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# Optimization and Accuracy Improvement of Power Prediction Models under the Influence of Turnaround Meteorology in Wind Farms

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**SUMMARY:** *The temporary meteorological state has a steady and reliable impact on power system performance. The power generation probability distribution attributes of wind farms are derived from the power attributes of wind turbines based on the Euclidean distance metric, combined with the Pearson correlation coefficient as the measure of difference and similarity among multiple types of wind speed profiles. With the two-parameter Weibull distribution as an example, the power attributes of wind turbines can be obtained. Combined with the probabilistic sparse self-attention model of Informer, long dependencies in historical power sequences are captured, leading to enhanced prediction ability for unexpected power cases. Experimental data are obtained from the wind farm in North China during a two-month observation period. The RMSE, MAE, and MAPE of the TCN-Informer model amount to 15.89 MW, 12.34 MW, and 13.89%, respectively. Moreover, the proposed method exhibits excellent stability and interval coverage in multi-step and probabilistic forecasting tasks, which suggests that it is appropriate for predicting wind power under transitional meteorological states and offers a viable solution endowed with high precision and flexibility.*

***KEYWORDS:*** *transitory meteorology; wind power prediction; Euclidean distance; self-attention mechanism; multi-step prediction*

## 1 Introduction

In recent years, carbon peaking and carbon neutrality have been continuously promoted, and all parties have deepened their understanding of the “dual-carbon” goal, which has led to the rapid development of wind farms. However, the turning meteorological scenarios represented by typhoons and strong convective weather should not be ignored, so the wind power output is difficult to predict due to its unique strong randomness and instability, and at the same time, it poses a great challenge to the reliable operation of wind farms [1, 2]. Therefore, improving the accommodation capacity of wind power and strengthening the efficient coordination among source, grid, and load make accurate and efficient wind power forecasting particularly critical. At present, only a limited number of studies have focused on ultra-short-term wind power forecasting under transient meteorological conditions. Existing approaches to ultra-short-term wind power prediction can generally be divided into two categories, namely physical modeling and data-driven modeling [3]. Physical modeling refers to modeling established based on the mathematical description of atmospheric motion. In this regard, with

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the help of information relating to meteorology, geography, and other information, hydrodynamics and other physical laws are utilized for modeling. Nevertheless, physical modeling mostly focuses on the optimization of the boundary conditions and physical solution rules and generally faces difficulty in constructing the model with great computing intensity, thus having low timeliness [4]. In contrast, data-based modeling mainly considers the establishment of linear or nonlinear mapping relationships between certain meteorological elements and power time series [5].

The paper by Lochmann, M. et al. studied ramps in East German wind parks and the behavior of wind power forecasting systems at different forecasting durations, i.e. 15 and 30 minutes. The research revealed that the forecasting system may be enhanced with different wind speed forecast products. Besides, adding real-time observations in short time intervals enhances forecasting quality, which underlines the significance of measuring winds in terms of forecasting wind energy [6]. Keerthisinghe, C. et al. has shown that wind power forecasting could be greatly improved by employing slope predictions along with power data of neighbouring wind farms to establish a low-delay feedback error-correction mechanism to a target power field. The slope predictor intended to use in wind power settings is able to acquire information continuously and its forecasting ability can be assessed using look-ahead time [7]. Yu, S. and Hur, J. provided better performance evaluation measures of wind power ramp event forecasting, and in their work they came up with an experimental slope event forecasting method through an indirect path to the wind power output. According to the simulation findings, the suggested approach is likely to become a significant contributor to the sphere of tool development allowing real-time limit predictions and aiding to make informed decisions in high-wind-power conditions [8]. Hossain, M. et al. presented a short-term forecasting model of wind power generation to enhance prediction accuracy that incorporates ensemble empirical mode decomposition, adaptive noise, monarch butterfly optimization, and long and short-term memory structures, known as CEMOLS. Their study shows that CEMOLS is less computationally intensive in terms of grid data, but sensitivity and statistical analysis are needed to determine the most robust forecasting model between several competing alternatives [9]. He, X. et al. have created a wind power prediction method based on graph convolutional networks, which combines the detection of slopes with error-correction schemes. Their findings reveal that more precise detection and classification of wind power slope events is possible, and that forecasting stability and accuracy increases significantly, with slope-event accuracy improving by approximately 28 percent over traditional models [10]. Jia, Y. et al. have proposed a holistic strategy of slope forecasting and control in offshore wind farms. Their scheme can be applied to check the effectiveness of the strategy in real-life offshore wind farm applications by analyzing the behavior of wind turbines during tropical storms and formulating a general slope-control framework [11]. Zhang et al. investigated the serious threats caused by extreme weather to wind power system operation and identified the importance of ramp periods. It was found that ramp-event forecasting becomes increasingly sophisticated but may still suffer from certain biases. At this point, systems must be created specifically for evaluating risks related to ramp events instead of forecasting using only traditional risk-related parameters by making use of physical data-modeling counters [12].

