Minusformer[1] is an improved method for time series prediction, which core is to use an enhanced Transformer[2] architecture. It achieves stepwise residual learning for time series data by changing the aggregation mechanism of information in Transformer from addition to subtraction, thereby avoiding overfitting problems. The specific framework is shown in Fig.1, where the preprocessed time series is extracted utilizing a sliding window, and the time series X∈RI×D is the historical data of le
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Hourly irradiance prediction based on Minusformer model with stepwise learning residuals

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Introduction

Solar power generation has the advantages of pollution-free, renewable, distributed generation, strong adaptability, etc., which can effectively reduce energy consumption and environmental pollution. Governments around the world attach great importance to and support the development of renewable energy. However, due to the influence of various complex factors such as climate change, seasonal changes, atmospheric conditions, geographical locations, etc. Solar irradiance has characteristics such as randomness, periodicity, intermittency, and non-stationarity, resulting in strong volatility and instability of photovoltaic (PV) output, which poses great challenges to power system dispatch management and grid operation safety. Therefore, accurately predicting solar irradiance is a key requirement to ensure the normal dispatch and operation of solar energy systems. Currently, mainstream models are prone to severe overfitting when applied to non-stationary time series. To prevent this overfitting problem, a Minusformer model based on stepwise residual learning is proposed for hourly irradiance prediction.

Methodology

Minusformer[1] is an improved method for time series prediction, which core is to use an enhanced Transformer[2] architecture. It achieves stepwise residual learning for time series data by changing the aggregation mechanism of information in Transformer from addition to subtraction, thereby avoiding overfitting problems. The specific framework is shown in Fig.1, where the preprocessed time series is extracted utilizing a sliding window, and the time series $x \in R^{I \times D}$ is the historical data of length l starting from the current time point t, which is embedded before passing through the first block. The time series input into each basic block performs the following steps: First, the input data X_l is feature-extracted into $\hat{X}_l$ through the Block module. Then, the residual $R_l = X_l - \hat{X}_l$ is computed such that the residual retains the feature portion of the time series that is not adequately processed by the model, the above steps are superimposed in the form of a block-residual several times, and then $\hat{X}_l$ is mapped to the same dimension as the predicted label Y to generate the irradiance prediction O_l=Linear($\hat{X}_l$), throughout the model layer, O_l is

$$\hat{Y} = i \sum_{l=0}^{\lfloor \frac{L}{2} \rfloor} O_{2l+1} - i \sum_{l=0}^{\lfloor \frac{L}{2} \rfloor} O_{2l}$$

Where $i = 1$ if $L \bmod 2 = 1$, else $i = -1$. L is the number of residual blocks. This approach allows Minusformer to efficiently capture complex features in time series data while avoiding overfitting problems.

