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Photovoltaic power forecasting based on PV-Client

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ABSTRACT

Photovoltaic (PV) power forecasting plays a crucial role in optimizing the operation and planning of PV systems, enabling efficient energy management and grid integration. However, uncertainties caused by fluctuating weather conditions and complex interactions between different variables pose significant challenges to accurate PV power forecasting. In this study, we propose PV-Client (Cross-variable Linear Integrated ENhanced Transformer for Photovoltaic power forecasting) to address these challenges and enhance PV power forecasting accuracy. PV-Client employs a linear module to learn trend information in PV power, and employs an ENhanced Transformer module to capture complex interactions in PV systems. Experiments with the real-world PV power dataset have confirmed the SOTA performance of PV-Client in PV power forecasting.

Keywords: PV power forecasting, PV-Client, linear, Transformer

NONMENCLATURE

Abbreviations	
PV	Photovoltaic
PV-Client	Cross-variable Linear Integrated ENhanced Transformer for Photovoltaic power forecasting
PV	Photovoltaic

1. INTRODUCTION

Photovoltaic (PV) power, as a clean and renewable energy source, has gained significant attention in recent years due to its potential for reducing carbon emissions and dependence on fossil fuels. The efficient utilization of PV energy relies heavily on accurate forecasting of PV system output. Accurate PV power forecasting enable effective power grid planning, load balancing, and resource management, contributing to the overall stability and efficiency of energy systems. Additionally, PV power forecasting facilitates the integration of PV energy into the existing power grid infrastructure, enabling the optimal utilization of renewable energy sources while ensuring grid reliability and stability [1].

However, PV power forecasting is confronted with several challenges that make accurate prediction a complex task. One of the major challenges arises from the inherent variability and uncertainty in weather conditions, as PV system output strongly depends on solar radiation levels, and rapid changes in solar radiation and diurnal patterns, pose challenges in capturing and modeling short-term and long-term variations accurately. Other weather factors such as temperature, cloud cover, and other atmospheric conditions can also have impacts on the production of PV power [2]. The inaccuracy of weather forecasts exacerbates this challenge. Another challenge lies in the non-linear relationships between input variables and PV power output. Traditional linear models often fail to capture the complex interactions and dynamics present in PV systems, resulting in less accurate predictions. Addressing these challenges and developing accurate PV power forecasting methods are of utmost importance to ensure the reliable integration and utilization of PV energy.

Numerous research studies have been conducted to devise accurate and computationally efficient forecasting models for PV power generation. These models can be broadly categorized as indirect and direct forecasting models. In the indirect forecasting models, various methods including numerical weather prediction (NWP) [3], statistical approaches [4], and image-based methods [5] have been utilized to predict solar radiation at different time scales. Subsequently, these forecasted solar radiation values, along with other relevant data, serve as inputs to estimate the PV power generation. On the other hand, the direct forecasting model directly predicts the PV power generation using historical PV power and associated meteorological data on the basis of relatively accurate weather forecast data. The direct

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forecasting models include persistence models [6], statistical models [7], machine learning models [8], and hybrid models [9]. The selection between indirect and direct forecasting models depends on factors such as data availability, computational resources, and specific forecasting requirements. In this research study, we have relatively sufficient historical data available, and the accuracy of weather forecast data is relatively high. Therefore, we adopt direct forecasting models.

Despite significant advancements in PV power forecasting technology, to the best of our knowledge, there is currently no model that effectively captures trend information from historical data while efficiently learning the complex nonlinear dependencies between weather factors (or other related factors) and PV power. To tackle this problem, we propose PV-Client (Cross-variable Linear Integrated ENhanced Transformer for Photovoltaic power forecasting). PV-Client incorporates a linear module to learn trend information in PV power and utilizes an Enhanced Transformer module to capture the intricate interactions within PV systems, as the attention mechanism in Transformer is supposed to capture the complex non-linear relations between features efficiently [10]. This integration of linear and non-linear modeling techniques allows PV-Client to effectively capture both the global and local patterns in the PV power, making it a powerful tool for accurate PV power forecasting. Through experiments conducted on the real-world PV power dataset, PV-Client has demonstrated state-of-the-art (SOTA) performance in PV power forecasting.