The Euclidean distance index and the Pearson correlation coefficient are presented in this paper as measures of dissimilarity and similarity between wind speed sequences based on wind turbine power features, and the probability distribution model is applied to describe the wind speed distributions. This connection between the wind power output and wind speed is viewed in terms of unit output at the wind farm. Multivariate nonlinear stepwise regression is used to determine the mapping relationship between principal components and regional wind power to predict the wind power during ramp periods. Informer captures long-term temporal dependence of power series and its main characteristics are obtained by convolution and pooling operation in the distillation layer. They are subsequently integrated with a decoder to perform multi-step inference. An additional TCN network is used to connect meteorological data to predicted power outcomes. Upon finishing TCN training, the acquired network weights are fixed and the past power encoder inputs, mapping outputs that are used as decode inputs, and the Informer are trained simultaneously, thus making it possible to predict sudden changes in wind power during transient meteorological conditions accurately.

# 2 Wind farm power characterization

## 2.1 Wind speed and wind power

To achieve the fact that the research in this paper will show the real case, it is done here using the measured wind speed data to calculate it.

Once the speed of the wind is measured the distribution parameters of power of the wind farm may be calculated using the power parameters of the wind turbin. Traditionally, the power parameters of the wind turbine generator (WTG) can be expressed in this way [13, 14]:

$$P_w = \begin{cases} 0, & 0 \le v < v_i, \\ a + bv^3, & v_i \le v < v_r, \\ P_r, & v_r \le v < v_o, \\ 0, & v \ge v_o. \end{cases} \tag{1}$$

where $v_i$ is the cut-in wind speed of the wind turbine, $v_r$ is the rated wind speed, $v_{\mathrm{o}}$ is the cut-out wind speed, and $P_{\mathrm{r}}$ is the rated output power of the wind turbine, with the parameters $a = P_r \cdot v_i^3 / \left(v_i^3 - v_r^3\right)$, $b = P_r / \left(v_r^3 - v_i^3\right)$.

## 2.2 Characterization of meteorological measurement field data

In order to facilitate comprehension of the meteorological information related to wind farms and maximize the production of wind energy, a large number of automatic meteorological stations or wind measuring towers are set up at wind farm sites. The spatially distributed automatic meteorological observation stations constitute a meteorological measurement field, which can provide meteorological data from different locations and reflect the meteorological changes in the region. There are different correlations between different stations in the meteorological measurement field, and analyzing the correlation between station data is the basis for research related to wind farm slope climbing events.

### 2.2.1 Correlation analysis of observatory data

The correlation between wind speed series from different stations in a meteorological measurement field can be described by distance correlation analysis, and in the paper, the Euclidean distance metric and the Pearson correlation coefficient are utilized to measure the degree of dissimilarity and similarity between wind speed series [15, 16]. The Euclidean distance is shown in equation (2):

$$d = \sqrt{\sum (x_i - y_i)^2} \tag{2}$$

where: $d$ is the Euclidean distance, $x_i$ and $y_i$ are measurements at different moments in time at the two stations, and $i = 1, 2, \cdots, n$. Pearson correlation coefficient metrics are as follows:

$$r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2} = \frac{\sigma_{xy}^2}{\sigma_x \sigma_y} \tag{3}$$

where: $n$ is the number of samples of measurements, $\sigma_{xy}^2$ is the covariance of $x$ and $y$ observations at the observatory, and $\sigma_x$ and $\sigma_y$ are the standard deviations of the observations.

### 2.2.2 Characteristics of wind speed distribution

Wind speed has obvious volatility and randomness, which can be characterized by using a probability distribution model to describe the distribution of wind speed [17].

Taking the two-parameter Weibull distribution as an example, the distribution function and probability density function of wind speed are:

$$P(v \le V) = 1 - \exp\left[ -\left( \frac{v}{c} \right)^k \right] \tag{4}$$

$$f_v(v) = \frac{k}{c}\left( \frac{v}{c} \right)^{k-1} \exp\left[ -\left( \frac{v}{c} \right)^k \right], v > 0 \tag{5}$$

where: $v$ is the wind speed value (m/s), $k$ is the shape parameter, and $c$ is the scale parameter (m/s), the shape parameter and scale parameter determine the distribution characteristics of the wind speed.

### 2.2.3 Wind turbine output characteristics

The power produced by the turbines of a wind farm is determined by the velocity of the wind passing through the region where the wind farm is located. The relation of wind energy generation and wind speed could be expressed as:

$$P = \begin{cases} 0, & v \le v_{cut-in}, v > v_{cut-out} \\ f(v) P_r, & v_{cut-in} < v \le v_r \\ P_r, & v_r < v \le v_{cut-out} \end{cases} \tag{6}$$

where $P_r$ is the rated output power of the WTG, $v_{cut-in} v_r$ and $v_{cut-out}$ are the cut-in, rated, and cut-out wind speed of the WTG, respectively. $f(v)$ stands for the wind speed criterion in the range limited by the cut-in wind speed and rated wind speed. Used to describe power generation, the equation is usually formulated in linear, quadratic, or cubic form, depending on the actual situation of the wind farm.

