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BiTCN-DCMA: Research on Prediction Method of Photovoltaic Power Generation Based on Dynamic Convolution and BiTCN-BiLSTM

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Abstract: *With the continuous progress of people's living standard, electricity has been applied to every aspect of people's daily life, and people's demand for electricity is also growing. Photovoltaic power generation, as a kind of power generation method, has been developing rapidly in recent years both domestically and internationally, and has made great breakthroughs. However, PV power generation is subject to fluctuations due to weather and other factors, and how to accurately forecast PV power generation is an issue that needs to be considered. In this study, BiTCN-DCMA model based on bidirectional temporal convolutional neural network is proposed for the prediction of photovoltaic power generation. BiTCN-DCMA uses dynamic convolution for forward and backward optimization to achieve features that can adapt to different scales; the bi-directional fused feature information enters the attention layer, which consists of a bi-directional long and short-term memory network and a multi-head attention mechanism, and the attention layer is able to carry out the contextual data that captures the complex interactions between different locations in the sequence, and these optimization methods strengthen the linear layer's prediction of power generation Accuracy. The results show that the root mean square error (RMSE) of BiTCN-DCMA is reduced by 75.81% and the correlation coefficient R^2 is improved by 12.50% compared to the Transformer model, showing good prediction accuracy and stability.*

Keywords: *Electric power, Photovoltaic power generation forecast, Deep learning, BiTCN, Dynamic convolution*

1. Introduction

Electricity is an energy source powered by electricity, a form of energy that is produced by the flow of electrons in a conductor [1]. Discovered in the 1870s, the discovery and application of electricity set off the second industrialization. It became one of the three scientific and technological revolutions that occurred in the world since the 18th century of human history, and since then science and technology have changed people's lives.The large-scale electric power system that appeared in the 20th century is one of the most important achievements in the history of human engineering science [2],[3], and is an electric power production and consumption system that consists of power generation, transmission, substation, distribution, and use of electricity [4],[5] It converts primary energy from nature into electricity through mechanical energy devices, and then supplies electricity to various users through transmission, transformation and distribution [6],[7]. Electricity is widely used in modern society to drive all kinds of electric equipment, provide lighting, run industrial production lines, and support communications and many other fields.

Photovoltaic (PV) power generation is the process of directly converting solar energy into electrical energy using solar cells based on the principle of photovoltaic effect. Whether used independently or grid-connected, a PV power generation system consists of three main components: solar panels (modules), controllers, and inverters, which are mainly composed of electronic components but do not involve mechanical parts, and which work together in order to generate electricity [8]. Therefore, photovoltaic power generation equipment is extremely refined, reliable and stable with a long life, easy to install and maintain. Theoretically speaking, photovoltaic power generation technology can be used in any occasion that requires power, up to spacecraft, down to household power supply, as big as megawatt-class power station, as small as toys, photovoltaic power can be everywhere.

Photovoltaic power generation works as follows: first, during the day, solar cells absorb photons from

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sunlight, excite electrons and generate a DC current. Then, an inverter converts the DC current to AC current, making it suitable for use in the grid or other AC devices. Secondly, the power generation system can inject the power into the grid, supply it to users, or store it in batteries for backup [9]. Photovoltaic power generation has a wide range of applications and great advantages. Photovoltaic power generation is a distributed energy source, and PV power generation systems can be distributed to sites of all sizes, including individual homes, commercial buildings and large-scale PV power plants. PV is also a clean, renewable energy source that does not produce harmful gases such as carbon dioxide. Since solar energy is constantly renewable, PV power systems are sustainable [10]. For individuals and businesses, generating electricity through photovoltaic (PV) can reduce electricity bills and provide a return on investment in the long term. Photovoltaic (PV) power generation technology is widely used around the world and is one of the main drivers in the clean energy sector. As the technology continues to evolve, the efficiency and cost-effectiveness of PV power systems are improving, providing positive support for a sustainable energy future.

