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EDITED BY

Zhengmao Li,
Aalto University, Finland

REVIEWED BY

Tao Chen,
Southeast University, China
Yingjun Wu,
Hohai University, China
Xiaolong Jin,
Technical University of Denmark, Denmark

*CORRESPONDENCE

Longwen Jia,
✉ 2294683296@qq.com

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Calculation of the available transfer capability of trading channels based on power network congestion forecasting

Congying Wei¹, Longwen Jia^{2*}, Xiongwei Wang¹, Yu Cai¹, Ying Huang¹, Yanbo Huang¹ and Siyang Liao²

¹Dispatching and Control Center, Central China Branch of State Grid Corporation of China, Wuhan, China, ²School of Electrical Engineering and Automation, Wuhan University, Wuhan, China

Against the backdrop of increasing renewable energy penetration, frequent power network congestion has become a key issue limiting the available transfer capability of trading channels. In order to avoid power network congestion while improving the overall utilization of trading channels, we propose a method for calculating the available transfer capability of a trading channel based on power network congestion forecasting. First, this study uses a histogram-based gradient tree boosting (HGTB) model to forecast the severity and probability of power network congestion, which enables power system operators to determine the specific circumstances of congestion occurrence. Second, we analyze the sensitivity of the power trading network and generating units to transmission lines, aiming to calculate the available transfer capability of the trading channel on the basis of taking into account the control of transmission line congestion and the balance of supply and demand in the power market. Finally, the validity of the validation methodology is verified based on a case study of the power system in central China.

KEYWORDS

feature selection, power network congestion, decision tree, trading channel, available transfer capability

1 Introduction

The rapid development of renewable energy sources, such as wind power and photovoltaic, is an important driving force to promote the energy transition of the power system. They are highly clean, renewable, and sustainable, can effectively reduce the dependence on traditional fossil energy, reduce the impact of energy consumption on the environment, and are of great significance in realizing the global green and low-carbon development goals (Zhou et al., 2018; Yang et al., 2023). The installed capacity of intermittent renewable energy sources such as wind power and photovoltaic in the power system has been increasing every year. This trend has led to a considerable rise in uncertainty in the power system, and the power network transmission congestion problem has gradually gained attention (Zhang et al., 2016). On the other hand, on the load side, the increased interactive demand of devices such as electric vehicles, heat pumps, and flexible buildings may also cause congestion problems (Hanif et al., 2017; Li et al., 2020a). Forecasting congestion is the key to solving the congestion problem, and many studies have applied data-driven control methods, such as support vector machines (Niu et al., 2006),

decision trees (Li et al., 2005), random forests (Li et al., 2020b; Wu et al., 2015), and neural networks (Lu et al., 2019; Chen et al., 2020; Rafi et al., 2021), in the prediction of load and new energy sources for power systems. In terms of power system stability assessment, data-driven control strategies can use machine learning algorithms, such as supervised learning, unsupervised learning, and reinforcement learning, to learn the power system operation data and forecast whether the power system will be destabilized (Yang et al., 2022). The application of data-driven control strategies in power systems has become more and more widespread, and in the future, with the continuous development of data science and artificial intelligence technology, data-driven control strategies will become an important means of power system intelligence and adaptability (Xue et al., 2015; Bi et al., 2002).

In a study of calculating the available transfer capability (ATC) based on the power market, Ding et al. (2018) discussed key technologies, such as the technical support platform, out-clearing method, model data management, and others, under the general framework of the power spot market. Zou et al. (2014) summarized the universal law in the process of spot market construction and analyzed the internal logic of spot market construction by comparing and analyzing the latest practices of electricity market construction in different countries. Xia and Guo (2009) discussed the market function and positioning of the spot electricity market from the perspective of market functionality and structure on the basis of a coordinated electricity market trading system. Zeng et al. (2020) measured the sensitivity of DC receiver and generator nodes to AC lines and proposed a simplified method of AC–DC hybrid network and an ATC-based inter-provincial transaction clearing model. Cheng et al. (2022) described the research and development of inter-provincial medium- and long-term trading systems taking the ATC into account. The above studies focus on analyzing the power market mechanism and the method of market clearing under the assumption that the channel ATC is known; however, studies on ATC calculation are lacking. Part of the literature considered the uncertainty of new energy generation (Bai et al., 2020; Li et al., 2022) and the deviation of load forecast (Liu et al., 2023), based on which Zhang et al. (2007) and Huang et al. (2013) accomplished the calculation of probabilistic ATC from the perspective of risk and return. However, the above studies focus on inter-provincial trading channels and simplify the network structure within the provincial network, which leads to the risk of congestion of intra-provincial transmission lines during trade execution.

