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Coupled Probabilistic Tidal Current Calculation of Electricity-Heat-Gas Taking into Account the Time-Series Correlation of Wind Power Output-Temperature

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Abstract: *In order to address the inadequacy of conventional probabilistic tidal current calculation methods in dealing with the impact of wind power output on line impedance, this paper proposes a coupled electricity-heat-gas probabilistic tidal current calculation model considering the wind power output-temperature time series correlation, firstly. The relationship between environmental factors and line temperature is established by introducing the heat balance equation, and an attention convolution network is used to capture the complex correlation between wind speed and air temperature, so as to realize the dynamic correction of system parameters. Secondly, the changes in the line impedance correction factor caused by wind power output in different scenarios are analyzed, and the operating parameters of the power system are adjusted accordingly. Finally, based on the IEEE-30 node system for testing and validation, the simulation results show that the error of the probabilistic tidal current calculation results is significantly reduced after considering the time-sequence correlation of wind power output. Specifically, the average absolute errors of line active loss, flow power, and voltage magnitude decrease by 61.0%, 33.3%, and 40.0%, respectively, while the root-mean-square errors decrease by 58.3%, 35.4%, and 20.0%, respectively. It is proved that the probabilistic tidal current model proposed in this paper, which takes into account the time-sequence of wind temperature, is closer to the actual operation situation, and can further improve the stability and economy of the power system operation.*

Keywords: *Probabilistic Currents; Temporal Correlation; Electrical-Thermal-Pneumatic Coupling; Wind Power*

1. Introduction

In order to build a new type of power system that realizes the goal of "double carbon", the proportion of new energy sources such as wind power and photovoltaic power has been rising in recent years, and the characteristics of the power system have changed to a “double high” power system, but due to the high uncertainty of the new energy power generation, it will pose significant challenges for the future. However, due to the high uncertainty of new energy power generation, it brings significant challenges to the stable operation, system planning and construction, and operation economy of the new power system.

Probabilistic current is regarded as one of the important means of power system trend analysis because it can comprehensively consider and calculate the random uncertainty of various new energy sources. The research focus in the field of probabilistic trend calculation at home and abroad is mainly concentrated on two aspects, one is the energy system trend modeling, considering more and more new energy access to the power system, mainly focusing on the degree of impact on the system trend model and the trend of change modeling; the second is the improvement and innovation of probabilistic trend algorithms, for the system of source-network-hoarding-storage equipment in the probabilistic trend algorithm in the refinement of modeling and convergence improvement[1]. The current probabilistic tidal current algorithms can be divided into Monte Carlo simulation method, analytical method, and approximation method according to different principles and accuracy[2]. The Monte Carlo simulation method establishes the uncertainty model of electric-heat-gas load and wind power output, and then iteratively generates a large amount of compliance data for the algorithm to perform trend calculation, and determines the next probabilistic trend running samples through statistical analysis, thus obtaining the trend calculation results reflecting the system's operating status. The analytical method uses equations to solve, calculate, and derive the voltage and power distribution of each node in the system, as well as parameters such as line power, through the uncertainty mathematical model of the system's electric-heat-gas load and wind power output. The approximation method is applied in scenarios where accurate solutions are difficult to obtain or rapid estimations are required. It simplifies the calculation or model, substituting exact values with approximate ones in the system probability calculation of tidal currents. Nowadays, due to the large influx of new energy and the use of new power electronic equipment, the new power system gradually presents the characteristics of “double-high” and “double-random”, which leads to the decision of the direction of the probability of the power system trend of the determining factors are no longer limited to the power supply and load probability characteristics, but also related to the outside world. As a result, the determining factors for the direction of the probabilistic current of the power system are no longer limited to the power supply and load probability characteristics, but also related to the external environment and equipment factors resulting in changes in the parameters of the system components themselves[3]. Current research on system probability trend calculations typically assumes line parameters at a fixed temperature of 25 °C, neglecting the impact of line impedance variations and complex environmental conditions on the operational behavior of system probability trends. However, in the actual operating environment, wind speed, temperature, humidity, light intensity and other changes in any element will have a significant impact on the results of the trend calculation, so it is necessary to consider the system inside and outside the “independent variable” changes in the probability of the trend of the “dependent variable” impact, and then Therefore, it is necessary to consider the effect of changes in the “independent variables” inside and outside the system on the “dependent variable” of the probabilistic tidal current, so as to correct the system probabilistic tidal current calculation process to obtain accurate iteration results[4].