Deep Learning (DL) is a new research direction in the field of Machine Learning (ML), which was introduced into machine learning to bring it closer to its original goal, Artificial Intelligence (AI) [11]. It is based on artificial neural networks, especially deep neural networks (DNN). Deep learning is the process of learning the intrinsic patterns and levels of representation of the sample data and the information gained from these learning processes can be of great help in the interpretation of data such as text, images and sound [12],[13]. It aims to learn and represent complex patterns and features of data through a multi-layered neural network structure, with the ultimate goal of enabling machines to be as analytical and learning as humans, capable of recognizing data such as text, images, and sound [14]. Deep learning is a complex machine learning algorithm that has achieved results in speech and image recognition that far exceed previous related techniques. Deep learning is a collective term for a class of pattern analysis methods that, in terms of specific research, involves three main types of methods:

(1) Neural network systems based on convolutional operations, i.e. Convolutional Neural Networks (CNN).

(2) Self-coding neural network based on multi-layer neurons, including self-coding (Auto encoder) and two types of sparse coding (Sparse Coding), which has received much attention in recent years.

(3) Deep Confidence Network (DBN) that is pre-trained as a multi-layer self-coding neural network and then further optimizes the weights of the neural network by incorporating the discriminative information.

After gradually transforming the initial low-level feature representations into high-level feature representations through multilayer processing, complex learning tasks such as classification can be accomplished with simple models. Deep learning can thus be understood as feature learning or representation learning. The success of deep learning is due in part to advances in hardware, the availability of large-scale data, and good algorithm design. This approach has been highly successful in many fields, providing an effective tool for solving complex pattern recognition and prediction problems.

2. Related work

Regarding TCN in power generation prediction, domestic and foreign scholars have done a lot of related researches before. Xiang et al. [15] who proposed a short-term PV power prediction method based on a hybrid model of Time Convolutional Networks and Gated Recurrent Units with Effective Channel Attention Networks (TCN-ECANet-GRU), which is effective in improving the prediction accuracy. Ma et al. [16] have proposed a combined LSTM-TCN prediction model based on NWP error correction model and TimeGAN, and the performance of the hybrid model was tested by the Chinese wind farm dataset to verify the effectiveness of the method. Mo et al. [17] who used TCN and Prophet to forecast electricity load data respectively, and then fused these two models using the least squares method and utilized their respective advantages to improve the forecasting accuracy. Experiments show that the proposed TCN-Prophet model has higher prediction accuracy than the classical ARIMA, RNN, LSTM, GRU and some integrated models, which can provide more effective decision-making references for the grid sector. Gao et al. [18] who proposed a Time Convolutional Network (TCN)-BiGRU-Attention short-period power load forecasting method based on Whale Optimization Algorithm (WOA). The results show that the method has more accurate prediction.

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3. Materials and methods

3.1. BiTCN-DCMA

The BiTCN-DCMA model is a combination of a bidirectional temporal convolutional neural network (BiTCN), Dynamic Convolution (DC), Long Short-Term Memory (LSTM), and Multi-head Attention (MHA) mechanism combined into one model. Dynamic convolution was used to improve the convolution module used in BiTCN-DCMA models of BiTCN by allowing the size or shape of the convolution kernel to dynamically change over different input sequence time data, catering for input sequences of different lengths and structures [19]. The attention layer consists of LSTM and MHA, the use of LSTM is mainly concerned with the feature extraction capability of the data in terms of cyclic variations in the temporal data and a multi-layer bidirectional LSTM (BiLSTM) similar to the BiTCN structure is used to capture the contextual information at any position in the sequence. This part of the information is sent to the MHA which is able to capture the complex interactions between different positions in the sequence in order to achieve the understanding of the meaning of each element in the sequence, and to make the model prediction results after the linear structure processing. The structure of the model is shown in Figure 1.

