An Industrial Photovoltaic Prediction Model Based on Probabilistic Sparse Attention Mechanism of Temporal Convolution Network

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Abstract. This paper presents an advanced predictive model, termed C-PASST, which synergizes signal decomposition, sophisticated deep learning algorithms, and cutting-edge optimization techniques to enhance the accuracy of short-term power forecasts for photovoltaic systems. The process commences with the dissection of original photovoltaic data sequences through a comprehensive empirical modal decomposition method augmented by adaptive noise (C-DAN), adept at distilling temporal characteristics through a probabilistic sparse self-attention framework. Following this, the refined photovoltaic sequences are entrusted to specialized temporal convolutional networks (TCN) for prognostication. In the final stage, an innovative multiple universe optimizer (MVO) approach, informed by the principles of NNCT, is harnessed to integrate weight coefficients derived from the TCN models, culminating in the reconstruction of the ultimate forecasting outcomes.

Keywords: multiple universe optimizer, photovoltaic, signal decomposition.

1 INTRODUCTION

With rapid development of urbanization and industrialization, global energy consumption continues to grow. The escalating consumption of energy has precipitated a crisis, exacerbating environmental contamination and intensifying the scarcity of power supplies[1]. However, solar energy has made photovoltaic power generation one of the most popular solutions for energy conversion due to its abundance, non-pollution, and lack of transportation[3]. Harnessing solar photovoltaic energy, while transformative, is subject to diurnal variations and meteorological conditions, epitomizing a quintessentially fluctuating and intermittent power source. Its integration on a grand scale within the electrical grid profoundly influences operational dispatch and market strategy for electricity. Consequently, devising a precise predictive model for photovoltaic power generation has emerged as a pivotal area of contemporary research[4].

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Photovoltaic power generation forecasting can be categorized on the basis of forecasting range, meteorological data patterns, and forecasting methods[5]. According to the range of PV power generation forecasting it can be categorized into short-term forecasting, medium-term forecasting, and long-term forecasting[6]. Usually, different neural network models have been used to predict solar irradiance or PV power generation[5]. The CNN model can effectively solve time series prediction problems. Temporal Convolutional Networks (TCN) represent a class of deep learning models specifically tailored for time series analysis. Distinct from neural network architectures, TCN boast a streamlined design free from the intricate architecture and gating mechanisms characteristic of GRU or LSTM. The unique causal configuration of TCNs ensures that predictions for the present are predicated solely on antecedent data, thereby precluding any prospective information from inadvertently influencing historical results.

Aiming at the above problems, this paper proposes a photovoltaic prediction model (C-PASST) based on the probability sparse attention mechanism of time convolution network, which combines signal decomposition method, TCN network and optimization algorithm. C-PASST model predicts photovoltaic power generation every 15 minutes.

The main contributions of this paper are as follows:

(1) This paper proposes a photovoltaic prediction model (C-PASST) based on the probability sparse attention mechanism of time convolution network, which combines signal decomposition method, TCN network and optimization algorithm.

(2) This paper puts forward a reasonable network training mechanism. This mechanism firstly removes data noise, and then uses deep TCN network to extract nonlinear features, thus achieving higher prediction accuracy and lower memory usage.

(3) Build a probability sparse self-attention mechanism and fuse it with TCN network to effectively predict photovoltaic power generation.

(4) To address the limitations inherent in conventional integration methodologies, which predominantly rely on positive weight optimization, a sophisticated weight optimization strategy has been devised, employing Multiverse Optimizer (MVO) Based NNCT.

2 LEARNING STRATEGY OF C-PASST

Prior to network training, data must undergo preprocessing to eliminate outliers and impute missing values. The preprocessing phase incorporates C-DAN decomposition technology, which effectively simplifies and stabilizes the variability inherent in the original photovoltaic power data. Subsequently, the refined output from the C-DAN decomposition is channeled into the network training phase for prognostication. C-PASST enhances the predictive accuracy by training the preprocessed subsequences through the construction of intricate deep neural networks of varying architectures. Moreover, forecasting photovoltaic power generation is inherently a time series modeling endeavor, typically approached through recursive methodologies. Nonetheless, the RNN model's sequential computation and memory retention requisites result in protracted training durations and substantial computational demands.