### 2.2.4 Regional power prediction based on climbing events

Figure 1 The regional wind power prediction model has been developed according to the meteorological influence of the climbing time period. Initially, the spatial measurement field data are preprocessed by height switching, distance leveling and local smoothing and the wind speed distance array is decomposed by EOF to obtain the orthogonal principal components of the wind speed sequence and the mapping relationship of the principal components and the regional wind power is built by means of multivariate nonlinear stepwise regression to forecast the wind power at the time of climbing [18, 19].

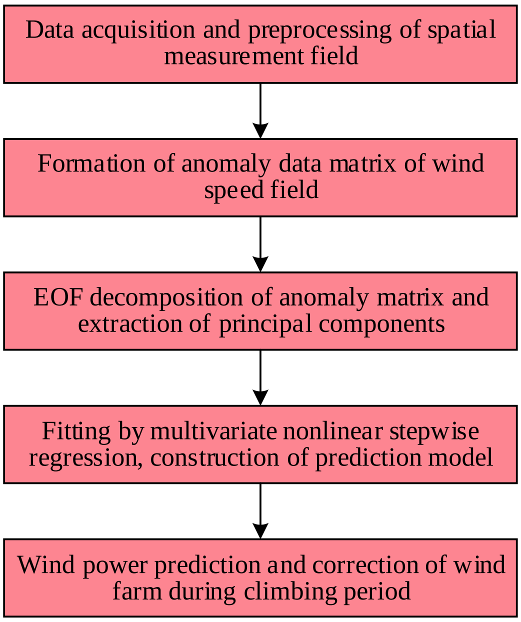


*Figure 1: Regional wind power prediction model*

The wind power forecast model with ramps is presented in Figure 1 and is derived taking into account the effect of weather on the process during the ramping period. On some occasions, it becomes evident that predicted values of wind power show volatility, as this model fails to accurately reflect the process of change in wind power in ramping hours. During ramping events at the wind farm, the temporary backflow of power in the ramping period can be determined by counting its frequency. Particularly, at the up-ramp phase, there is likely to be a decrease in wind power, while at the down-ramp phase, an increase in wind power is possible. The above facts indicate that wind power fluctuation has high levels of consistency, and thus, it is unlikely that sudden changes take place in short periods of time. As a result, predictions about wind power need adjustments, and fluctuation points will have to be substituted by the mean value of points right next to them.

## 2.3 Predictive modeling

The general training process of a deep learning network with historical data can be separated into two phases, that is, an unsupervised feature learning phase and a supervised learning phase. Unsupervised feature learning process is the process of completing the comprehension and evaluation of the data, wherein the deep learning network finishes the extraction and classification of the patterns of wind speed changes and the patterns of power changes. On the other hand, the supervised learning process completes the next fine-tuning of the parameters, which is the correction of the labeled data, and the correction of the autonomous judgment outcomes of the deep learning network. Though the feature learning process involves getting features by autonomous deep learning, the network structure is manually implanted. The process of predicting wind power with the help of the deep learning network can be viewed as a sequence of iterations between low-level abstraction and high-level abstraction of raw data.

The deep belief network, the historical wind speed data, the corrected wind speed data. The historical data of the last period, with the power data, are input variables, whereas predicted power is an output variable, therefore, the multi-step wind power prediction framework is built. An architecture of the framework is depicted in Fig. 2. The procedure of developing a framework of forecasting wind farms is to divide the whole data set into two halves, namely, historical-day data and forecast-day data. It is assumed that two days in the history are taken as forecasting days. Thus, to predict with the help of numerical weather forecast data of just these two days, the training of a calibration model and a direct wind power prediction model using deep learning networks is done with data of recent three to six months. These two days of historical weather and power data are then used as bench-marked measures of assessing the predictive accuracy of the model.

