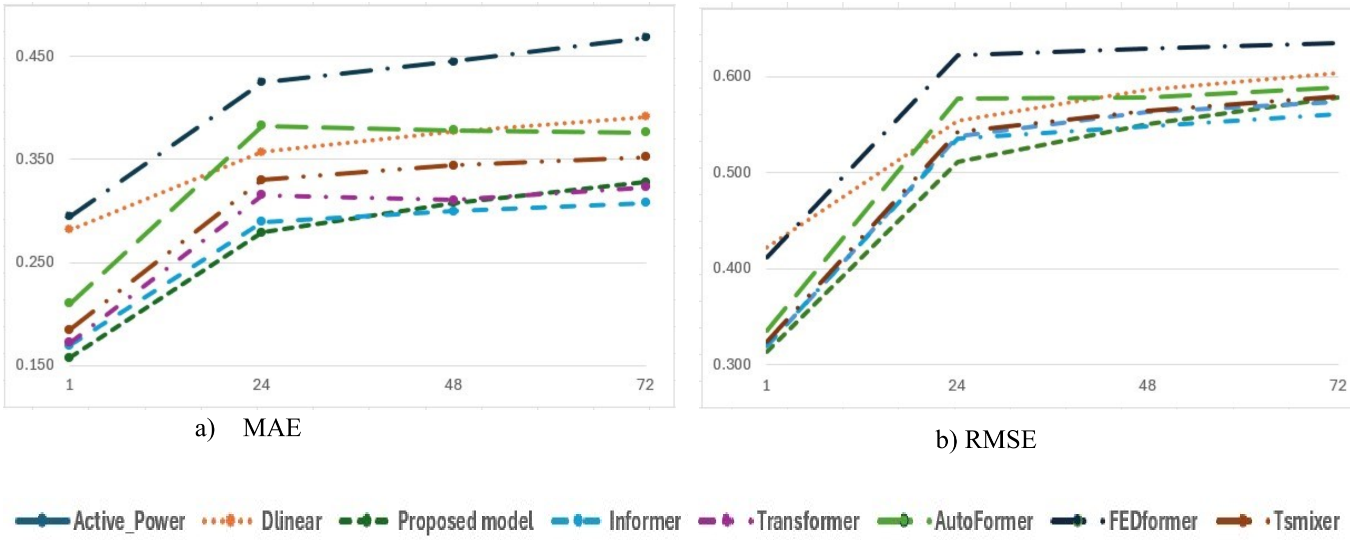


Fig. 3. Impact of the look-back window length on the accuracy of models.



a) MAE

b) RMSE

Fig. 4. Impact of the prediction length on the accuracy of models.

5.4.1. *Sunny vs cloudy day*

The forecast graph for a typical sunny and rainy day (e.g., sunny or rainy all day) in Da Nang, Vietnam, is illustrated in Fig. 5. A look-back window of $L = 72$ and a unistep forecast were selected. The MAE and $RMSE$ error indices are recorded as in Table 2.

For the sunny day, most methods effectively captured the output energy response pattern, achieving accuracy levels above 94% and up to 99% with the proposed method. However, on the cloudy day, due to the highly variable and noisy data, the forecasting methods performed less effectively, resulting in higher forecast error indices. The Informer model effectively learns the changing patterns of the graph, but the prediction error remains high. Overall, in both scenarios, the proposed method consistently outperformed the old transformer method, the linear method, and the TSMixer method across almost evaluation metrics.