Therefore, to improve the computational speed of the model, this paper uses C-PASST for PV power prediction. The overall frame diagram of C-PASST is shown in Figure 1.

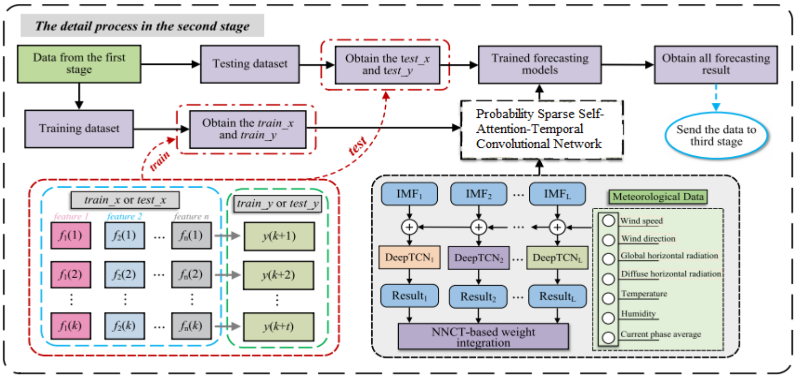

Fig. 1. Overall framework of C-PASST

3 EXPERIMENT

3.1 Datasets

This article selects the 1B PV system data of DKASC, Alice Springs, with few faults and relatively complete data for simulation experiments. Information specific to photovoltaic plants is shown in Table 1.

Table 1. Parameter information

Attribute	Value
Array Rating	23.4KW
PV Technology	mono-Si
Panel Rating	195w
Number of Panels	4×30
Panel Type	Trina TSM-195DCO1A
Array Area	4 × 38.37 m^2
Type of Tracker	DEGERenergie 5000NT, dual axis
Inverter Size/Type	4 x 6kW, SMA SMC 6000A
Array Tilt/Azimuth	Variable: Dual axis tracking

The experimental data set includes 35136 observation examples from September 1, 2015 to August 31, 2016, with a resolution of 15 min. In addition, the data was divided into three parts as follows: the first 80% of the data is used for model training, the second 10% is used to validate the model, and the last 10% is used for the model test set.

The selection of model parameters is a critical step that requires full consideration of various factors and adequate experimental evaluation. Selecting appropriate model parameters can not only improve the running efficiency and model quality of the algorithm, but also improve the prediction accuracy of the combined model. After several pre-training and optimization adjustments, the main parameters of the experimental method are shown in Table 2.

Table 2. Parameter Settings

Method	Parameter setting
ARIMA	q = 1, d = 1, p = 3
ELM	nits=100
GRU	uunits=32, 64
CNN	filters=64, 128, 256, stride=2
LSTM	units=100, 200
C-PASST	filters=256, k=3, h=3

3.2 Evaluation Metric

In order to better analyze the experimental results and assess the prediction performance of the model, this paper uses the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2) as the evaluation metrics:

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

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left[y_i - \hat{y}_i\right]^2}{\sum_{i=1}^{n}\left[y_i - \bar{y}_i\right]^2} \tag{2}$$

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{4}$$

Where $\hat{y}_i$ represents the final predicted value of the predicted PV power, and $\bar{y}_i$ represents the average value.

3.3 Results and Analysis

In the first experiment, six benchmark methods were compared and their prediction accuracy was discussed. The framework encompasses a statistical approach, a machine learning technique and four sophisticated deep learning strategies. Figure 2 offers a graphical depiction of the comparative outcomes of various models, encompassing statistical, machine learning, and deep learning approaches. For a more precise evaluation of their predictive accuracy, Figure 3 illustrates a comprehensive visualization of their prediction errors, detailing four critical error metrics: R2, RMSE, MAE, and MAPE.