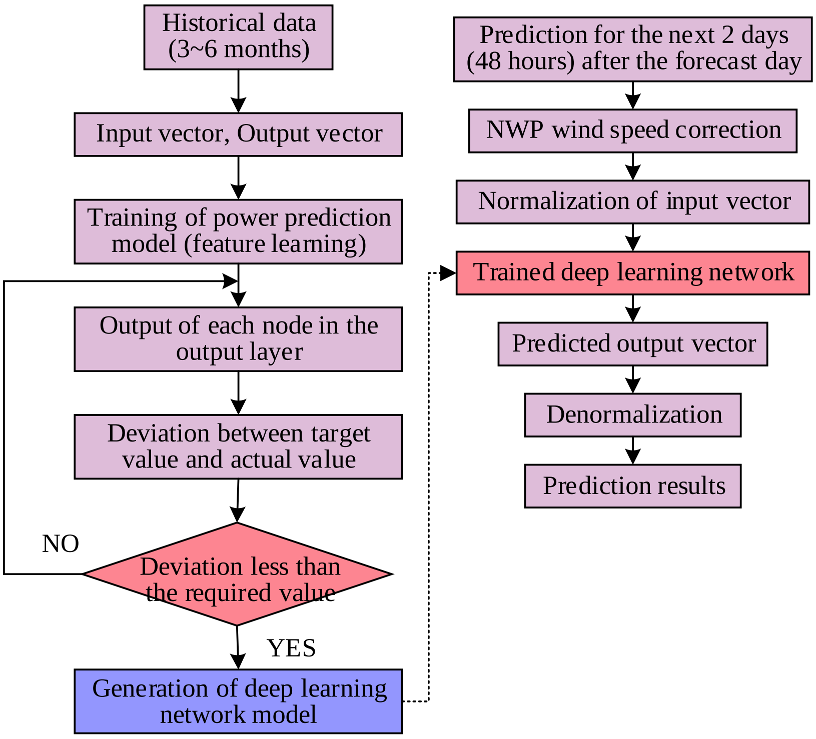


*Figure 2: Schematic model structure*

# 3 Construction of forecasting models considering meteorological transitions

Although the forecasting techniques based on stages have improved the accuracy of predictions of the wind power under complicated weather conditions up to some extent, there are still many shortcomings. For example, the optimization technique designed for the cases of abrupt changes of power induced by extreme changes of weather cannot meet the needs of high precision. Furthermore, the deterministic forecasting method is unable to meet the requirement of accuracy and reliability of the forecast when the wind power is small. Besides, uncertainty forecasting requires a large amount of computation, and its confidence intervals are too broad when the wind power is small.

## 3.1 Predictive information space selection

In general, the time series forecasting problem can be described as, assuming $t$ is a time variable, selecting specific information as the forecasting input $x_t$ in the given forecasting information space $\Phi_t(v)$, and constructing the mapping of the forecasting inputs $x_t$ to the forecasting objects $y_{t+h|t}$ mapping. Where $x_t \subseteq \Phi_t(v)$, $v = \{v_1, v_2, \ldots, v_n\}$ are the input variable features, $y_{t+h|t}$ is the value of wind power output at the moment of $t+h$, and $h$ is the forecast advance time step. In short-term prediction, it generally refers to the prediction in advance of several hours or days before the day or days before the day, take the prediction of wind power before the day with 15min resolution as an example, at this time $h = [1, 2, \ldots, 96]$ [20, 21].

The input $x_t$ of the model is the carrier of the prediction information, how to reasonably construct the prediction information space $\Phi_t(v)$, and then select the appropriate input directly determines the effect of the prediction model. Where the prediction information space $\Phi_t(v) = \{\Phi_{t,1}(v), \Phi_{t,2}(v), \Phi_{t,3}(v)\}$ usually contains three parts, namely $\Phi_{t,1}(v)$, the historical statistical information of the forecast object itself. $\Phi_{t,2}(v)$ historical measured statistical information of the external explanatory variables, $\Phi_{t,3}(v)$ external explanatory variable prediction information. As a result of low resolution capability of the deep learning model along with wind shear and wake effects, using the model only to fit the short-term wind power would normally result in relatively large errors. However, forecasting using wind power alone becomes progressively less accurate when the autocorrelation of the series declines.

To enhance the accuracy of forecast outcomes, the information space applied in prediction is given in Table 1. Timestamp variable is converted into a time code vector that has year, month, day, hour, and minute variables. Following the analysis of the wind power characteristics, various meteorological factors influencing the wind power production were found, such as wind speed, wind direction, temperature, humidity, pressure, etc. Including all the variables as the input data of the model could lead to inclusion of redundant information and thus decrease accuracy. Therefore, numerical weather predictions need additional treatment before use in forecasting.

*Table 1: Predictive information space selection*

| Information space $\Phi_t(v)$ | Contains |
|---|---|
| $\Phi_{t,1}(v)$ | Historical power data |
| $\Phi_{t,2}(v)$ | Historical timestamp data |
| $\Phi_{t,3}(v)$ | Numerical weather forecast, future time (time to be predicted) labels |

## 3.2 Historical information extraction based on Informer modeling

Wind power prediction considering the effects of transitory meteorology can be summarized as a multi-step prediction of the power series. With respect to multi-step forecasting, the accuracy of predictions generally reduces as time progresses into the future. The main cause is that the historical data will become increasingly unclear, and the autocorrelation of wind power will gradually decrease. Hence, the selection of the proper model to extract useful features and make predictions about the future power production is crucial.