Teng Yong and other scholars combine heat balance equation, gas balance equation and trend calculation equation, and analyze the examples to show that weather factors and geographic factors have influence on line impedance, which changes the distribution of system trend. Huang Ling et al. verify and analyze the seasonal trend change and spatial node distribution of overhead lines along the route by using historical real weather data, and establish a system trend model based on the temporal and spatial distribution of weather data and a distribution coordination cutting and settlement algorithm by using the conductor temperature and line parameters as the entry point, and verify that the algorithm and its simulation results improve the accuracy of the power grid state analysis. Bow et al. consider that the existing electric-thermal-gas coordinated tidal model ignores the impact of line random meteorological changes on the grid tidal current and line temperature, propose a R-ETC tidal model that takes into account line meteorological stochasticity, and validate the effectiveness of the model through arithmetic simulation. The above literature establishes a probabilistic tidal current calculation model with electric-thermal-gas coupling and incorporates the changes in transmission line parameters caused by the uncertainty of environmental factors for tidal current calculation, but does not further consider the influence of correlation between environmental factors on tidal current calculation. Watkins used trend correlation analysis to analyze the strong correlation between the output of wind turbines, but due to the long term dependence of copula function, orthogonal transform method, Rosenblatt transform and other methods for strong correlation, it is not possible to memorize the correlation process in the short term, and there are cases where the correlation data and the resulting correlation data cannot be quantified. However, due to the long-term dependency of the current copula function, Rosenblatt transform and other methods for strong correlation, which cannot memorize the stochastic calculation process in the short term, and the occasional inability to quantify the correlation and the consequent dependency of the processing, there is very little literature on the intrinsic correlation between the wind speed and the air temperature to be effectively accounted for in the calculation of the probabilistic currents of the electricity-heat-air related power system[5]..

Aiming at the above research deficiencies and defects, this paper extracts the wind power output uncertainty prediction results directly, extracts the wind power output sequences with timing correlation and dependence in the corresponding sequences, in order to establish the rank-long and short-term memory neural network model, and puts forward a new coupled electricity-heat-gas method considering the timing correlation of wind power output, in order to solve the problem of the stochasticity of wind power output, which is difficult to be overcome by simple coefficient matrices[6]. We propose a new probabilistic tidal current calculation method that takes into account the temporal correlation of wind power output, and correct the relevant line impedance based on the wind speed and air temperature

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related characteristics, so that the simulation results are more in line with the actual production situation, and carry out a simulation analysis in the IEEE-30 node system to verify the validity and accuracy of the proposed algorithm.

2. Modeling Input Parameter Uncertainty

The probability distributions of the random variables are first modeled to facilitate probability trend calculations using Monte Carlo simulation.

2.1. Load Uncertainty Modeling

When the electricity-heat-gas loads of the current power system all show random volatility, and the probability distribution can be characterized as a Gaussian distribution, then the load uncertainty expression is uniformly expressed as:

$$\begin{cases} f(P) = \dfrac{1}{\sqrt{2\pi}\sigma_P}\exp\left[-\dfrac{\left(P-\mu_P\right)^2}{2\sigma_P^2}\right] \\ f(Q) = \dfrac{1}{\sqrt{2\pi}\sigma_Q}\exp\left[-\dfrac{\left(Q-\mu_Q\right)^2}{2\sigma_Q^2}\right] \end{cases} \tag{1}$$

Where $f(P)$, $f(Q)$, represent the probability distribution function of active and reactive power of electric-heat-gas loads, respectively; μ_P , μ_Q , σ_P , σ_Q are the mean and standard deviation of active and reactive power, respectively.

2.2. Modeling Uncertainty in Wind Power Generation

As one of the rapidly developing renewable new energy sources in recent years, wind power is of great significance for China to promote energy transition and achieve carbon peak and carbon neutrality. However, considering its strong randomness in output, the efficient utilization of wind power generation is more challenging. Currently, the modeling of wind power can generally be expressed as:

$$f(v) = \frac{k}{c}\cdot\left(\frac{v_w}{c}\right)^{k-1}\cdot\exp\left[-\left(\frac{v_w}{c}\right)^k\right] \tag{2}$$

where , v_w , k , c denote the wind speed to which the fan impeller is subjected, the shape parameter of the wind distribution and the wind speed scale parameter, respectively.

