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Decision Model of Transmission Capacity Based on Expected Quantile for Wind Farm

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Abstract: **[Purposes]** The new energy generation represented by wind power is the most realistic strategic choice to achieve the goals of carbon peaking and carbon neutrality. To absorb renewable energy electricity in power grids, a new probabilistic evaluation method for available transmission capacity in transmission systems is proposed based on joint cumulants, and a decision model for risk available transmission capacity based on expected quantiles is proposed accordingly. As a vital component of available transmission capacity (ATC) calculation, the transmission reliability margin (TRM), as a reserved transmission capacity, reflects the impact of uncertainty factors on transmission capacity. However, in traditional calculation methods, TRM is determined through deterministic or probabilistic methods, which is difficult to reflect the risks brought by large-scale wind power consumption to ATC and cannot meet the requirements for transmission capacity risk management. **[Methods]** Firstly, to address the issue that the cumulative method requires variables to be independent of each other and cannot consider the correlation of wind power output, a joint cumulative method combined with FGM Copula function is proposed to characterize the correlation of wind power output; Secondly, for the probabilistic assessment of available transmission capacity, a probabilistic assessment model for available transmission capacity is established by combining the partition integration method and the Cornish Fisher expansion; Finally, in response to the problem that decision methods based on value at risk only consider the probability achieved at the tail of the probability distribution and cannot describe the risks generated throughout the distribution, a risk available transmission capacity index based on expected quantiles is proposed, and its evaluation process is proposed. **[Results]** Verify the feasibility and practicality of the proposed indicators and models through case analysis.

Keywords: ATC; ERATC; FGM Copula; Wind power

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1 INTRODUCTION

The capacity to assure adequacy exists in the form of transmission capacity during the transmission procedure. At present, wind power is being imple-

mented through centralized access and large-scale development. Transmission of wind energy's output to the load center is accomplished over long distances and at high voltage and power. Because of the transmission network's constrained capacity, the integra-

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tion of large-scale wind power into the power grid may impede transmission capacity between system regions and hinder the maximization of renewable energy electricity acceptance.

In this context, the calculation of available transfer capability (ATC) of the transmission network has become a prerequisite for electricity market participants to complete electricity transactions^[1]. One of the main goals of system operators is to ensure stable, dependable, and efficient operation of the power system. ATC is an important indicator for evaluating the safety of power systems. The ATC calculation methods that consider the uncertainty of wind power output include Monte Carlo simulation (MCS) and approximation methods^[2]. To obtain convergent calculation results, MCS requires a large amount of simulation calculations, which require a large amount of computation. The approximation method represented by the cumulative quantity method can quickly obtain the probability characteristics of the system's transmission capacity under certain assumptions and mathematical operations, while sacrificing a certain level of computational accuracy. However, with the large-scale integration of wind power into the grid and the development of the electricity market, electricity market transactions emphasize the coordination and linkage of resources within or across regions. Therefore, wind farms cannot be regarded as independent units and their interdependence should not be ignored. Instead, all wind power resources in the region should be considered. The cumulative quantity method operates under the assumption of independence among random variables, which presents a challenge in effectively integrating large-scale wind power into the grid. The correlation between wind farm output and the interaction between wind farms must be considered.

As a vital component of ATC calculation, the transmission reliability margin (TRM), as a reserved transmission capacity, reflects the impact of uncertainty factors on transmission capacity^[3]. However, in traditional calculation methods, TRM is determined through deterministic or probabilistic methods, which is difficult to reflect the risks brought by

large-scale wind power consumption to ATC and cannot meet the requirements for transmission capacity risk management.

The planning models in most published papers typically include random variables such as load, renewable generation, and operation and maintenance costs. Additional variables encompass potential disruptions in the system's infrastructure or the generator's operations^[4]. The models' variables are represented using robust sets, which allows for solving robust optimization models^[5-7]. In the case of this paper, the variables are also represented using probability distributions, enabling the solution of stochastic optimization models. The selection criterion for most stochastic models is to optimize the expected value of the objective function^[8-9]. However, certain models focus solely on minimizing the Conditional Value at Risk (CVaR), where β represents the planner's predetermined balance between the expected value and the level of risk, as indicated by CVaR. Additional selection criteria encompass the standard deviation (std). The standard deviation (std) is calculated as the square root of the variance of the objective function^[10-11]. It quantifies the spread or dispersion of the objective function's values in relation to the expected value^[12]. Simulation is integrated into solution approaches for stochastic optimization problems^[13]. In simulation-optimization approaches, random variables are drawn from their respective probability distributions. The optimization model is then solved deterministically for each instance of the random variable, while a stopping rule is employed to terminate the simulation. The rules pertain to the computational efficiency and solution accuracy of the solution and encompass metrics of variance^[14-16].