The Informer is a neural network that relies on the attention mechanism, whose structural diagram is shown in Figure 3 below. Conventional attention mechanisms consume a lot of computation resources, due to the numerous multiplication operations performed as a result of the layer stacking in the network. This makes training very costly in terms of computation and time, which limits its use for long-horizon multistep forecasting of time series. The Informer network tackles this problem by using a probabilistic sparse self-attention mechanism to decrease complexity of matrix computations, convolution and pooling in the distillation layer to extract key features of the time series, and a decoder for making multi-step prediction for long sequences. Therefore, the Informer model will be used in this study to extract historical information and forecast wind power generation under transient meteorological conditions [22, 23].

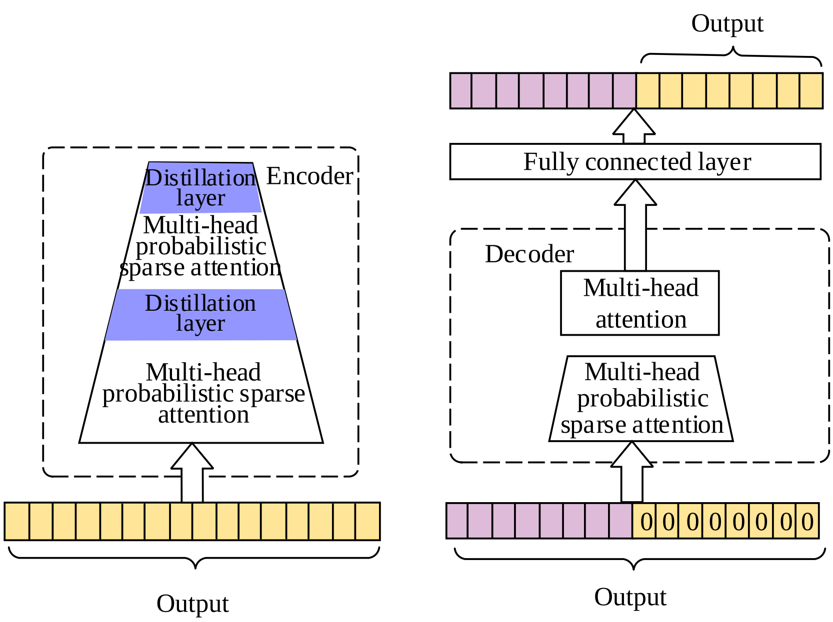


*Figure 3: Informer structure*

## 3.3 TCN-Informer prediction model structure

The Informer model uses a time masking strategy, namely a multi-step output, whereby the decoder inputs are masked to prevent the leakage of future time by putting zeros on any data to be predicted. The selected input variables to be used in this paper are historical power data, numerical weather forecast data, and time coded vectors. Because of the mismatch between the historical power data and the numerical weather forecast data on the timeline, there is an information interference when they are directly fed into the prediction model as one, and the numerical weather forecast data cannot be directly taken as an input to the decoder. Therefore, in order to adapt to the characteristics of transitory weather affecting wind power prediction, this paper utilizes the TCN network to adjust the input of the Informer decoder, and proposes a two-stage training model, and the TCN-Informer structure is shown in Fig. 4.

In this case, the TCN network implements the input of numerical weather forecast data before decoding by the decoder, which aims to achieve the mapping of meteorological data to predicted power using the TCN network [24]. Use the output of the TCN as the prediction value to replace the original Informer decoder set 0 operation, at this time the decoder can read the input directly without the use of time masking, and after the completion of the training of the TCN to freeze the training completed TCN network weights. With the historical power as the encoder input of Informer and the mapped output of TCN as the input of Informer decoder, the prediction of the power output at future time is realized by training Informer [25].