2.3. Modeling uncertainty of wind power generation on transmission line surfaces

Due to the influence of geographical location of the transmission lines and line parameters, the wind speed and temperature on the surface of the transmission lines cannot be modeled by simple and traditional Gaussian distribution models. Therefore, it is proposed to use the Gaussian kernel density estimation method, which has a better fit, to model the uncertainty of wind power generation. The modeling of wind speed and temperature based on the Gaussian kernel density estimation method can be expressed as:

$$\begin{cases} \hat{f}(v) = \dfrac{1}{\sqrt{2\pi}nh_w}\sum\limits_{i=1}^{n}\exp\left[-\dfrac{1}{2}\left(\dfrac{v-v_i}{h_w}\right)^2\right] \\ \hat{f}(t) = \dfrac{1}{\sqrt{2\pi}nh_w}\sum\limits_{i=1}^{n}\exp\left[-\dfrac{1}{2}\left(\dfrac{t-t_i}{h_w}\right)^2\right] \end{cases} \tag{3}$$

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where , v , t represent the wind speed and ambient air temperature series of the turbine, respectively; v_i , t_i , n , h_w , represent the ith wind speed and ambient air temperature data, the number of samples, and the width of the Gaussian kernel density window in the sample data model.

3. Wind power timing correlation processing method

Considering the high stochasticity and volatility of wind speed and air temperature due to the changes of environment and time flow in the actual state, it is difficult to model the correspondence between the two using the traditional modeling methods, therefore, a wind speed-temperature correlation model is proposed based on the attentional convolutional neural network, which can deal with the wind speed-temperature correlation model of wind power generation efficiently.

3.1. Attentional Convolutional Neural Networks

Attention convolutional neural network is a special recurrent neural network suitable for processing and predicting time series data, through its unique memory unit and gating mechanism to effectively capture the existence of long-term dependence on the time series, in order to solve the traditional neural network in the long time series processing easy to appear in the iterative gradient disappearance or explosion problem. Therefore, when analyzing the change of wind speed with time series, the attention convolutional neural network can extract the time series autocorrelation relationship based on the historical data, and carry out accurate prediction of the corresponding coupling relationship, and then reveal the future change rule and trend prediction of the wind speed, in which the attention convolutional neural network unit data processing expression can be expressed as:

$$\begin{cases} f_t = \sigma\left(W_f \cdot \left[h_{t-1}, \alpha_t\right] + b_f\right) \\ i_t = \sigma\left(W_i \cdot \left[h_{t-1}, \alpha_t\right] + b_i\right) \\ \tilde{C}_t = \tanh\left(W_C \cdot \left[h_{t-1}, \alpha_t\right] + b_C\right) \\ C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\ o_t = \sigma\left(W_o \cdot \left[h_{t-1}, \alpha_t\right] + b_o\right) \\ h_t = o_t \odot \tanh\left(C_t\right) \end{cases} \tag{4}$$

where , f_t, i_t, o_t represent the network oblivion gate state, input gate state, and output gate state (0,1), respectively; W , b , C_t , $\tilde{C}_t$ represent the network neuron weights, bias, and the current convolutional memory unit state, and the input unit state, respectively; α_t , h_{t-1} , t represent the current network input, the hidden layer input of the previous moment, and the current moment, respectively; $\cdot$, $\odot$ are the network quantile product, the Hadamard product, respectively, and σ , $\tanh$ are the discretization activation functions.

3.2. Order substitution law

The order substitution method can rearrange the target sequence according to the size of the reference sequence, and give the information of the time sequence change contained in the reference sequence $p = \left\{p_1, p_2, \cdots, p_n\right\}$ to the target sequence $X = \left\{x_1, x_2, \cdots, x_n\right\}$, and the process can be briefly described as follows:

Step1, sort the reference sequence P from smallest to largest to get $P^{sorted} = \left\{p_{(1)}, p_{(2)}, \cdots, p_{(n)}\right\}$;

Step2, rank the sequences $R = \left\{r_1, r_2, \cdots, r_n\right\}$ to obtain the order , where r_i can be expressed as:

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$$r_i = Rank\left(p_i, P^{sorted}\right), i = 1,2,\cdots,n \tag{5}$$

where r_i represents the index of the *ith* p_i element of the reference sequence *p* in the sorted sequence P^{sorted} .