After carefully reviewing relevant literature the papers are designed as follows:

(1) Based on anticipated quantiles, this paper presents a decision model for the available transmission capacity of wind power systems. To consider the correlation of wind farm output and solve the problem of independent variables required by the cumulative quantity method, a joint cumulative quantity combined with FGM Copula function is proposed

to characterize the correlation of wind power output.

(2) A probabilistic evaluation model for available transmission capacity is proposed by combining partition integration method and Cornish Fisher expansion to address the issue of available transmission capacity.

(3) To more comprehensively describe the risk of available transmission capacity, a risk available transmission capacity decision-making model based on the expected quantile is proposed by selecting an appropriate profit loss ratio according to the risk preference of decision-makers. Through numerical analysis, the efficacy and viability of the procedure proposed were validated.

2 RISK AVAILABLE TRANSMISSION CAPACITY DECISION MODEL BASED ON EXPECTED QUANTILE

In the probability assessment of available transmission capacity, to measure the influence of uncertain factors, a series of probability indexes can be defined to carry out probability statistics on the sample values of transmission capacity. On the contrary, if the probability is specified, the corresponding ATC can be easily determined. This section analyzes ATC deficiency risk based on risk theory to determine ERATC indicators. Based on the assessment results of ATC probability assessment, this section proposes a method to determine the optimal available transmission capacity based on the expected quantile. Firstly, the definition of expected quantile is described. On this basis, the risk available transmission capability index based on expected quantile is proposed, and its evaluation process is proposed.

To obtain the required ERATC, the system operator can set parameter θ after conducting a probability evaluation of ATC to obtain the profit and loss ratio $\theta/(1-\theta)$. Then, according to equations $EVaR_{\theta}(X) = -e_{\theta}(X)$ and $ERATC = EVAR_{\theta}(ATC) = -e_{\theta}(ATC)$, ERATC can be obtained. The method based on expected quantiles can be used to evaluate both VaR and CVaR of ATC simultaneously.

In conventional methods for determining Avail-

able Transfer Capability (ATC), a specific transmission capacity, known as the Transmission Reliability Margin (TRM), is typically reserved to account for the influence of uncertain factors in the power system on transmission capacity. This ensures the safe operation of the system. Subsequently, the ATC of the system is indirectly calculated after determining the TRM. Nevertheless, this approach fails to fulfill the demands of risk management. The ERATC indicators presented in this section assess the influence of extensive wind power utilization on the transmission system and calculate ERATC based on the principles of minimal risk management. Simultaneously, decision-makers have the option to select appropriate parameters based on their risk preferences to fulfill the demands of risk management and differential management of transmission resources.

According to the definition of expected quantile, this section analyzes the physical meaning of ERATC from the following two perspectives and designs its application scenarios:

1. The decision-maker can make a reasonable profit and loss ratio of $\theta/(1-\theta)$ according to the needs of risk management, and set the ATC issued equal to ERATC. At this time, ATC can be understood as ensuring that the ratio of ATC expectation lower than ERATC to ATC expectation higher than ERATC is not higher than the maximum transmission capacity of no $\theta/(1-\theta)$.

2. According to Formula $e_{\theta}(X) - E(X) = \frac{2\theta - 1}{1 - \theta} E[(X - e_{\theta}(X))_+]$, parameter θ can also be regarded as the ratio of ATC expectation lower than ERATC and system ATC expectation. Therefore, ERATC value can be considered as a measure of the risk of ATC deficiency. The decision-maker can determine the acceptable risk level and issue a reasonable ERATC as the safety threshold of ATC of the system.

In the probability assessment of available transmission capacity, to measure the influence of uncertain factors, a series of probability indexes can be defined to carry out probability statistics on the sample values of transmission capacity. On the contrary, if

the probability is specified, the corresponding ATC can be easily determined. This section analyzes ATC deficiency risk based on risk theory to determine Expected Risk Available Transfer Capability (ERATC) indicators. Based on the assessment results of ATC probability assessment, this section proposes a method to determine the optimal available transmission capacity based on the expected quantile. Firstly, the definition of expected quantile is described. On this basis, the risk available transmission capacity index based on expected quantile is proposed, and its evaluation process is proposed.