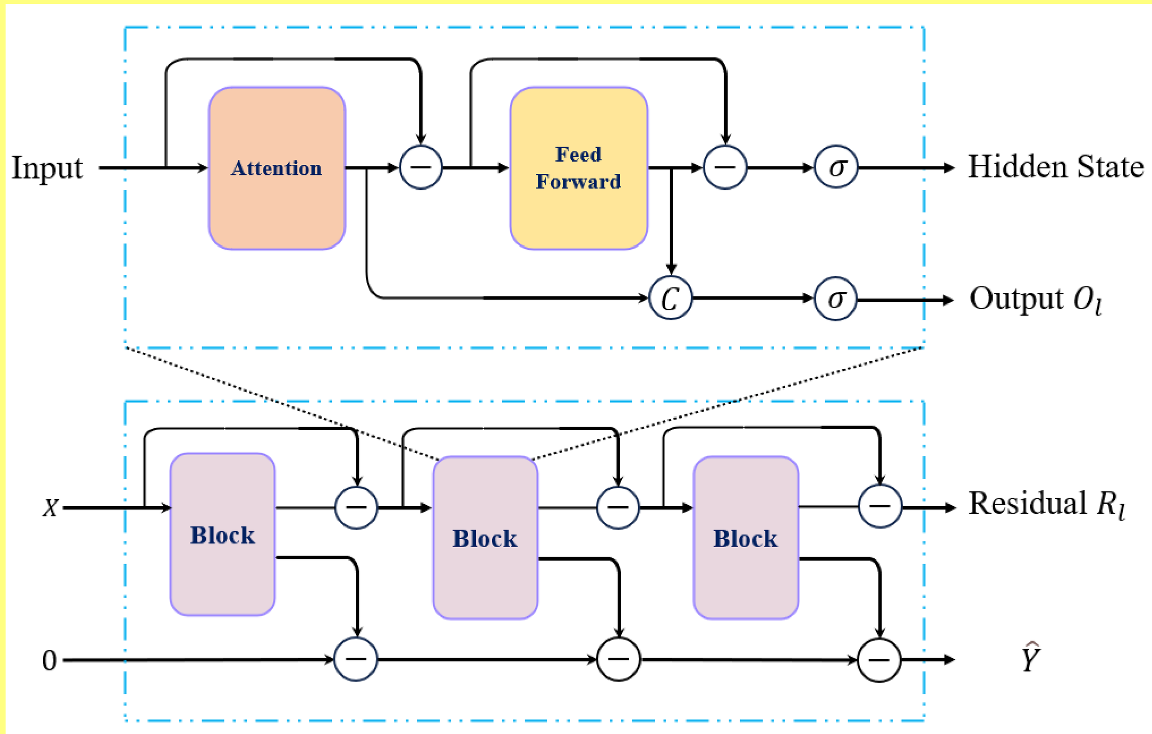

Fig. 1. The solar irradiance forecasting framework based on Minusformer

Results And Discussion

DATA SET ANALYSIS

The dataset used in this study is Folsom (38°39′N, 121°90′W, California, USA) [3]. This dataset contains three years of data from 2014 to 2016. To ensure optimal dataset utilization and model generalization capability, we chose a training, validation, and test set split ratio of 7:1:2.

EVALUATION INDICATORS

The RMSE (Root Mean Square Error), the nRMSE (Normalized Root Mean Square Error), the MAE (Mean Absolute Error), and R^2 (R-squared) are used to evaluate the forecasting performance. Some results related to model performance are summarized in Table 1 and the overall prediction results for the Folsom dataset partial test set are shown in Fig.2 and Fig.3.

PREDICTION RESULT ANALYSIS

Table 1 Model performance evaluation metrics of different methods for the prediction of the Folsom dataset.

Method	RMSE	nRMSE	MAE	R^2
LSTM	43.39	20.89	18.80	97.77
Transformer	41.20	20.21	16.86	98.74
LSTM-Transformer	37.13	18.24	15.28	98.68
Minusformer	**30.31**	**13.53**	**13.35**	**99.01**

Table 1 clearly shows that using the Minusformer model has better prediction accuracy, with all four evaluation metrics outperforming the other models

On the other hand, from Fig. 2, it can be found that the overall envelope area of the predicted irradiance values and the measured values can almost overlap together, indicating that the prediction effect is relatively satisfactory.