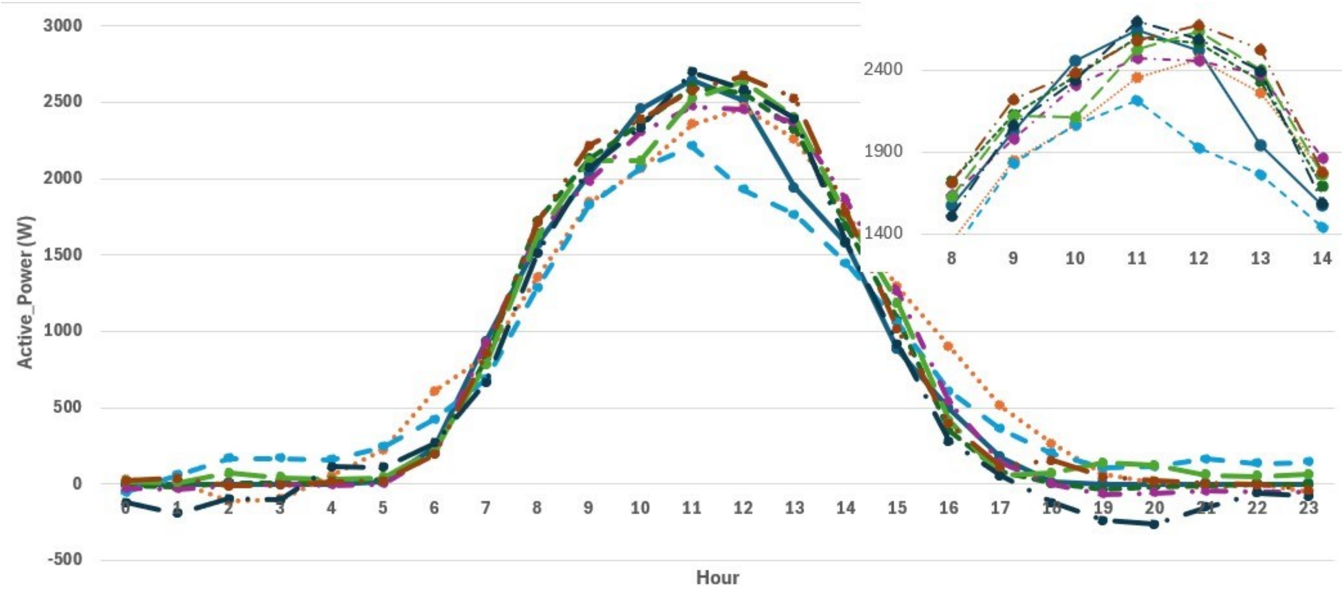
5.4.2. *Monthly observation*

The evaluation of the forecast results is shown in Fig.6, focusing on two key indicators: MAE and RMSE. Due to data limitations, the forecasting was conducted from July to November 2023. In Central Vietnam, there are two distinct seasons each year: the dry season and the rainy season. The rainy months start in September and last until the end of the year. During transitional months like September, the weather often changes unpredictably, making it difficult to forecast accurately. As a result, the forecast data for July and August shows lower errors compared to September, October, and November. Among the seven methods compared, the proposed method exhibited the lowest error rates and the highest accuracy. Following this was the Transformer method, with TSMixer using neural networks coming next.

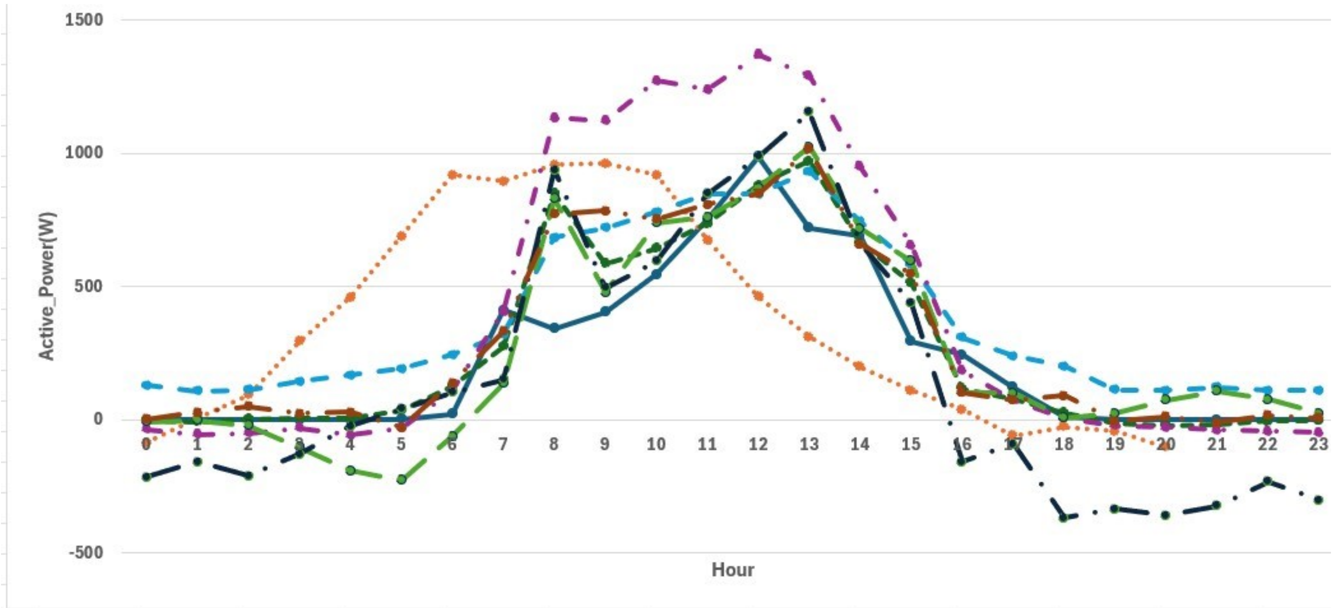
Other Transformer variants, such as Informer, Autoformer, and FEDformer, which have more complex architectures, did not yield promising results in the solar power forecasting task.