The objective of this paper is to examine the influence of wind power consumption on the ATC of the transmission system. To achieve this, an ATC probability assessment model and a risk available transmission capacity assessment index utilizing the expected quantile are presented. Drawing upon the joint cumulant method and FGM Copula, the probability assessment model of ATC is derived while considering the correlation of wind power output among wind farms. This model also provides the distribution of ATC. The cumulant method avoids the integration of many input variables during large-scale wind power grid integration, thus improving the cal-

culation efficiency. According to the probability distribution of ATC, this paper proposes the evaluation index ERATC based on the expected quantile. The Expected Risk Available Transfer Capability (ERATC) proposed in this article describes the ratio of the expected value of ATC that is lower than ERATC to the expected value of ATC that is higher than ERATC for a given profit and loss ratio of $\theta/(1-\theta)$ and designs the application scenario of ERATC on this basis. The specific steps of the assessment decision of the risk available transmission capacity based on the expected quantile proposed in this article are as follows.

Step 1: The parameters for estimating the probability distribution of wind speed for each wind farm should be estimated using historical wind speed data.

Step 2: Determine the cumulative output of each wind farm using equation , obtain the probability distribution of the output for each wind farm using equation, and compute the output of each wind farm using the wind speed wind power conversion function.

$$k_{z,2} = E[(\sum_{i=1}^n a_i X_i)^2] - [E(\sum_{i=1}^n a_i X_i)]^2 = \sum_{i=1}^n a_i^2 k_{X_i,2} + 2 \sum_{i=1, i < j}^n a_i a_j k_{X_i, X_j}$$

$$F_{w_j}^{i_w}(P_w \leq x) = \begin{cases} 0, \forall x < 0, \\ 1 + \exp\left(-\left(\frac{v_{out}}{\lambda}\right)^k\right) \\ - \exp\left[-\left(\frac{\left[\frac{x}{i_w^{num} * P_{w_{rated}}}(v_{rated}^3 - v_{in}^3) + v_{in}^3\right]^{\frac{1}{3}}}{\lambda}\right)^k\right], \forall 0 \leq x < i_w^{num} P_{w_{rated}} \\ 1, \forall x \geq i_w^{num} P_{w_{rated}} \end{cases}$$

Step 3: Determine the suitability of the FGM Copula method for characterizing the correlation between wind farms by calculating the correlation coefficient between wind farms. Then, estimate the FGM Copula parameters using each wind farm's output.

Step 4: The joint cumulants of each order of the wind power output of the system are computed using the partition integration method to calculate the ex-

pected value of the product of random variables.

Step 5: Substitute the random variables into the ATC evaluation model. According to the ATC evaluation model based on the joint cumulant method, the probability distribution function of available transmission capacity is obtained by using Comish Fisher expansion.

Step 6: Determine the profit and loss ratio

$\theta/(1-\theta)$, calculate the risk available transmission capacity based on the expected quantile according to the probability distribution function of the available transmission capacity, and calculate the VaR and CVaR corresponding to the confidence level.

3 CASE ANALYSIS

3.1 Test System and Data

The ATC evaluation framework proposed in this section is based on the modified 6-node system, as shown in Figure 1.

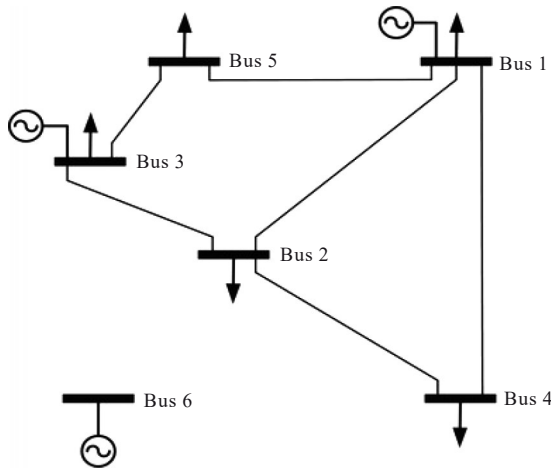


Fig. 1 6-Bus System Diagram

This system has six buses and 15 rights-of-way for the addition of new circuits. The demand is 760 MW and the relevant data are given in Tables 1.