Sort the target sequence X from smallest to largest to get $\boldsymbol{X^{sorted}} = \left\{\boldsymbol{x}_{(1)}, \boldsymbol{x}_{(2)}, \cdots, \boldsymbol{x}_{\boldsymbol{n}}\right\}$, and finally use the ranking sequence R to rearrange the sorted target sequence X^{sorted} to get the new target sequence $X^{\mathrm{new}} = \left\{x_1^{new}, x_2^{new}, \cdots, x_n^{new}\right\}$, where:

$$x_i^{new} = x\left(r_i\right), i = 1,2,\cdots,n \tag{6}$$

where x_i^{new} represents the first *i* element in the new target sequence.

4. Probabilistic Trend Modeling and Analysis

Transmission line impedance will change due to changes in environmental factors, which in turn will have an impact on the distribution of power system tidal currents. The probabilistic tidal current calculation model of the power system based on electricity-heat-gas energy coupling can be established through the introduction of the heat balance equation and centered on the impedance and the temperature of the conductor, and the relationship between the wind speed & temperature-system probabilistic tidal currents can be included in the calculation of the probabilistic tidal currents of the system.

4.1. Heat balance equation

When the line is in thermal equilibrium, the line heat intake-dissipation is equal, and contribute to the stabilization of the line temperature, and the commonly used models for calculating the overhead line current-conductor temperature include IEEE-738 and CIGRE-207, both of which can take into account the accuracy of the model calculations and the timeliness of the model, but the former model error is smaller, so this paper adopts the IEEE-738 model to calculate the line heat balance equations. Therefore, the IEEE-738 model is used in this paper to calculate the heat balance equation of the line:

$$Q_1\left(T_w\right) + Q_s = Q_f\left(T_w\right) + Q_r\left(T_w\right) \tag{7}$$

Where, Q_1 , Q_s , Q_f , Q_r respectively, on behalf of the conductor conductor current heat production, sunlight line heat, line - air convection heat dissipation, line radiation heat dissipation; T_w for the transmission line temperature, and only Q_s with its irrelevant.

$$R\left(T_w\right) = \left(1 + k'\right) R_{20}\left[1 + \alpha_{20}\left(T_w - T_{20}\right)\right] \tag{8}$$

Where , k' , R_{20} , α_{20} respectively, represents the line skin effect coefficient, line AC resistance and resistance temperature coefficient under the reference temperature (this paper sets the reference ambient temperature as 20°C, so $\alpha_{20} = 1/0.00395$℃).

Considering only the sunlight irradiation line heat generated with the line temperature has nothing to do, its power expression can be expressed as:

$$Q_s = \alpha_s J_s D \tag{9}$$

Where , α_s , J_s , D respectively, represents the line conductor heat absorption coefficient, effective sunlight radiation intensity, wire diameter.

According to the high, medium and low wind speed, the line convection cooling can be divided into no wind in the case of natural convection cooling, low wind speed under the forced convection cooling, high wind speed under the forced convection cooling, this paper takes the maximum of the three cases, the specific calculations are as follows:

$$\begin{cases} q_{f1} = 3.645\rho_f^{0.5} D^{0.75} \left(T_w - T_e\right)^{1.25} \\ q_{f2} = k_{angle}\left[1.01 + 1.35 N_{\mathrm{Re}}^{0.52}\right]\lambda_f \left(T_w - T_e\right) \\ q_{f3} = k_{angle} 0.754 N_{\mathrm{Re}}^{0.6} \lambda_f \left(T_w - T_e\right) \end{cases} \tag{10}$$

where , N_{Re} , k_{angle} , λ_{f} and ρ_{f} represent the Reynolds coefficient, wind direction factor, air thermal conductivity, and air density, respectively.

Radiant heat dissipation is mainly determined by the difference between the line temperature and the surrounding ambient temperature, which can be expressed as:

$$Q_r = \pi D \varepsilon \delta \left[\left(T_w + 273\right)^4 - \left(T_e + 273\right)^4\right] \tag{11}$$

where, ε represents the Boltzmann constant (5.67×10^{-8}), δ represents the line surface radiation coefficient.