In summary, for the risk of transmission line congestion during transaction execution, through a data-driven strategy, we propose an optimization method for the available transfer capability of trading channels based on power network congestion prediction, aiming to calculate the available transfer capability of trading channels on the basis of taking into account the control of transmission line congestion and the balance of supply and demand in the power market. First, data processing and characterization are performed to extract effective information for predicting power network transmission congestion from redundant data and features. Second, a histogram-based gradient tree boosting (HGTB) multi-classified probabilistic prediction of power network transmission congestion is proposed to predict the severity and probability distribution of congestion. Finally, a network coupling model

based on the power distribution factor is proposed to consider the impact of the trading volume of the trading channel on the congestion line, and a quadratic objective function is designed to maximize the spot trading capacity and power transfer capacity. Compared with existing studies, the main contributions of this paper are as follows:

- 1) A multi-classified probabilistic prediction model of power network transmission congestion based on HGTB is proposed. The proposed model obtains knowledge directly from data, thus avoiding the physical modeling challenges for large and complex power systems. The real-time power system information is fully utilized to accurately predict the probability and trend of future power network transmission congestion.
- 2) An optimization method for the available transfer capability of trading channels is proposed. By calculating the equivalent sensitivity, the coupling relationship between the trading network and the provincial transmission lines is modeled, and the impact of the trading volume on the provincial transmission lines is analyzed. Taking into account congestion control and supply–demand balance, a normalized quadratic objective function is established to improve the overall utilization rate of the trading channel while avoiding excessive restrictions on the available transfer capability of some trading channels.

The rest of this paper is organized as follows: Section 2 introduces the HGTB-based multi-classified probabilistic prediction model for power network transmission congestion. Section 3 presents the calculation method for the available transfer capability of the trading channel. Section 4 gives the simulation results. Section 5 concludes the paper.

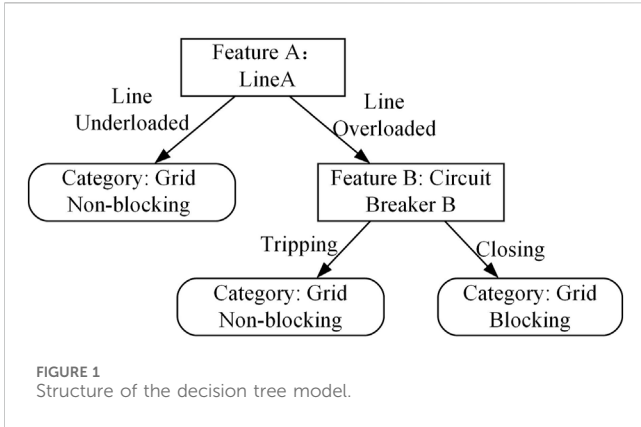
2 Multi-classified probability prediction of power network transmission congestion

This section implements a data-driven approach to real-time prediction of power network transmission congestion in power systems by combining the feature selection theory and the gradient boosting tree theory.

2.1 Feature selection

Due to the large number of feature variables in an actual power grid, filtering out redundant variables before making predictions can greatly improve computational efficiency. At the same time, the power network transmission congestion prediction puts forward the requirement of multi-classification for feature extraction, so we choose the Relief-F algorithm based on the expansion of the Relief algorithm. The specific steps of the Relief-F algorithm are as follows:

- 1) Initializing the relevant parameters: We set the dataset D , which contains m samples and n features. The samples contain



L categories. We set the weight threshold θ , initialize the feature weight vector W , and set the loop exit condition.