Table 1 Generator Operation Parameters

Bus Number	$P_{\text{Generation}}/\text{MW}$		$P_{\text{Load}}/\text{MW}$
	Maximum	Level	
1	150	50	80
2	0	0	240
3	360	165	40
4	0	0	160
5	0	0	240
6	600	545	0

3.2 Assessment Results and Analysis of Transmission Capacity

To display the correlation more intuitively between wind farms, wind farms connected at Node 4 and Node 6 are selected for research and recorded as Wind Farm 1 and Wind Farm 2, respectively. Scatter plots of wind power output sample data and its empirical probability density function histogram of wind farms 1 and 2 are shown in Figure 2.

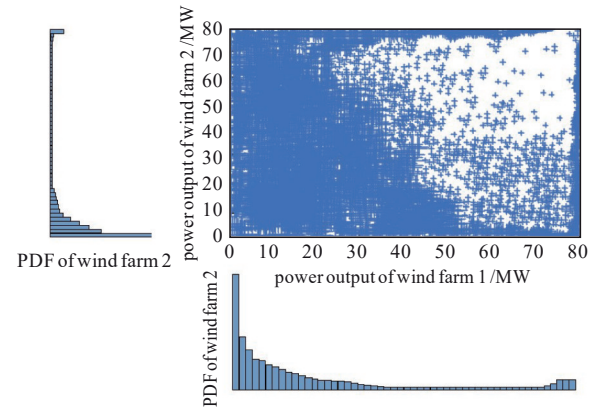


Fig. 2 Scatter diagram and histogram of wind power output of wind farm 1 and wind farm 2

The scatter plot shows the output correlation between wind farm 1 and wind farm 2. As shown in Figure 2, although the edge distribution of wind farm 1 and wind farm 2 is consistent, the correlation of wind farm output is not obvious. By calculating the correlation coefficient, the linear correlation coefficient of wind farm 1 and wind farm 2 is 0.291 8. Therefore, the correlation between wind farm 1 and wind farm 2 is weak, and it is not suitable to use linear regression to fit the relationship between them. Through calculation, the Spe between the output of wind farm 1 and that of wind farm 2. The correlation coefficient of an is 0.194 2, and the correlation coefficient of Kendal is 0.156 2. It is suitable to use the FGM Copula for fitting to describe the dependency between the two.

The shape and scale parameters of the Weibull distribution for each wind farm are derived by fitting the distribution to the actual data of wind farms. To compare the results under different dependency modeling assumptions, the following three scenarios are designed in this article.

Scenario 1: It is assumed that wind farms are independent of each other.

Scenario 2: Gaussian Copula is used to fit the output dependency between wind farms.

Scenario 3: FGM Copula is used to describe the dependency between wind farms.

When there are uncertain variables in the system, the ATC evaluation model can be regarded as a special probabilistic Optimal Power Flow (OPF) model, which can be solved by writing the Karush Kuhn Tucker (KKT) condition for the problem and

using the primal dual interior point method. According to the available transmission capacity assessment model, it can be deduced that the KKT condition in the model has a linear summation term of the wind farm output. Therefore, this section compares the cumulative probability distribution of wind farm output summation under different scenarios. The fitting results of different dependency relationships are shown in Figure 3.

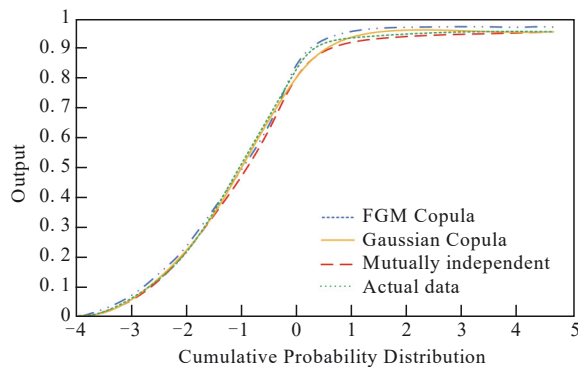


Fig. 3 Cumulative Probability Distribution of System Wind Power Output

According to Figure 3, the fitting result of actual wind farm output data, this proves that FGM Copula can better fit the wind farm output data than Gaussian Copula. As the correlation of wind farm output is weak, scenario 1 can also get a better fitting result. To further compare the depiction of wind farm output distribution under different scenarios, this section calculates the JS divergence of wind farm output probability distribution and actual data probability distribution under different scenarios. The principle of JS divergence is to use the probability of information entropy to realize the quantitative measurement of information, which is used to calculate the distance between two probability distributions. The greater the JS divergence, the greater the difference between the probability distributions. On the contrary, the smaller the difference between the two. The JS divergence under different scenarios is shown in Table 2.