2. METHODOLOGY

The fundamental concept underlying PV-Client is to incorporate cross-variable attention in lieu of the typical cross-time attention utilized in traditional Transformer models. Additionally, a linear module is integrated into the model. These designs can enable the model to better utilize the variable dependencies and trend information in PV power. In this section, we detail the PV-Client model components.

2.1 Cross-variable Transformer

The cross-variable Transformer module is used to learn variable dependencies in place of time dependencies in PV power, as shown in Fig. 1.

The Encoder block consists of a multi-head attention (MHA) component and a feed-forward network (FFN) component. The input look-back time series (historical PV power along with weather data) **H** is a 2D Tensor with the shape of *L x C*, and the input series needs to be flipped first. The cross-variable attention is the key part of MHA, which is defined as Eq. (1):

$$\mathrm{Attention}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \mathrm{softmax}\left(\frac{\mathbf{QK}^{\top}}{\sqrt{L}}\right)\mathbf{V} \qquad (1)$$

where **Q** is queries, **K** is keys, and **V** is values. **Q**, **K** and **V** are generally obtained by applying some transformations to the original input **H**, and *L* is length of input.

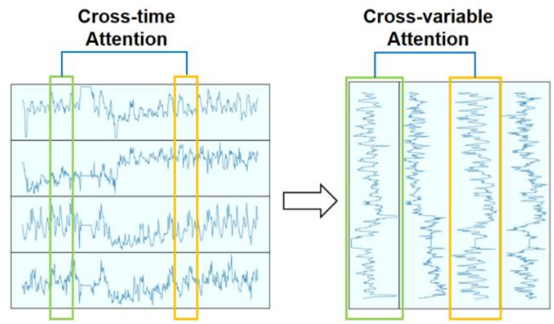

Fig. 1 Cross-variable attention.

The input PV power series is put into the Encoder blocks directly, without the embedding layer because the extra embedding layer compromises temporal information and results in inferior performance. Besides, we remove the position encoding layer in the Transformer since there are no temporal ordering among different variables. After extracting features from Encoder blocks, the input series is put into a projection layer and flipped to get the prediction of the cross-variable Transformer, without passing a decoder block, as we find that including a Decoder leads to decreased performance. The process of projection is defined as:

$$\mathbf{F}_{\mathrm{trans}} = \mathrm{Proj}(\mathbf{X}_{\mathrm{enc}}).\mathrm{Permute}(1,0) \qquad (2)$$

where $\mathbf{X}_{\mathrm{enc}}$ is the output of Encoder blocks, and $\mathbf{F}_{\mathrm{trans}}$ is the Transformer's prediction. The cross-variable Transformer's prediction often contains the details of the PV power.

2.2 Linear Integration and ReVIN Modules

The integrated linear module is used to learn trend information from the PV power, and it is channel-independent. The linear model is deemed proficient in extracting trend information. The input PV power series is flipped and put into linear module to get the linear's prediction, as defined:

$$\mathbf{F}_{\mathrm{lin}} = \mathrm{Linear}\big(\mathbf{H}.\mathrm{Permute}(1,0)\big).\mathrm{Permute}(1,0) \qquad (3)$$

The cross-variable Transformer's prediction and the linear's prediction are combined with learnable weights

$\mathbf{w}_{\text{trans}}$ and $\mathbf{w}_{\text{lin}}$ to get the final prediction of PV power, as described in:

$$\mathbf{F} = \mathbf{w}_{\text{trans}} \times \mathbf{F}_{\text{trans}} + \mathbf{w}_{\text{lin}} \times \mathbf{F}_{\text{lin}} \tag{4}$$

weather factors may also impact it. As both the PV power and weather data are sampled hourly, the input length is 192 with a feature dimension of six. We predict the PV power for the following day as day-ahead forecasts are