4.2. Probabilistic flow modelling

In order to achieve accurate and efficient probabilistic tidal current calculation results at the same time, this paper adopts the Newton-Raphson iterative algorithm with linear model combined with Monte Carlo simulation based on Latin hypercubic sampling for the probabilistic tidal current calculation of the electric power system, and obtains the matrix of node power equations as:

$$\begin{cases} \mathbf{U} = f(\mathbf{W}) \\ \mathbf{Z} = g(\mathbf{U}) \end{cases} \tag{12}$$

Where, $\mathbf{W}$, $\mathbf{U}$ represent the state variables of injected active and reactive power P & Q, voltage magnitude and phase angle of all nodes except the balanced node, and $\mathbf{Z}$ represent the flowing active and reactive power of each branch, indicating the output; f , g represent the relevant equations for calculating the node voltages and branch powers, respectively.

The node injection point power equations and branch power equations in matrix form are obtained by expanding them into Taylor series and neglecting higher order terms:

$$\begin{cases} \boldsymbol{U} = \boldsymbol{U}_0 + \Delta\boldsymbol{U} = \boldsymbol{U}_0 + \boldsymbol{E}_0\Delta\boldsymbol{W} \\ \boldsymbol{Z} = \boldsymbol{Z}_0 + \Delta\boldsymbol{Z} = \boldsymbol{Z}_0 + \boldsymbol{K}_0\Delta\boldsymbol{W} \end{cases} \tag{13}$$

where , $\mathbf{U}_0$, $\boldsymbol{Z}_0$ represent the expectation values of node state variables and branch outputs; $\Delta\mathbf{U}$, $\Delta\mathbf{Z}$, can be regarded as interference terms obeying random distribution; $\mathbf{E}_0$, $\mathbf{K}_0$, $\mathbf{J}_0$, represent the state variable sensitivity coefficient array, the branch output sensitivity coefficient array, and the Niu-La tidal current computation of the Jacobian matrix, respectively.

4.3. Coupled electricity-heat-gas probabilistic currents considering the time-series correlation of wind power outputs

Combined with the calculation process shown in Figure 1, comprehensively considering the parameter changes of line impedance in environmental factors, using line temperature and impedance as

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the link, combined with Equations (7)-Equation (13), the CIGRE standard was introduced to establish the thermal equilibrium equation, and iteratively solve the temperature of the conductor of the transmission line repeatedly iterated to take into account the accuracy and efficiency of the model and reduce the single calculation amount of the model. This paper uses the current values of each line calculated by the conventional probability flow as the input of the proposed electric and thermal coupling model to obtain an impedance correction factor, and corrects the probability flow results based on the correction factor.

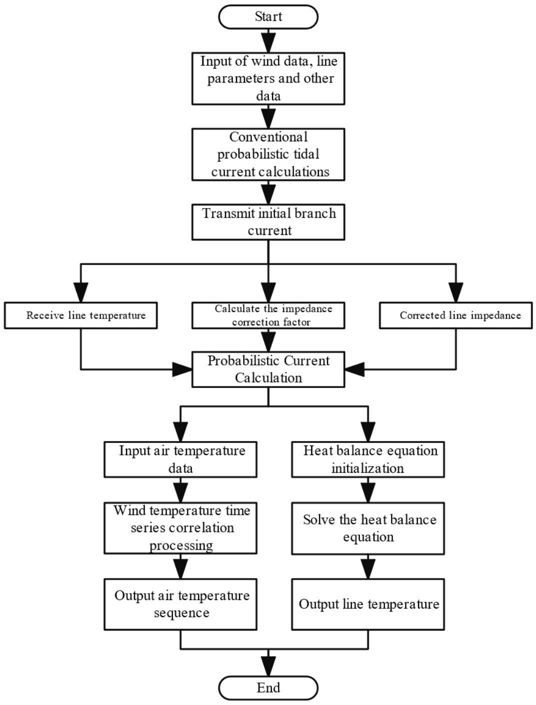

Fig. 1 Calculation flow of probabilistic tidal current of electro-thermal coupling considering the time series correlation of wind temperature