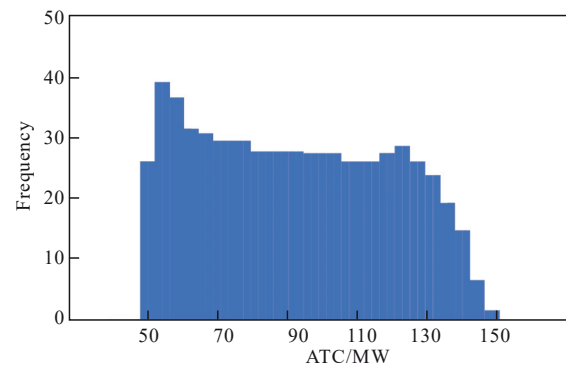
Table 2 JS divergence under different scenarios

Divergence Type	Scenario 1	Scenario 2	Scenario 3
JS divergence	0.136	0.137	0.113

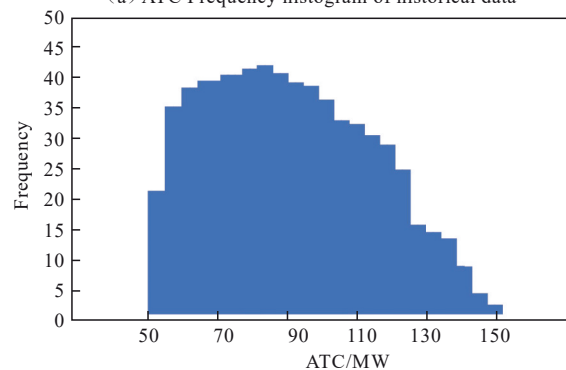
According to Table 2, the JS divergence of wind farm output probability distribution and actual

wind power output probability distribution in Scenario 3 is the smallest, while that in Scenario 2 is the largest. The results are consistent with Figure 2. Therefore, by comparing different dependency scenarios, it can be concluded that the FGM Copula adopted in this article can accurately obtain the probability distribution of wind farm output.

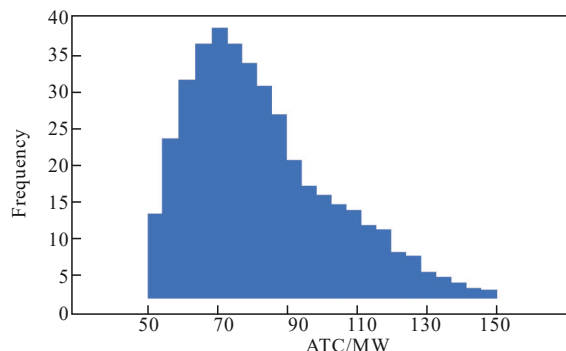
Figure 4 shows the ATC probability distribution calculated based on historical data and the ATC probability distribution calculation results under different scenarios. Figure 4 (a) is the ATC frequency histogram calculated based on historical data; Figure 4 (b) is the ATC frequency histogram calculated under Scenario 1; Figure 4 (c) is the frequency histogram calculated under Scenario 2.



(a) ATC Frequency histogram of historical data



(b) ATC Frequency histogram under scenario 1



(c) ATC Frequency histogram under scenario 2

Fig. 4 ATC Calculation Results under Different Scenarios

As the ATC probability evaluation method proposed in this article is solved by analytical method, it has obvious advantages in computing time compared with MCS. The calculation time under different scenarios is shown in Table 3.

Table 3 Comparison of calculation time in different scenarios

Time	Actual data	Scenario 1	Scenario 2
Calculation time/s	60.28	59.38	55.45

According to Table 3, since the methods are based on actual data, scenario 1 and scenario 2 are all based on MCS simulation results, the calculation time is long. The calculation time of the ATC evaluation method proposed in this paper is significantly lower than that based on MCS simulation results.