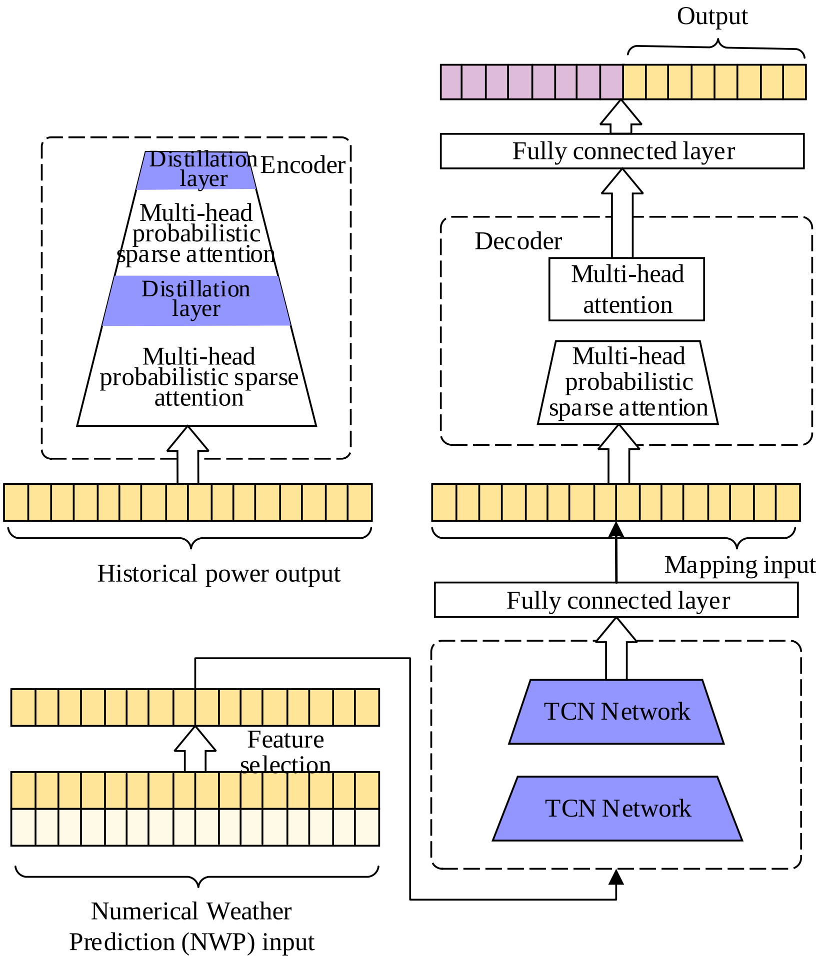


*Figure 4: TCN-Informer structure*

The model considers numerical weather prediction while extracting information from historical power data, solves the problem of aligning the input vectors in the time dimension, enhances the predictive capability of the model, and improves the prediction accuracy of the data under the influence of transitory meteorology.

## 3.4 Evaluation indicators for wind power prediction

The criteria used in evaluating the prediction model for this study have been classified into deterministic prediction criteria and probabilistic prediction criteria. The term reliability refers to statistical agreement between predictions and observations and may be evaluated using interval coverage:

$$E_{\text{PCIP}}^{(\beta)} = \frac{1}{T}\sum_{t=1}^{T}\xi\left(y_{t+h} - \hat{q}_{t+h}^{(\alpha)}\right)\xi\left(\hat{q}_{t+h}^{(\bar{\alpha})} - y_{t+h}\right) \tag{7}$$

where $E_{\text{PCIP}}^{(\beta)}$ is the prediction interval coverage with confidence $\beta = \left(\bar{\alpha} - \underline{\alpha}\right) \times 100\%$. $y_{t+h}$ is the predicted value at the moment $t+h$ $\bar{\alpha}$ and $\underline{\alpha}$ are the upper and lower quantile levels of the interquartile range, and $\xi\left(x\right)$ is the schematic function, defined as:

$$\xi\left(x\right) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{8}$$

The interval coverage obtained from the prediction should exceed the given confidence level as much as possible; if $E_{\text{PICP}}$ is less than the confidence level $\beta$, the prediction is invalid. Conversely, the prediction is valid.

Index for sharpness of probabilistic forecasts indicates how concentrated the probability distribution of forecast values is. Average width percentage (AWP) is widely used as an indicator of sharpness of the forecast range. AWP can be expressed as follows:

$$\bar{W} = \frac{1}{h}\sum_{t=1}^{h}\left(\hat{q}_{t+h}^{(\bar{\alpha})} - \hat{q}_{t+h}^{(\alpha)}\right) \tag{9}$$

where $\bar{W}$ is $\text{AWP}\left(\text{MW}\right)$, $\hat{q}_{t+h}^{(\bar{\alpha})}$ and $\hat{q}_{t+h}^{(\alpha)}$ are the upper and lower bounds of the prediction intervals expressed in quartiles, respectively; smaller $\bar{W}$ indicates better model sharpness.

# 4 Predictive model performance and analysis

## 4.1 Experimental setup

The TAPM model, which was created by the Commonwealth Scientific and Industrial Research Organization (CSIRO), Australia, is used in this study for the mesoscale meteorology model of the wind energy forecast model. The complete model is made up of two models, namely, the meteorological model and the pollutant forecast model. The model can simulate the near-surface wind speed well, and also has good simulation ability for transient weather such as typhoon. It is utilized for a two-month monitoring of a wind farm in North China for a July-August 2024 forecasting experiment. The meteorological numerical model reports daily from 0:00 a.m. and forecasts the hour-by-hour wind speed for the next 72h.

## 4.2 Power Characterization in Transitional Meteorology

To measure the effectiveness of the suggested model to predict power based on the weather effect of wind farms, this paper will use the power variation of this wind farm when a typhoon passes through it (July-August). 110 time points are chosen randomly and points to sample were also chosen randomly and as shown in figure 5, the difference between wind speed and wind power. As we can see on the graph, the greatest wind speed occurs at time intervals 60 and 70 with values of 22.1 m/s and 21.3 m/s. At the same time, the wind power also achieves its peak at 158 MW and 180 MW respectively which indicates that the line is going up. However, the least wind speed and power are observed at time periods 100 and 110.