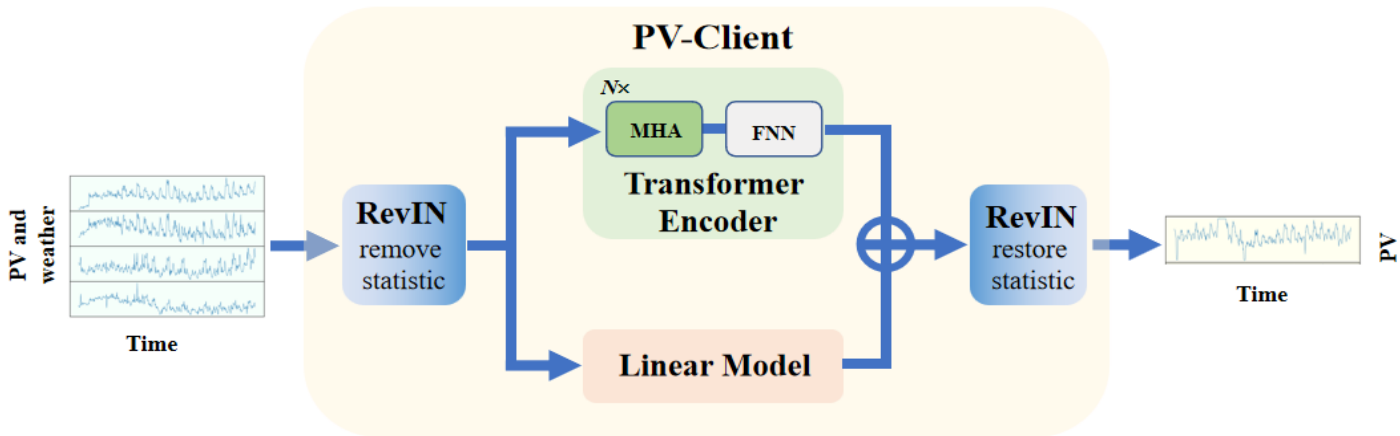

Fig. 2 PV-Client architecture. The RevIN module is used to address the issue of distribution shift of PV power series. The linear model is used to capture trend information, while the enhanced Transformer model is used to capture nonlinear and cross-variable dependencies in PV power series.

To address the issue of distribution shift in PV power, a reversible instance normalization (RevIN) [11] module is adopted in the model, which is symmetrically structured to remove and restore the statistical information of a PV power series instance and promote the model's stability during forecasting.

2.3 Overall PV-Client Architecture

PV-Client uses the linear module to capture the trend information and the enhanced Transformer module to capture nonlinear information and cross-variable dependencies in PV power. Fig.2 shows the architecture of PV-Client. The input PV power series is firstly smoothed with the RevIN module. Then the smoothed series is put into the cross-variable Transformer module and the linear module respectively. The final prediction of PV power is the combination of these two module's predictions.

3. EXPERIMENT

3.1 Data description and experiment setting

In this study, we take the PV power data of Jingang Photovoltaic Power Station in ShenZhen, China, as a study case. In the experiments, PV-Client utilize historical PV power data from the previous two days and weather forecast data, including radiation, temperature, humidity, wind speed, and surface pressure. While radiation strongly influences PV power output, other critical for power generation scheduling. In terms of model training, we set the number of Encoder layers to 2 and the hidden state dimension 128. We use the ADAM optimizer with a learning rate between 1e-3. The batch size is 128, and the training epoch is set to 30. The initial weight for the Transformer model $\mathbf{w}_{\text{trans}}$ and the initial weight for the linear model $\mathbf{w}_{\text{lin}}$ are both set to 1.

3.2 PV power forecasting results

To conduct the PV power forecasting experiments, the models are trained using nearly a year of historical offline data. However, we test the models online and follow the online results for one month (from 9.10-10.10). This evaluation process is taken to more objectively measure the performance of the models.

To evaluate the models, we utilize both the mean square error (MSE) and accuracy metrics. The accuracy metric is used to assess the relative error of each model's predictions, as defined in:

$$\text{Acc} = 1 - \frac{\sqrt{\sum_{i=1}^{n}(G_i - P_i)^2}}{\text{Cap}\sqrt{n}} \tag{5}$$

where G_i represents the actual PV power output for a given time step i, while P_i represents the predicted PV power output, and Cap represents bootCapacity.