Table 2. Performance metrics of sunny day vs. cloudy day

Model	**SUNNY DAY**			**CLOUDY DAY**		
	MAE	**RMSE**	R^2	**MAE**	**RMSE**	R^2
Proposed model	**0.096**	**0.153**	**0.990**	**0.112**	**0.194**	0.846
DLinear	0.241	0.454	0.948	0.169	0.245	0.859
Informer	0.275	0.320	0.982	0.218	0.241	**0.875**
Transformer	0.121	0.198	0.979	0.284	0.456	0.864
Autoformer	0.156	0.217	0.975	0.167	0.408	0.801
FEDformer	0.181	0.226	0.982	0.293	0.360	0.803
TSMixer	0.126	0.207	0.983	0.142	0.2199	0.835



a) Prediction of sunny day



b) Prediction of sunnay day

Fig. 5. Impact of weather on forecasting accuracy.

Although the Dlinear method, as discussed in [41], was suggested to be more effective than the Transformer architecture, it did not perform best when applied to actual solar energy forecasting data.

5.5. Algorithm Complexity

The complexity of an algorithm is a metric used to assess its suitability for integration into local processing units. If an algorithm has high complexity, training on lower-end computing units becomes challenging to complete. Models based on transformer architectures typically offer parallel processing capabilities, resulting in faster completion times compared to recurrent network structures like LSTM. Let L represent the length of the look-back window and S the stride. The models were written in Python and trained on the same processing unit configured with an NVIDIA Tesla T4.

The complexity of the models and the average training time taken for each epoch with $L = 24$ and prediction length is 1 was also shown in Table 3.