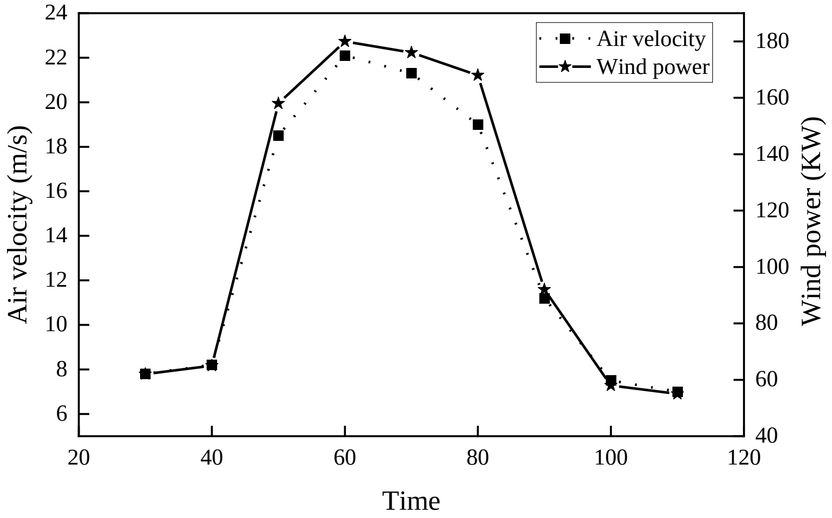


*Figure 5: Variation of wind speed and wind electric power*

## 4.3 Validation of model prediction performance

### 4.3.1 Comparison of deterministic prediction performance

To test the forecasting accuracy of the presented model using transitional atmospheres, the models chosen for evaluation purposes are as follows: LSTM, TCN, CNN-LSTM, and Attention-LSTM. The error criteria used to test the accuracy include the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The results of forecasting from deterministic evaluation are shown in Table 2 below. For the TCN-Informer model, the results show RMSE = 15.89 MW, MAE = 12.34 MW, and MAPE = 13.89%. All these errors are less compared to other models, showing that the TCN-Informer model is more accurate.

*Table 2: Comparison of Deterministic Prediction Performance*

| Model | RMSE(MW) | MAE(MW) | MAPE(%) |
|---|---|---|---|
| LSTM | 18.92 | 14.67 | 16.34 |
| TCN | 17.45 | 13.56 | 15.12 |
| CNN-LSTM | 16.78 | 13.01 | 14.56 |
| Attention-LSTM | 15.89 | 12.34 | 13.89 |

### 4.3.2 Comparison of multi-step prediction performance

The RMSEs of different forecasting models in the multi-step prediction task are displayed in Fig. 6, where the upper horizontal line indicates the maximum upper limit and the bars represent the mean interval. The mean values of the RMSEs of TCN-Informer, Informer, and LSTM are 8.84MW, 9.86MW, and 12.03MW, respectively, and at the step length of 16, the RMSEs of TCN-Informer, Informer, LSTM are 13.45 MW, 15.23 MW, and 18.92 MW, respectively. Compared with the single Informer and LSTM models, the model proposed in this paper has better multi-step prediction performance, which indicates that the model can be applied to transient meteorological weather prediction, and shows better long-term prediction capability for wind farm power prediction.