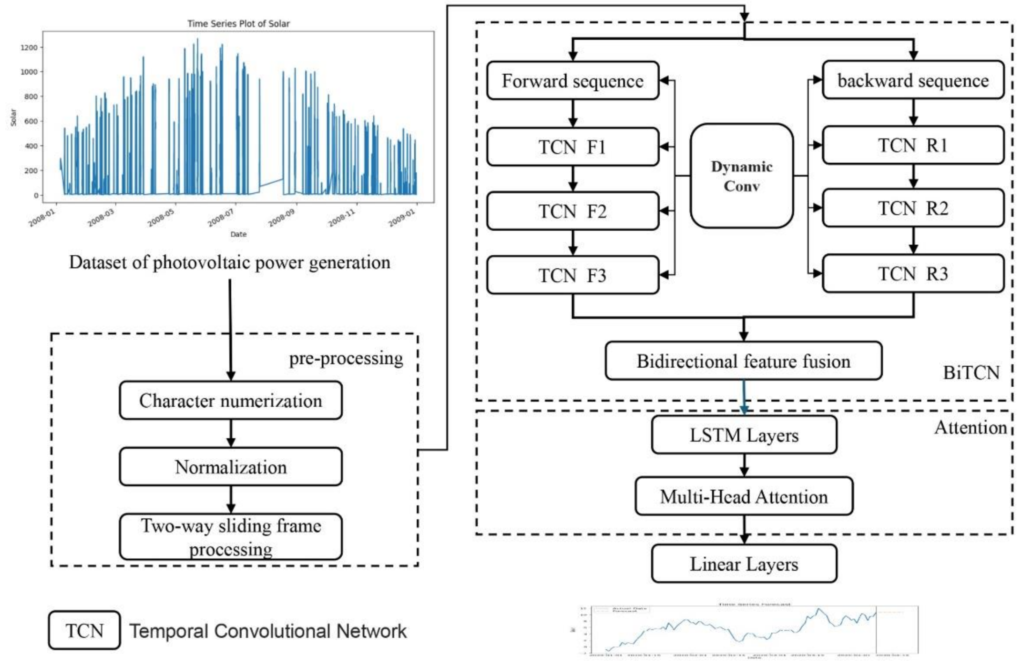

Figure 1: BiTCN-DCMA modeling architecture.

BiTCN (Bidirectional Temporal Convolutional Neural Network) is a deep learning model for modeling time-series data [20]. Compared to the traditional time convolutional network TCN, BiTCN adds the ability to process sequence data in both directions, which allows for better capture of backward and forward dependencies in time-series data.The structure of the BiTCN model is shown in Figure 1.

Bidirectional long and short-term memory network (BiLSTM) consists of front and back two-way long and short-term memory network (LSTM), and each unit contained in the LSTM consists of a memory gate, an oblivion gate and an output gate [21]. The memory gate will store several specific information of meteorological data into the information state, and complete the information update through the sigmoid function and tanh function; the forgetting gate will eliminate the useless information in the meteorological data information to ensure its validity; and the output gate will output the meteorological data information obtained at the moment (e.g., Figure 2).

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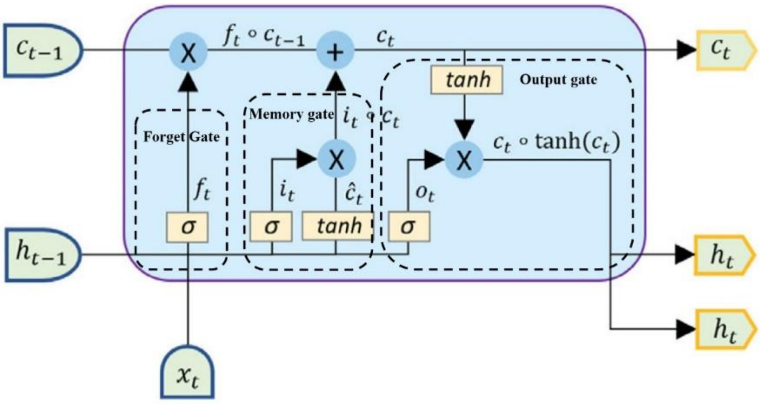

Figure 2: BiLSTM module structure.