The impact of wind farm grid connection on ATC can be determined by its expected value, and its fluctuation can be determined by its variance. By comparison, the mean generated by historical data for wind power scenarios is 72.14 MW, with a variance of $5.11 (\text{MW})^2$, while the mean generated by Copula function for wind power scenarios is 71.28 MW, with a variance of $5.88 (\text{MW})^2$; The extreme values of the two schemes are the same. From the two probability density curves in Figures 5 and the evaluation indicators, the wind power output is calculated directly using historical wind power output data considering correlation and wind power output samples obtained through Copula function sampling

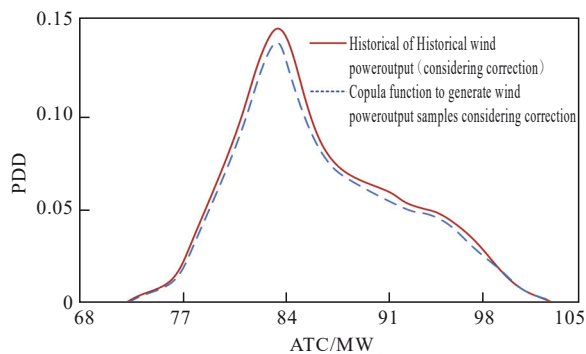


Fig. 5 ATC Probability Density Distribution Curve in Different Scenarios

According to the various locations of wind farms connected to the grid, the impact of large wind farms on ATC exhibits distinctive characteristics. This part focuses on evaluating the impact of different correlations in wind farm output on ATC and compares

them in the following two situations.

Case 1: Two wind farms integrated at nodes 2 and 5 in the power generation area;

Case 2: Two wind farms are integrated at 5 nodes in the receiving area and 6 nodes in the receiving area.

When the wind farm is integrated into the power generation area and the correlation coefficient changes from 0.45 to 0.9, the probability density curve corresponding to ATC as shown in Figure 6, corresponding to the scenario in Case 1; When the wind farm is integrated in the receiving area, the correlation coefficient changes from 0.45 to 0.9. The probability density curve corresponding to ATC is shown in Figure 7, which corresponds to the scenario in Case 2.

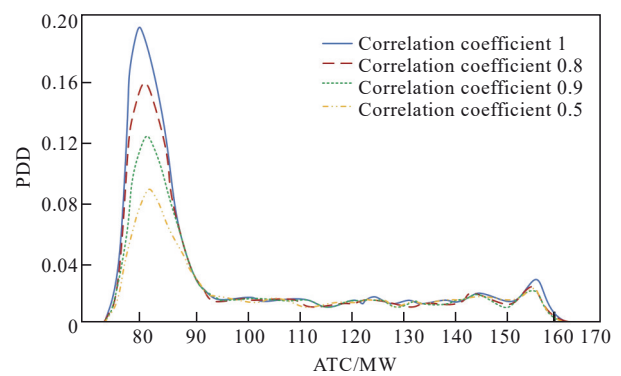


Fig. 6 Case 1 ATC probability density distribution curve of different correlation coefficients

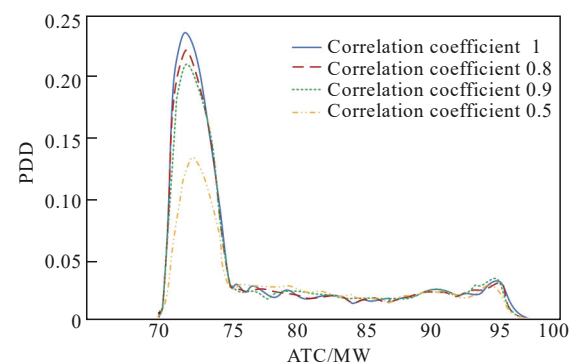


Fig. 7 Case 2 ATC probability density distribution curve of different correlation coefficients

The location and correlation factors of wind farm integration have a certain impact on the variance of ATC, which can characterize the volatility of the system; The probability distributions corresponding to different correlation coefficients in Figures 6 and 7 also show that when the wind farm is integrated in

different regions, the wind power correlation also has a certain impact on the fluctuation amplitude of ATC.

The influence of correlation factors on the probability evaluation indicators of ATC varies when wind farms are integrated in distinct regions. Consequently, wind power correlation factors and the position of the wind power grid connection must be accounted for during the ATC evaluation procedure.

3.3 Comparative Analysis

This section compares the ATC values obtained based on VaR and CVaR with the ERATC values obtained based on the expected quantile method. The comparison results are shown in Table 4.