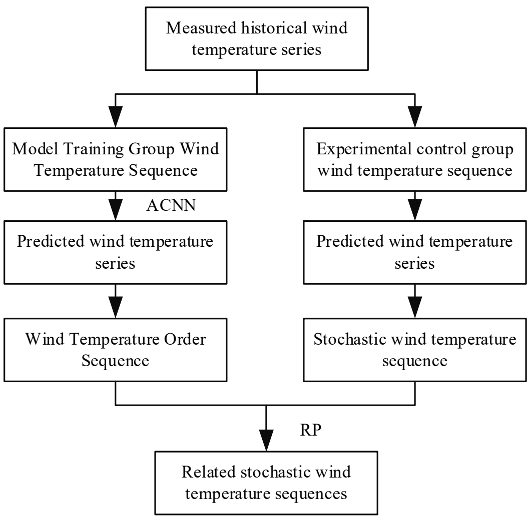

Fig. 2 ACNN neural network model

According to the correlation, the data of wind power generation are cleaned, screened and processed, and the random wind power output prediction sequence and the measured wind power output sequence before and after considering the correlation are obtained, which are used as the input values of wind power generation in each scenario and used for subsequent probabilistic power flow calculation. However, considering the complex changing trend of wind speed and temperature, an attention

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convolutional neural network model suitable for this paper is proposed based on the convolutional neural network. The process is shown in Figure 2, which is used to process the prediction and actual trend in the data.

And the main steps of ACNN model are:

Step1, input two copies of the same wind power historical processing data, and divided into control group and experimental group, train, screen the data, eliminate the bad data, and get the wind power prediction output sequence;

Step2, extract the autocorrelation and inter-correlation timing change information in the predicted wind power processing sequence in STEP1, wind power output order sequence;

Step3, adopt hypercubic sampling theory to randomly sample the historical data of wind power output of the control group, and get the random sequence of wind power output;

Step4, according to the order information in the wind power output order sequence, the random sequence of wind power output is aligned by RP means, and the random wind power output sequence considering the temporal correlation of wind power output is obtained by simultaneously considering the autocorrelation of wind speed and air temperature.

Initialize the heat balance equation, set the corresponding heat balance parameters according to the actual situation of the environmental parameters, and solve the heat balance equation under the scenarios of different initial values of branch currents; finally, transmit the calculated line temperature data to the trend calculation submodule. Among them, the detailed steps of heat balance equation solving are:

Step1, calculate the sunshine heat absorption power independent of the line temperature, and set the process iteration accuracy as $\varepsilon_d = 10^{-6}$℃ ;

Step2, set the initial temperature of the line $T_{\mathrm{w}}^{(0)}$ and obtain the wire impedance correction factor K_r ($K_r = (1+k')\left[1+\alpha_{20}(T_w - T_{20})\right]$) according to the initial temperature;

Step3, according to the initial branch current I_0 received to correct the line impedance, and calculate the conductor's own heating power Q_1;

Step4, based on the established environmental conditions, solve the heat balance equation to obtain the line temperature $T_w^{(1)}$;

Step5, if $T_w^{(1)} - T_w^{(0)} \leqslant \varepsilon_d$, the line temperature convergence, then jump to step6, or vice versa $T_w^{(0)} = T_w^{(1)}$, so that the jump back to Step3, re-enter the cycle of iterative computation, until the iteration accuracy requirements are met ε_d;

Step6, stop iteration, output line temperature.

Firstly, input the preset parameters of the algorithm, including the wind speed sequence of the wind farm and the given relevant data of the power system; then, carry out the conventional current calculation, obtain the initial current of each branch, and process the initial branch current data in the heat balance equation; and through the heat balance equation to obtain the line temperature and the line impedance correction factor, and complete the correction of the line impedance; finally, calculate the probability of electric-heat-gas coupling current and analyze and evaluate the results. Finally, the electric-heat-gas coupling probabilistic current is calculated and the results are analyzed and evaluated.

4.4. Case analysis

The simulation platform uses the IEEE-30 node test system to carry out simulation, in which the relevant parameters include: in order to simulate the impact of distributed new energy access on the stability of the system in the actual complex power grid, a group of 20 wind turbines with rated power of 2.5MW is set up at node 24; the cut-in wind speed, the rated wind speed, the cut-out wind speed, and the power factor are set to 2.5m/s, 10m/s, 21m/s, 96%, respectively; the shape parameter and the scale parameter are set to 5, 12, respectively. s, 96%; the shape parameter and scale parameter are set to 5 and

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12, respectively.The example data are obtained from the publicly available wind power historical data of a northern province from January 2023 to March 2024, with a time interval of 1h, as shown in Fig. 3.