3.2. Dynamic convolution

Dynamic Convolution (DC) is an improved convolution operation designed to enhance the flexibility and performance of Convolutional Neural Networks (CNNs) when dealing with different input data [22]. Unlike the fixed convolution kernel in traditional convolutional layers, the convolution kernel of dynamic convolution is dynamically generated or selected based on the input data. The structure of dynamic convolution is shown in Figure 3.

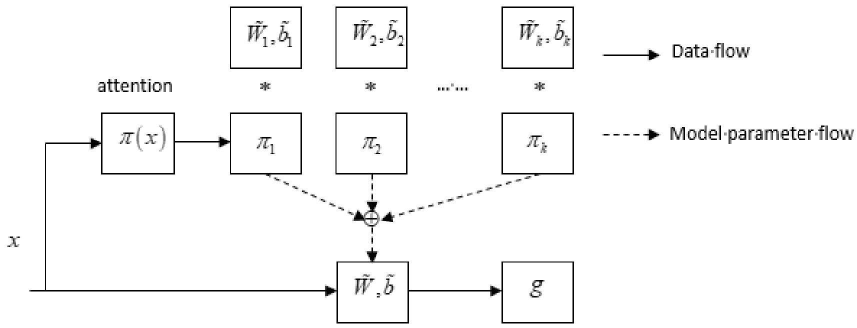

Figure 3: Dynamic convolutional structures.

3.3. Multiple attention mechanisms

Multi-Head Attention Mechanism (MHA) is one of the core components of the Transformer model, which is widely used in the fields of natural language processing (NLP) and computer vision (CV) [23]. It enhances the representation capability and performance of the model by computing multiple attention (attention) heads in parallel to capture different features in the input data. The structure of the multi-head attention mechanism is shown in Figure 4.

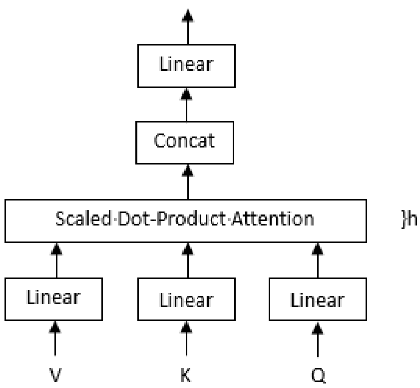

Figure 4: Structure of the multi-attention mechanism.

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3.4. Dataset construction

The dataset used in this experiment is the dataset of PV power generation and meteorological parameters for Amherst, Massachusetts for the year 2008 provided by the National Weather Service (NWS) and the University of Management and Technology (UMT). The parameters in this dataset include time, temperature, humidity, dew point temperature, wind speed, maximum wind speed, wind direction, precipitation, barometric pressure and PV power generation. Among these parameters, the prediction of PV power generation is done based on the given meteorological parameters such as temperature, humidity and dew point temperature. The number of training, testing and validation sets in the dataset used for this experiment are 12355, 3524 and 1739 respectively, based on which the accuracy of BiTCN and its related models for PV power generation prediction is judged. The following Figures 5 (a) to 5 (d) show each meteorological parameter in a particular day for the dataset used in this experiment.