- 2) We randomly select a sample $x_i \in D$, let it belong to the k th category, find the nearest neighbor sample $x_{i,nh}$ of the same category of sample x_i , and for each dissimilar category, find an opposite-class nearest neighbor $x_{i,l,mh}$, with subscript l denoting the l th category.
- 3) For each feature $j \in 1, 2, \dots, n$, we calculate the relevance weight W_j of feature j and update the weight of feature j :

$$W_j = W_j - \text{diff}(x_{ij}, x_{i,nh})^2 + \sum_{l \neq k} (\rho_l \text{diff}(x_{ij}, x_{i,l,mh}))^2. \quad (1)$$

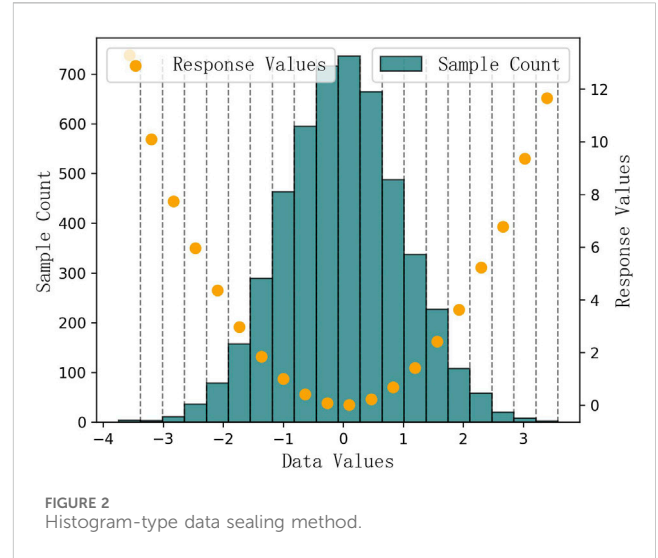
- 4) We repeat steps (2) and (3) until the loop exit condition is satisfied.
- 5) We sort the features according to their weights W and select the features with weights greater than the weight threshold θ as the optimal feature subset.

2.2 Histogram-based gradient tree boosting

A decision tree is a weak learner, as shown in Figure 1. Gradient tree boosting (GTB) is a boosting integration algorithm that boosts the decision tree into a strong learner by means of integration. In the process of boosting, the latter learner will successively pay attention to the samples where the prediction result of the previous learner differs greatly from the actual result. For power network transmission congestion caused by system uncertainty, additional learning on misjudged samples enables the model to gradually improve its prediction accuracy.

GTB first predicts the target value or category label of a sample using a combination of all the current weak learners and then calculates the error between the predicted value and the true value. GTB then uses these errors as the target value to train the next weak learner, and this process is repeated until a preset number of iterations or a stopping criterion is reached. The set of all trained weak learners becomes a strong learner, represented by an additive model:

$$F_M(x) = \sum_{m=1}^M f_m(x), \quad (2)$$



where $f_m(x)$ denotes the m th weak learner. Choosing the CART tree as the weak learner of the GTB algorithm makes the lifting process highly robust and interpretable.

As shown in Figure 2, HGTB is a boosted tree method that reduces model complexity and improves model generalization using the histogram data sealing method. Compared with GTB, HGTB converts continuous eigenvalues into discrete data boxes by means of histogram boxing, which drastically reduces computation and memory consumption, and especially performs better when dealing with large-scale data.

In the figure, the height of the squares indicates the number of samples in the box, and the scatter indicates the response values of the individual boxes. After the histogram closure process, the response values of all the boxes can be used as predictions.

2.3 HGTB-based multi-classification prediction

The HGTB-based multi-classification prediction method provides not only the future congestion stall but also the probability of occurrence of each congestion stall. The training method for the HGTB-based multi-classification probabilistic prediction model is as follows:

- 1) For a K -class classification problem, it is first transformed into K binary classification problems.
- 2) Histogram blocking is performed on each continuous feature of the dataset.
- 3) Initializing the model: For each category k , we use the CART algorithm on the training dataset to construct a regression tree $T_{k,0}(x)$ for predicting the probability score $z_k(x)$ of a sample x belonging to category k . The prediction score $z_k(x)$ of a leaf node is the average of the samples belonging to category k among the training samples on that leaf node.

$$F_0(x) = \sum_{k=1}^K T_k(x; \Theta_0). \quad (3)$$

4) Updating the model.