As shown in Figure 3, compared with other methods, ARIMA has the worst evaluation results on RMSE and R2. Generally speaking, compared with the other six benchmark methods, the proposed prediction method obtains the best results and has a wide range of applications.

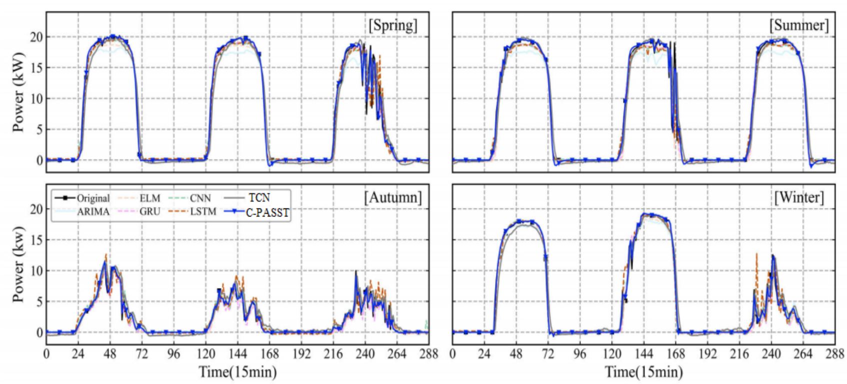

Fig. 2. Power prediction of different benchmark methods

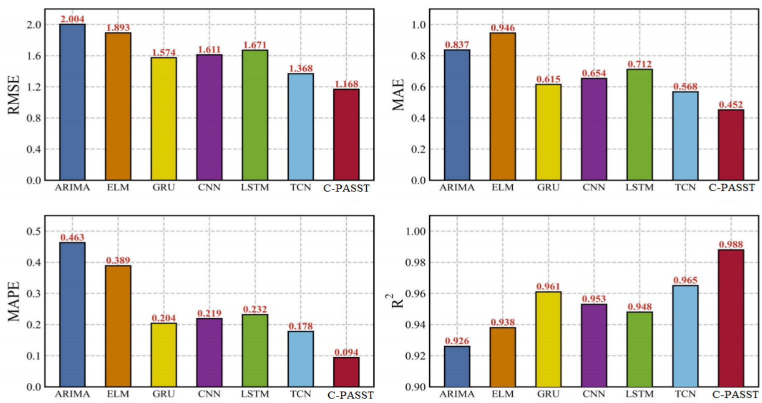

Fig. 3. Performance indicators of different benchmark methods

4 CONCLUSION

The accurate forecasting of PV is a critical component of intelligent grid management, providing essential insights for strategic decisions in power system, regulation, and market transactions. This study introduces an advanced integrated learning approach for short-term PV power prediction, characterized by enhanced precision and consistency. Utilizing a synergistic blend of C-DAN technology, the C-PASST network, a probabilistic sparse attention mechanism, and a novel NNCT weight integration strategy informed by MVO, the method offers a significant leap forward in forecasting methodologies. Initially, the C-DAN process purifies the raw photovoltaic sequence data, followed by the extraction of nonlinear characteristics through C-PASST, and the probabilistic sparse attention mechanism adeptly identifies temporal patterns within the photovoltaic power generation dataset. Subsequently, we advocate for an innovative optimization of NNCT weights underpinned by MVO, which acknowledges the variability among different data series and expands the weighting spectrum to include negative values, thereby elevating system's predictive precision. The efficacy and robustness of this approach are rigorously assessed using four traditional performance metrics and two statistical tests. The assessments reveal that C-DAN technology significantly mitigates noise interference, substantially enhancing the predictive capabilities of the composite method. Simulation outcomes further corroborate that an optimal integration strategy is instrumental in achieving superior performance and accuracy in photovoltaic power forecasting.

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