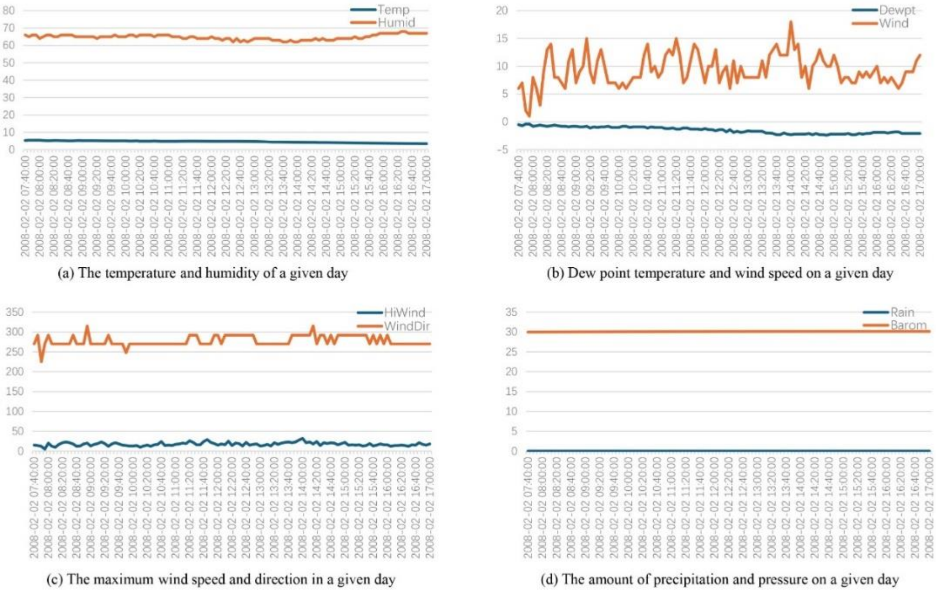

Figure 5: (a) temperature and humidity conditions during a given day, (b) dew point temperature and wind speed conditions during a given day, (c) maximum wind speed and direction conditions during a given day, (d) precipitation and barometric pressure conditions during a given day.

The data in Figures 5 (a) through 5 (d) show that the temperature was relatively smooth on this day with a slight downward trend. The humidity fluctuated slightly on this day, with the humidity around noon being slightly lower than the rest of the day. The dew point temperature on this day fluctuated slightly and showed a gradual downward trend. Wind speed and maximum wind speed fluctuated quite a bit on this day, with strong and weak winds, and the wind direction was relatively stable and did not change much. Precipitation for the day was basically 0, not much precipitation. The barometric pressure on this day did not fluctuate much and showed a gradual upward trend.

3.5. Evaluation metrics

In this experiment, the accuracy of PV power generation prediction is evaluated using three assessment metrics: mean absolute error (MAE), root mean square error (RMSE) and R^2. Among them, the mean absolute error (MAE) is used to measure the average absolute error between the predicted value and the true value, which is a non-negative value, and a smaller MAE indicates a better model. The RMSE is a typical metric for regression models, which is used to indicate how much error will be incurred in the prediction of the model. For larger errors, the weights are higher. The benefit is that the results are normalized and it is easier to see the gap between models. The greater the weight, the better the model. The formulas for these 3 evaluation metrics are listed below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \in 0, +\infty) \tag{1}$$

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$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \in 0, +\infty) \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \in [0,1] \tag{3}$$

4. Results and analysis

4.1. BiTCN-DCMA performance analysis

In order to judge the accuracy of BiTCN-DCMA and its related models for PV power generation prediction, this experiment is carried out on the given dataset and the results are shown in Table 1:

Table 1: Experimental results of BiTCN-DCMA and its related models for PV power generation prediction.

Model	MAE	RMSE	R^2
BiTCN-DCMA	0.077	0.112	0.801
Transformer	0.341	0.463	0.712
Reformer	0.729	0.856	0.457
FEDformer	0.619	0.759	0.568
Pyraformer	0.662	0.858	0.489

From the data in Table 1, it can be found that the values of the three evaluation indexes, MAE, RMSE and R^2, of the experiments conducted by the BiTCN-DCMA model are relatively better than the other four models, indicating that the BiTCN-DCMA model is able to better capture the relationship between PV power generation and meteorological parameters when compared to the other four models for the PV power generation prediction. BiTCN-DCMA reduces the RMSE by 75.81% and improves the R^2 by 12.50% compared with the Transformer model. The BiTCN-DCMA model achieved optimal performance with an MAE of 0.077, an RMSE of 0.112, and an R^2 of 80.1%. The PV power generation is predicted according to the corresponding relationship, which makes the accuracy of PV power generation prediction using the BiTCN-DCMA model higher compared to the other four models, and this model can be selected for PV power generation prediction.