We compare six baseline models: Linear Regression (LR) [12], Support Vector Regression (SVR) [13], XGBoost [14], LightGBM [15], Gated Recurrent Unit (GRU) [16], as well as a cross-time based Transformer model (T-Transformer for short). LR is a basic and widely used statistical model that aims to establish a linear relationship between the input variables and the output variable, while SVR is a regression model that attempts to find a hyperplane in a high-dimensional feature space that optimally separates the data points and creates a regression line with minimal error. XGBoost and LightGBM are both gradient boosting frameworks that employ an ensemble learning technique. They create a strong predictive model by sequentially adding weak models and focusing on the data points with higher residuals. GRU is a type of recurrent neural network that utilizes gating mechanisms to selectively update and forget information in the hidden state, allowing it to capture long-term dependencies and make accurate predictions for time series data. T-Transformer utilize efficient attention mechanism to capture temporal dynamics and dependencies across different time steps in time series data.

The prediction MSE and accuracy of different models are shown in Table 1. Remarkably, PV-Client achieves the most favorable outcomes in both MSE and accuracy metrics, indicating its superior performance compared to the other models.

Fig. 3 visually demonstrates the exceptional prediction performance of PV-Client, while also providing a comparison of the predictions made by LR and SVR. The horizontal axis represents time, while the vertical axis represents the values of PV power. The red line corresponds to the actual PV power values, the light blue line represents the predictions made by PV-Client, the dark blue line represents the LR's predictions, and the purple line represents the SVR's predictions. As shown, it is evident that PV-Client's predictions are much closer to the actual PV power output when compared to the predictions made by LR and SVR.

Table 1. MSE and accuracy of different models. The best result is indicated in bold font.

Model	MSE	Accuracy
LR	1693.707	0.894
SVR	2043.094	0.887
XGBoost	1879.130	0.890
LightGBM	1952.271	0.889
GRU	1555.194	0.881
T-Transformer	4167.539	0.835
PV-Client (ours)	**1469.132**	**0.903**

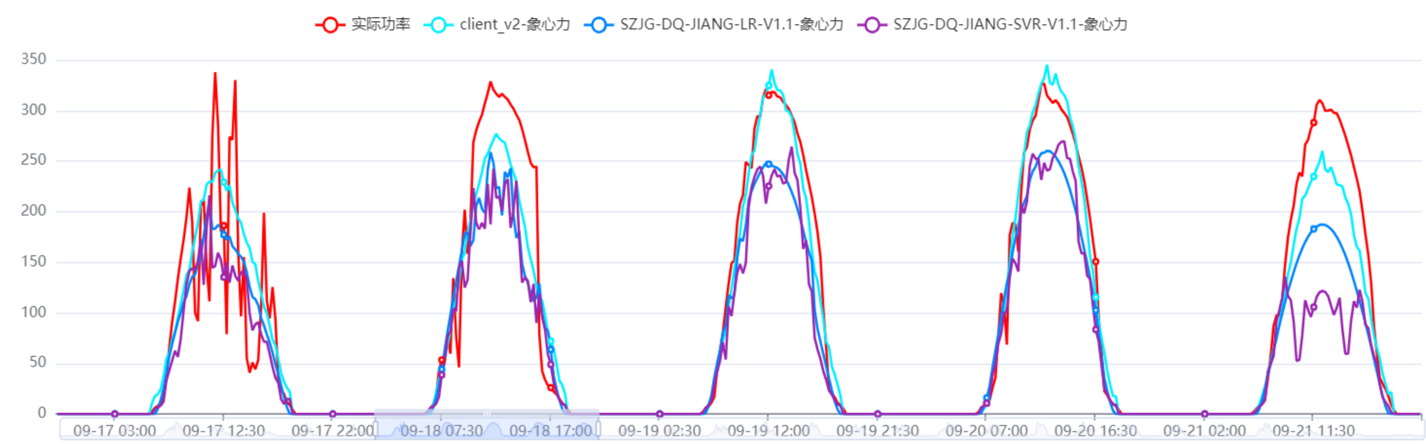

Fig. 3 PV power forecasting showcases of different models.

4. CONCLUSION

In this study, we proposed PV-Client, a more accurate and efficient model for PV power forecasting. In PV-Client, the trends of PV power are predicted by the linear module, and the cross-variable dependencies are obtained from the enhanced Transformer module. By leveraging the combined strength of these components, PV-Client effectively captures both global and local patterns in the PV power and demonstrates superior performance in PV power forecasting.

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