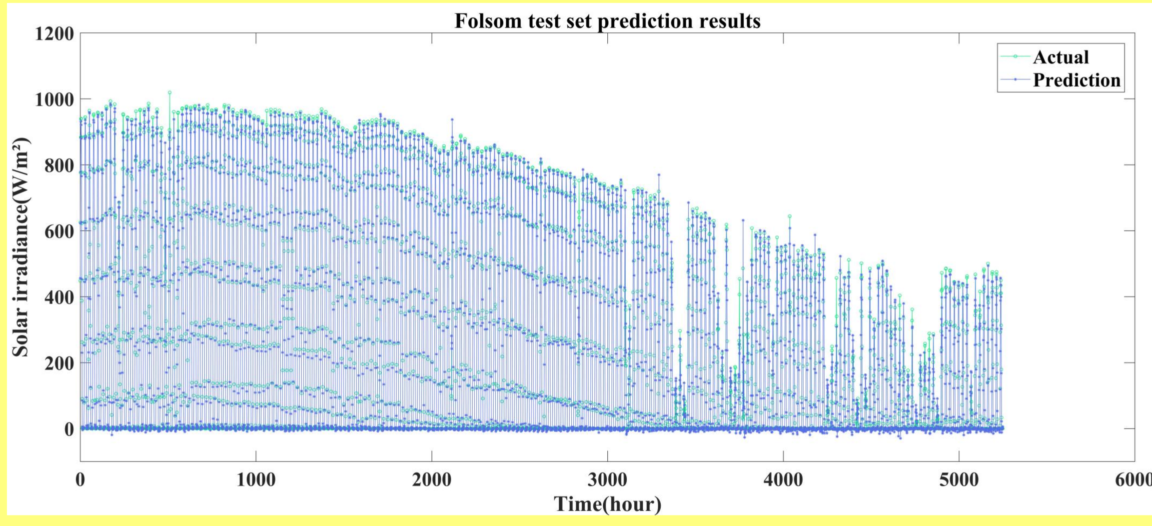

Fig. 2. The overall prediction of Folsom test set by Minusformer model

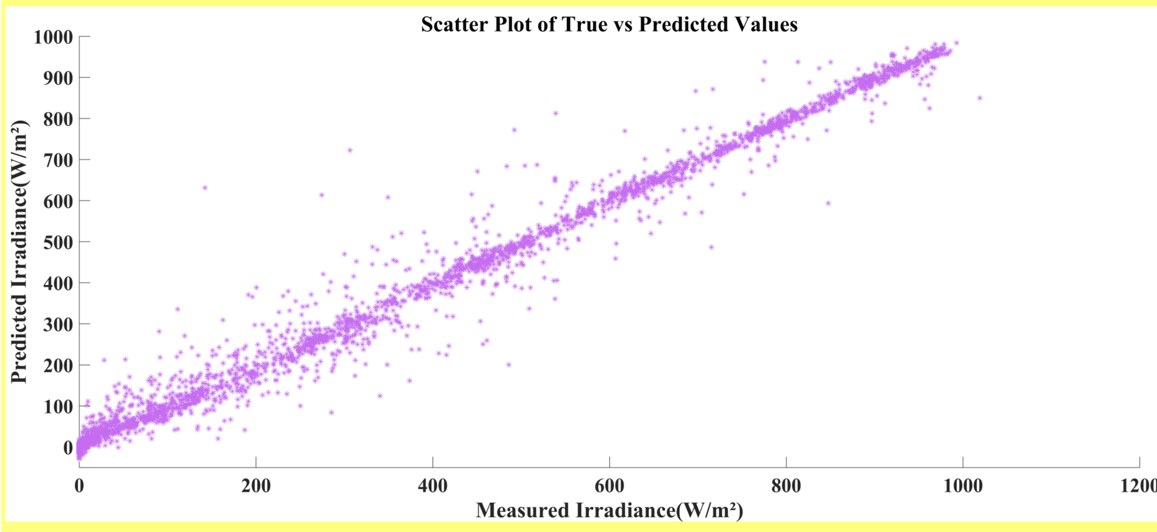

Fig. 3. Scatterplot of true versus predicted values for the Minusformer model on the overall Folsom test set

Fig. 3 also shows that the predicted irradiance values show a good linear relationship with the true values, which further proves the excellent prediction using the Minusformer model.

In summary, the four performance metrics and visualization results from the Folsom dataset more intuitively show that the Minusformer model is capable of extracting features from time series data more accurately and automatically. The method proposed in this paper shows better performance in short-term irradiance prediction.

Conclusions

In this study, Minusformer gradually learns the residual information of the time series by changing the information aggregation mechanism from additive to subtractive operation. This change not only enhances the ability of the model to capture the intrinsic dynamic changes of the time series but also reduces the risk of overfitting, which can effectively improve the accuracy of solar irradiance prediction. The results provide a new and effective feature extraction method for solar irradiance prediction research based on the Minusformer model.

References

[1] D. Liang, H. Zhang, D. Yuan, B. Zhang, M. Zhang, Minusformer: Improving Time Series Forecasting by Progressively Learning Residuals, arXiv preprint arXiv:2402.02332 (2024).https://doi.org/10.48550/arXiv.2402.02332.
[2] Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A.N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, Advances in neural information processing systems.30 (2017).https://doi.org/10.48550/arXiv.1706.03762.
[3] H.T.C. Pedro, D.P. Larson, C.F.M. Coimbra, A comprehensive dataset for the accelerated development and benchmarking of solar forecasting methods,J. Renew. Sustain. Energy 11(2019),036102,https://doi.org/10.1063/1.5094494.