4.2. Training performance analysis

The training and validation process of BiTCN-DCMA model is shown in Figure 6, and the whole process was carried out for 60 Epochs, using the MSE loss function, the optimizer using Adam, the learning rate is 0.01, and other hyperparameters are kept as default. The loss curve of the whole process decreases more obviously, and the performance of the validation curve in the four subgraphs fluctuates more sharply and decreases or rises more slowly. In Figure 6 (b) training and validation MAE, the validation curve is located below the training curve and tends to run in the direction of zero. In Figure 6 (c) training and validation R^2, the starting point of the validation curve R^2 is above 0.65, which is 44.44% higher than that of the starting point of the training curve, which is above 0.45, indicating that the model's initial fitting ability is strong, and also indicating that the selection of the interval point of the time-series data reaches a better level. overall, the proposed model predicts the PV according to the meteorological parameter among the three indicators. power generation is better.

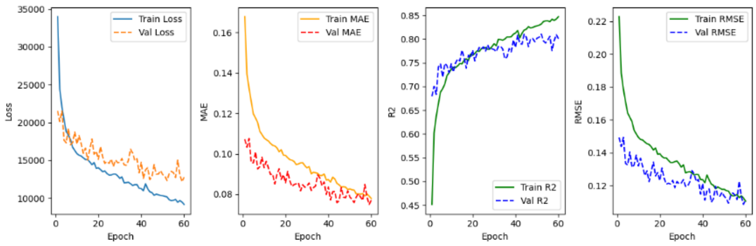

Figure 6: (a) training and validation loss, (b) training and validation MAE, (c) training and validation R2, (d) training and validation RMSE.

5. Conclusions

Electricity has become an integral part of modern life, powering countless aspects of our daily routines and offering remarkable convenience. As science, technology, and society have advanced, our reliance on electricity as a fundamental energy source has only intensified. In recent years, photovoltaic power generation has emerged as a promising form of clean energy, gaining widespread adoption and attention due to its environmental benefits and cost-effectiveness. However, a critical challenge in the field of PV energy is developing accurate methods for forecasting power generation.

Deep learning, as one kind of machine learning, can be widely used in many fields to solve many problems and difficulties. In this paper, a BiTCN-DCMA model combined with meteorological parameters is proposed to predict photovoltaic power generation. Through experiments, it is found that the BiTCN-DCMA model has a higher accuracy compared with other related models for PV power generation prediction, with an RMSE of 0.112 and an R^2 of 80.1%, and the model can be well applied to the prediction of PV power generation.