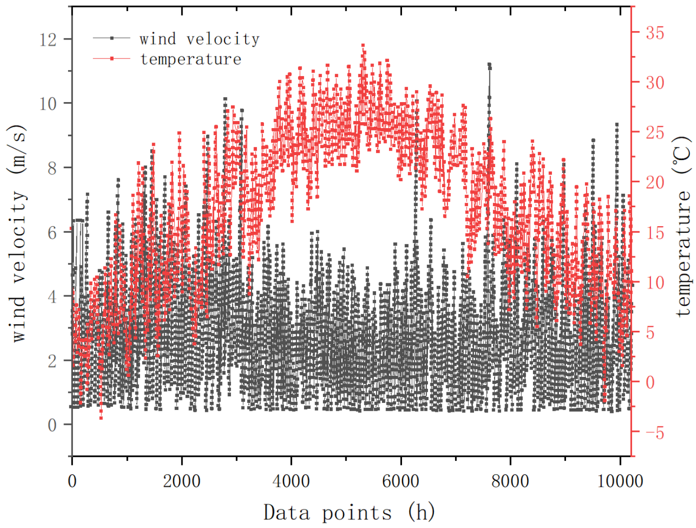

Fig. 3 Time series curve of measured wind temperature in a northern province

At the same time, under the premise of not affecting the effectiveness of the model, in order to simplify the calculation process, the following settings are made: as the line impedance parameters are mainly affected by wind speed, air temperature, light and wind direction, so other factors are ignored for the line impact; and set the environmental factors of each line are the same, and the type of wire for the steel-core aluminum stranded wire LGJ-400/35; due to the sunshine-induced heat absorption is small compared to the other sources of heat, the effective radiation intensity is set to be constant at 400W/m2; the rest of the important parameters are set as shown in Table 1. Set the effective radiation intensity of sunshine constant 400W/m2; the rest of the important parameters are set as shown in Table 1.

Table 1 Model parameters

Parameter	Numeric value	Parameter	Numeric value
Wire Diameter /mm	27.63	Coefficient of skin effect	0.0025
Air density /($kg \cdot m^{-3}$)	1.29	Wind direction factor	0.8
Reference impedance /($\Omega \cdot km^{-1}$)	0.072	Thermal emissivity	0.9
Reference temperature /°C	20	Sunshine Heat Absorption Coefficient	0.9

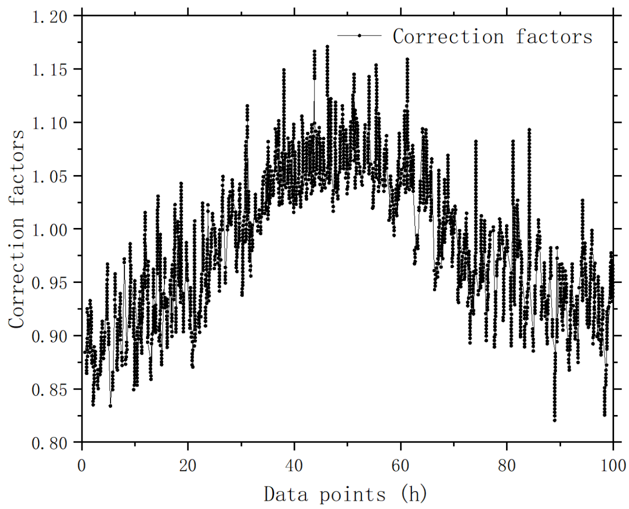

Figure 4 Branch 22-24 impedance correction factor for selected measured data

In order to verify the impact of wind-temperature time-sequence correlation on electric-heat-gas coupled power system, simulation experiments are carried out in different wind power scenarios, and the results of the respective probabilistic trend calculations are evaluated in nodes 22, 23, and 24 of the IEEE30 node system, and the results are shown in Fig. 4, which indicate that the impedance modification

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factor of the line is basically greater than 1 in summer scenarios where the wind speed is lower and the temperature is higher, while the opposite is true in winter, indicating that the impedance correction factor is more significantly affected by the wind speed and ambient air temperature time series associated with wind power output.

In order to verify the effectiveness of the proposed model considering the correlation of wind power output, simulation experiments are carried out using three wind power output scenarios in Fig. 1, and three simulation scenarios are set up as shown in Table 2, and the results of the probability trend in Monte Carlo simulated wind power output scenarios before and after the consideration of correlation, as well as in actual wind power output scenarios, are shown in Figs. 5.