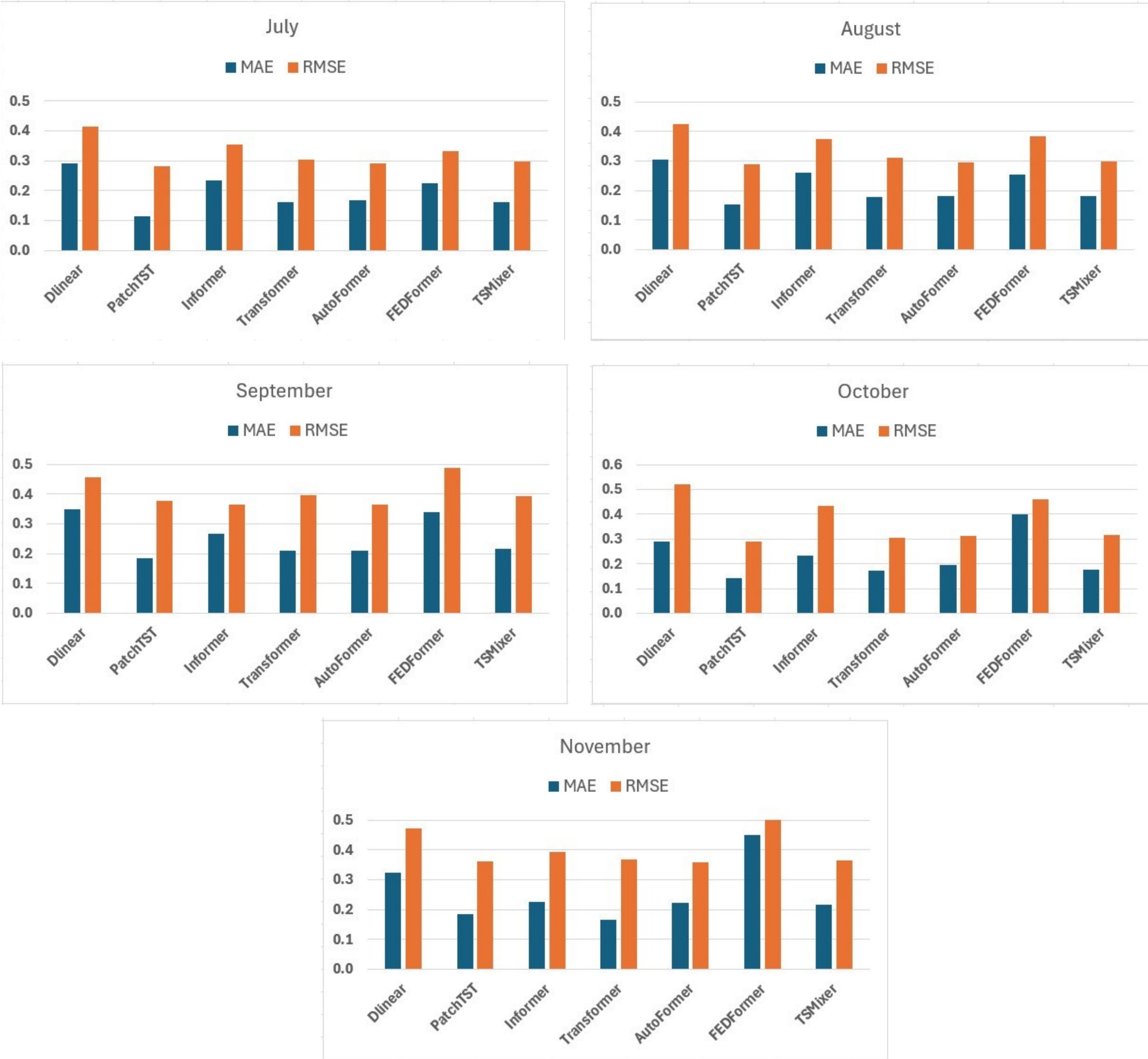


Fig. 6. Impact of weather on the forecasting accuracy.

Table 3. Complexity analysis of different models

Model	Complexity	Training time/epoch(s)
Dlinear [41]	O(L)	1.5
Proposed model [40]	$O((L/S)^2)$	7.2
Informer [36]	O(LlogL)	20.4
Transformer[34]	$O(L^2)$	24.2
Autoformer[37]	O(LlogL)	35.7
FEDformer[38]	O(LlogL)	117.8
TSMixer[39]	O(hL)	15.3

In Table 3, the method that is the least resource-intensive and has the fastest training time is DLinear, while the method that requires the most training time is FEDFormer. The FEDFormer method utilizes many parameters, resulting in higher resource consumption and longer training times. By incorporating additional patch and channel-independent learning, the proposed method achieves an S-fold reduction in complexity compared to other transformer architectures, leading to faster training times per epoch. Although the shift from attention mechanisms to the MLP network structure in the TSMixer model also significantly improves training speed, it is still slower than the patching mechanism.

6. Conclusion

Accurate forecasting of solar power generation from rooftop photovoltaic systems remains a challenging task. In this paper, a novel patching-based transformer model for multivariate time series forecasting to address data loss issues during storage is proposed. Experimental results on a real-world dataset from a household in Da Nang, Vietnam, demonstrate that the proposed model outperforms state-of-the-art baselines in single-step forecasting, e.g. by comparing with DLinear model the proposed model reducing 43.97% by MAE, 34% RMSE and increasing 6% in R^2 metric. Further analyses, including multi-step forecasting, variations in weather conditions, and seasonal patterns, confirm the superior performance of our proposed approach. The patching architecture not only enhances accuracy, optimizing the future use of renewable energy, but also accelerates training, making it a practical solution for real-world applications.

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