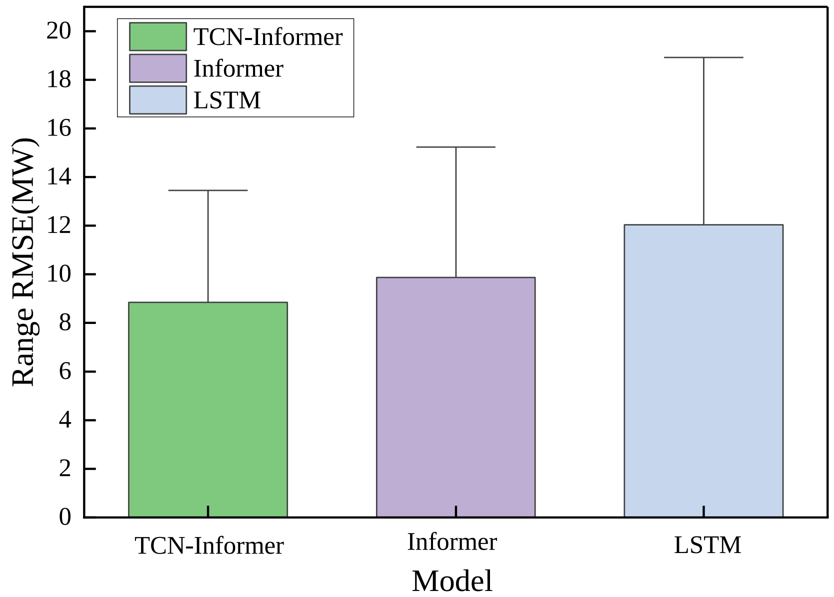


*Figure 6: Multi step prediction of RMSE using different prediction models*

### 4.3.3 Probabilistic Prediction Performance Evaluation

The probabilistic prediction comparisons are shown in Table 3.From the interval coverage (PICP), the interval coverage of LSTM, TCN, CNN-LSTM, Attention-LSTM, and TCN-Informer are all close to or over the 90% confidence level, which indicates that all of these models provide effective probabilistic prediction. In terms of the average bandwidth width (AWP) metric, the TCN-Informer model has an average bandwidth width of 32.45 MW, which is significantly lower than the other models. Narrower prediction intervals imply higher prediction accuracy and less uncertainty, indicating that the TCN-Informer model can provide more accurate and focused probabilistic predictions under fluctuating meteorological conditions.

*Table 3: Comparison of probability predictions*

| Model | PICP(%) | AWP(MW) |
|---|---|---|
| LSTM | 92.4 | 42.56 |
| TCN | 92.7 | 40.34 |
| CNN-LSTM | 92.1 | 41.23 |
| Attention-LSTM | 91.8 | 39.12 |
| TCN-Informer | 91.2 | 32.45 |

## 4.4 Feature Importance Analysis

The Figure 7 illustrates the ranking of important features, historical power data are the most significant features with an importance score of 0.42, the importance score of wind speed is 0.31, and the importance score of time vector is 0.15, indicating the daily and seasonal periodicity of wind power. The next most important feature is the wind speed that has an importance value of 0.31. The time vector importance value is 0.15, which indicates a certain influence of the daily and seasonal wind power variations on the output.

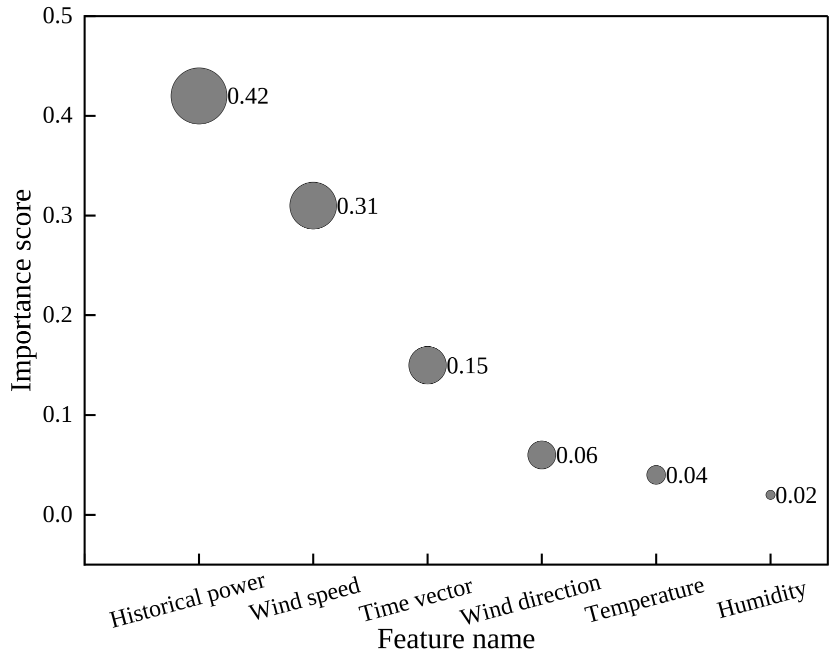


*Figure 7: Ranking of important features*

# 5 Conclusion

Inspired by transient meteorology, this paper develops a hybrid prediction model of TCN-Informer to enhance the power prediction accuracy of wind farms, and the experimental findings indicate that:

(1) At time points 60 and 70, the wind power rises to 158 MW and 180 MW, with a climbing trend, and the model demonstrates a strong ability to capture sudden power changes.

(2) As observed from the result, for the TCN-Informer, the RMSE, MAE, and MAPE are 15.89 MW, 12.34 MW, and 13.89%, respectively. They are all lower compared to the other three methods, suggesting an increased accuracy for predicting wind power using the TCN-Informer method.

(3) With a multi-step horizon of 16, the RMSE of TCN-Informer, Informer, and LSTM are 13.45 MW, 15.23 MW, and 18.92 MW, respectively. This result demonstrates better forecasting capabilities compared to the two other models that are only used individually.

(4) Historical power and wind speed are ranked first and second, with an importance value of 0.42 and 0.31, respectively, which means the forecasts made by the model can be trusted.

Consequently, these results confirm the effectiveness of the model. The model presents an effective approach to enhancing the forecasted wind power generation accuracy in transient meteorology conditions.

# 6 Acknowledgement

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