Table 2 Description of scene settings

Scene	Description
Scene1	Considering the actual historical wind power output, the measured wind power output sequence, and its corresponding results are used to verify the validity of the model against each other.
Scene2	Without considering the correlation of stochastic wind power output, the kernel density estimation method is used to obtain the same probability density distribution as the measured wind power output data of the experimental group, and Latin hypercubic sampling is used to obtain the stochastic wind power output sequence.
Scene3	Wind power output considering wind power output correlation, correlation process for scenario 2, input is a random sequence considering wind temperature time series correlation as.

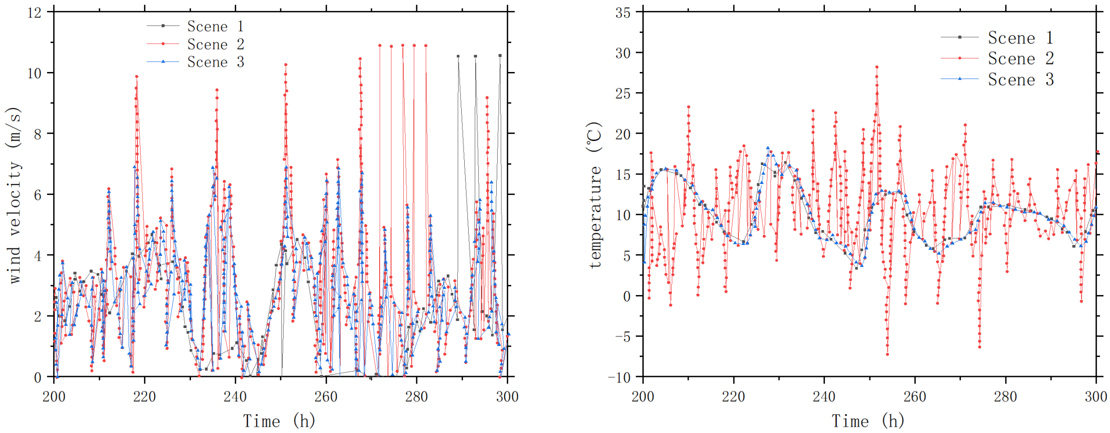

Fig. 5 Characteristic curves of air temperature time series in each scenario

In the evaluation of model effectiveness, the mean absolute error and root mean square error are used to evaluate the model. Based on the power flow results in scenario 1, the distribution error statistics are carried out on the probabilistic power flow calculation results obtained by Monte Carlo simulation before and after considering the temporal correlation of wind power output and the power flow results under the actual wind power output data. The results in Table 3 show that the MAE and RMSE of the probability density curves of the active loss, flow power and voltage amplitude of the branch are significantly reduced after considering the timing correlation of wind power output. Specifically, the MAE decreased by 61.0%, 33.3%, and 40.0%, respectively, while the RMSE decreased by 58.3%, 35.4%, and 20.0%, respectively. This shows that the output accuracy of probabilistic power flow calculation has been significantly improved after considering the time series correlation of wind power output, which proves that the correlation between wind speed and temperature has a significant impact on the probability power flow calculation results. Taking this correlation into account in a power flow analysis can greatly improve the accuracy of the results and make them more realistic.

Table 3 Analysis of probabilistic tidal current results before and after considering wind power output correlation

Data type	Scene	MAE	RMSE
Active Loss	Before considering relevance	20.5	30
	After considering the relevance	8	12.5
Voltage amplitude	Before considering relevance	4.5	6.5
	After considering the relevance	3	4.2
Branch active power	Before considering relevance	0.02	0.035
	After considering the relevance	0.012	0.028

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5. Conclusion

The time-varying line impedance correction factor in this paper's model can take the influence of environmental factors on power system parameters into account, and then effectively correct the line impedance. Moreover, according to the results obtained from the three scenario experiments, the MAE and RMSE of the power system probabilistic tidal current calculation results are significantly reduced after considering the time-order correlation of wind power output, indicating that the power system probabilistic tidal current results under the consideration of the time-order correlation of wind temperature can be improved by the ACNN model, which is more in line with the actual production situation, and enhances the reliability of the model and the reliability of the model.

The MAE and RMSE of the power system probabilistic tidal current results after considering the wind power output timing correlation of the model are obviously reduced, which proves that the probabilistic tidal current results can be effectively improved by considering the wind power output timing correlation of the RLSTM neural network model to make it more close to the actual grid operation situation and enhance the effectiveness and accuracy of the model.

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