Table 4 Assessment Results of Different Risk Assessment Methods under the Profit and Loss Ratio of 0.005

Confidence level	VaR	CVaR	ERATC
0.996	79.96	47.24	79.96

According to Table 4, when the profit and loss ratio of ATC adequacy is 0.005, the ATC issued according to this standard is 79.96 MVA, and the confidence level of its corresponding VaR is 0.995 3. That is, the probability of ATC higher than 79.96 MVA is 0.995 3. The expected value of ATC lower than 79.96 MVA is 47.24 MVA.

To assess the effects of various influencing factors on ERATC, this section conducts a comparative analysis of the effects of distinct wind power penetration rates and profit and loss ratios chosen by decision-makers. The corresponding results are illustrated in Figure 8 and Figure 9.

Figure 8 compares the impact of different P/L ratios on ERATC. As shown in Figure 9, ERATC increases with the increase of the selected P/L ratio. This shows that when ATC is released according to ERATC, with the increase of the profit/loss ratio selected by the decision-maker, the decision-maker can bear more risk of ATC shortage. Therefore, the selected ERATC is more aggressive and tends to select a higher ERATC value.

The ERATC is compared across various wind power permeabilities in Figure 10. As illustrated in Figure 10, as wind power penetration increases, ERATC decreases. According to the analysis in the pre-

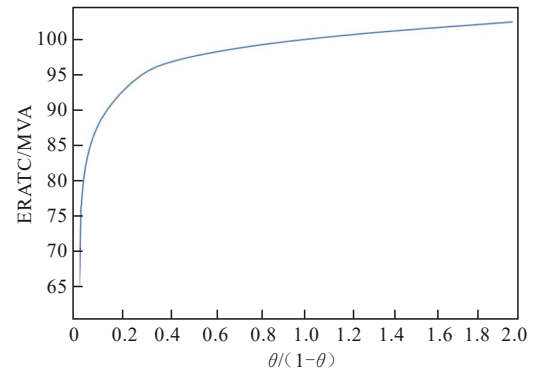


Fig. 8 Relationship between profit loss ratio and ERATC

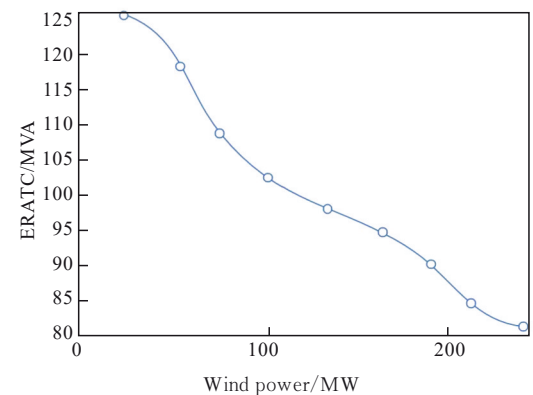


Fig. 9 Relationship between ERATC and system wind power permeability

vious part, ERATC can be regarded as a measure of ATC deficiency risk of the system. Therefore, under the parameter θ of phase N, with the increase of wind power permeability, the increase of wind power output uncertainty will lead to the increase of system uncertainty, which will lead to the increase of ATC deficiency risk, making the value of the optimal ERATC gradually conservative, thus causing the decline of ERATC.

4 CONCLUSION

When wind power is connected to the grid, the number of wind farms increases, increasing the number of random variables in the transmission system adequacy evaluation and decision-making model. Analytical calculation of multidimensional integration is difficult, and the simulation method is computationally intensive. The ATC probability assessment method proposed in this article significantly improves the calculation speed of ATC probability assessment, provides ideas for ATC probability assessment, and has practical application value. This pa-

per's risk available transmission capacity assessment method based on expected quantiles can also help power system reliability managers make more scientific decisions. This paper scientifically guides transmission system planning and scheduling by making reasonable transmission capacity scheduling arrangements to maximize transmission channel use, ensure channel stability, and avoid transmission resource waste and contract breach due to unreasonable decisions.

5 LIST OF ABBREVIATIONS

Available transfer capability (ATC)

Monte Carlo simulation (MCS)
Transmission reliability margin (TRM)
Conditional Value at Risk (CVaR)
Farlie Gumbel Morgen stem Copula (FGM Copula)
Jensen Shannon Divergence (JS Divergence)
Optimal Power Flow Model (OPF)
Karush Kuhn Tucker Condition (KKT)
Probability Density Distribution Curve (PDD)
Cumulative Distribution Function (CDF)

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