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References

[1] Chen S, Bai Y, Zhang Y, et al. A Framework of Decentralized Electricity Market Based on The Collaborative Mechanism of Blockchain and Edge Computing[C]//2019 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI). 2019: 219-223.
[2] Fu J, Shi Z, Zhang Z. An Edge Computing Framework for Digital Grid[C]//2020 IEEE 3rd International Conference on Electronic Information and Communication Technology (ICEICT). 2020: 670-673.
[3] He X, Cai W, He H, et al. Top-level design of electricity consumption information collection system based on edge computing[C]//2021 13th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA). 2021: 522-526.
[4] Yao J, Li Z, Li Y, et al. Cost-Efficient Tasks Scheduling for Smart Grid Communication Network with Edge Computing System[C]//2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC). 2019: 272-277.
[5] Chen S, Wen H, Wu J, et al. Internet of Things Based Smart Grids Supported by Intelligent Edge Computing[J]. IEEE Access, 2019, 7: 74089-74102.
[6] Hu J, Li Y, Zhao G, et al. Deep Reinforcement Learning for Task Offloading in Edge Computing Assisted Power IoT[J]. IEEE Access, 2021, 9: 93892-93901.
[7] Xu Z, Han G, Zhu H, et al. Adaptive DE Algorithm for Novel Energy Control Framework Based on Edge Computing in IIoT Applications[J]. IEEE Transactions on Industrial Informatics, 2021, 17(7): 5118-5127.
[8] Wang Y, Shen Y, Mao S, et al. LASSO and LSTM Integrated Temporal Model for Short-Term Solar Intensity Forecasting[J]. IEEE Internet of Things Journal, 2019, 6(2): 2933-2944.
[9] Wang Y, Shen Y, Mao S, et al. Adaptive Learning Hybrid Model for Solar Intensity Forecasting[J]. IEEE Transactions on Industrial Informatics, 2018, 14(4): 1635-1645.
[10] Wang Y, Zou H, Chen X, et al. Adaptive Solar Power Forecasting based on Machine Learning Methods[J]. Applied Sciences, 2018, 8(11): 2224.
[11] Jan Z, Ahamed F, Mayer W, et al. Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities[J]. Expert Systems with Applications, 2023, 216: 119456.
[12] Ke S, Dai G, Pan H, et al. Intelligent vineyard blade density measurement method incorporating a lightweight vision transformer[J]. Egyptian Informatics Journal, 2024, 26: 100456.
[13] Dai G, Fan J, Tian Z, et al. PPLC-Net:Neural network-based plant disease identification model supported by weather data augmentation and multi-level attention mechanism[J]. Journal of King Saud University - Computer and Information Sciences, 2023, 35(5): 101555.
[14] Zhu Z, Lei Y, Qi G, et al. A review of the application of deep learning in intelligent fault diagnosis of rotating machinery[J]. Measurement, 2023, 206: 112346.
[15] Xiang X, Li X, Zhang Y, et al. A short-term forecasting method for photovoltaic power generation based on the TCN-ECANet-GRU hybrid model[J]. Scientific Reports, 2024, 14(1): 6744.

ISSN 2616-5775 Vol. 7, Issue 7: 23-30, DOI: 10.25236/AJCIS.2024.070704

[16] Li S, Ma W, Liu Z, et al. Short-Term Prediction of Wind Power Based on NWP Error Correction with TimeGAN and LSTM-TCN[C]//Yadav S, Arya Y, Muhamad N A, et al. Energy Power and Automation Engineering. Singapore: Springer Nature, 2024: 939-948.
[17] Mo J, Wang R, Cao M, et al. A hybrid temporal convolutional network and Prophet model for power load forecasting[J]. Complex & Intelligent Systems, 2023, 9(4): 4249-4261.
[18] Gao Q, Chen J, Ji Y, et al. Short-term Load Prediction Based on Whale Optimized WTCN-BiGRU Hybrid Neural Network[C]//Jia Y, Zhang W, Fu Y, et al. Proceedings of 2022 Chinese Intelligent Systems Conference. Singapore: Springer Nature, 2022: 806-814.
[19] Chen Y, Dai X, Liu M, et al. Dynamic Convolution: Attention Over Convolution Kernels[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020: 11030-11039.
[20] Zhang D, Chen B, Zhu H, et al. Short-term wind power prediction based on two-layer decomposition and BiTCN-BiLSTM-attention model[J]. Energy, 2023, 285: 128762.
[21] Woźniak M, Wieczorek M, Siłka J. BiLSTM deep neural network model for imbalanced medical data of IoT systems[J]. Future Generation Computer Systems, 2023, 141: 489-499.
[22] Altaheri H, Muhammad G, Alsulaiman M. Dynamic Convolution With Multilevel Attention for EEG-Based Motor Imagery Decoding[J]. IEEE Internet of Things Journal, 2023, 10(21): 18579-18588.
[23] Ge Y, Ma J, Sun G. A structural pruning method for lithium-ion batteries remaining useful life prediction model with multi-head attention mechanism[J]. Journal of Energy Storage, 2024, 86: 111396.