The K -predicted scores, $z_k(x)$, are transformed by the Softmax function to obtain the probability distribution $P_k(x)$ of the samples belonging to each category k :

$$P_k(x) = \frac{\exp(z_k(x))}{\sum_{j=1}^K \exp(z_j(x))}, k \in [1, K]. \tag{4}$$

We calculate the negative gradient and fit a new regression tree to update the model parameters by minimizing the cross-entropy loss function:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K y_{ik} \log P_k(x_i), \tag{5}$$

where N denotes the number of samples in the training set. The cross-entropy loss function measures the difference between the probability distribution predicted by the model and the true distribution; the smaller the value of cross-entropy, the closer the prediction is to the true label.

We stack the regression tree $T_k(x; \Theta_m)$ for each category into the original model:

$$F_m(x) = F_{m-1}(x) + \sum_{k=1}^K T_k(x; \Theta_m). \tag{6}$$

Iterating the above process, we will output a trained integrated tree model for multi-classified probabilistic prediction of power network transmission congestion. This integrated model actually outputs the probability distribution of the samples, taking the category with the highest probability as the predicted category.

2.4 Method application

This section theoretically proposes a power network transmission congestion prediction method that can meet real-time scheduling requirements. First, using a Relief-F-based feature selection method for multi-classification problems, the relevance of feature variables to the classification task can be derived, and then, the feature variables that are most conducive to labeling line congestion can be selected. The selected feature variables are fed to the prediction model as labeled historical data can equip the model with the ability to classify and predict the power network transmission congestion state at future moments. Second, following the above ideas, this paper chooses GTB as the basis of the prediction model, which is characterized by interpretability, efficient training, and high accuracy. The HGTB model is formed by the method of histogram data sealing box, which improves the generalization ability of the model and makes the prediction model more applicable to the power network transmission congestion prediction problem in the real-time scheduling process.

3 Calculation method of the available transfer capability of a trading channel

The current inter-provincial power trading network does not take into account the structure of the provincial transmission lines, which leads to inconsistency between the trading network and the

physical transmission network and the risk of congestion of the provincial transmission lines during trade execution. In this regard, the constraints of transaction execution are formed by calculating the sensitivity of the transaction channel and the sensitivity of the generating unit to the transmission line, based on which the calculation method of the available transfer capability of the transaction channel that takes into account the congestion of the intra-provincial transmission line is proposed.

3.1 Sensitivity calculation formula

By performing the power flow calculation by Newton's method, the Jacobi matrix can be obtained as follows:

$$J_0 = \begin{bmatrix} \frac{\partial P}{\partial \theta} & \frac{\partial P}{\partial V} \\ \frac{\partial Q}{\partial \theta} & \frac{\partial Q}{\partial V} \end{bmatrix}, \tag{7}$$

where P is the node injected active power, θ is the node voltage phase angle, and V is the node voltage.

The sensitivity matrix G of the injected power at node k to the flow of branches $i-j$ is expressed as follows:

$$G = \frac{\partial S_{ij}}{\partial U_k} J_0^{-1}, \tag{8}$$

where $\frac{\partial S_{ij}}{\partial U_k}$ denotes the partial derivative of the power flow of branches $i-j$ with respect to the voltage variation at node k and J_0^{-1} denotes the partial derivative of the node voltage with respect to the injected power at each node.

The sensitivity of each node to the provincial transmission line is shown as follows:

- 1) Sensitivity of the trading channel to the provincial transmission line

Specifying the positive direction of power transmission as the direction of incoming power to the province, the sensitivity G_i^L of the inter-provincial physical link to the current of branches $i-j$ is

$$G_i^L = \frac{\partial S_{ij}}{\partial U_i} J_0^{-1}, \tag{9}$$

where $\frac{\partial S_{ij}}{\partial U_i}$ denotes the partial derivative of the power flow of branches $i-j$ with respect to the variation of the voltage at the sending node i of the trading channel.

- 2) Sensitivity of critical generating units to provincial transmission lines

We consider the role of the critical generating unit on the provincial transmission line, where the sensitivity G_n^{RG} of the critical generating unit n to the provincial transmission lines $i-j$ is

$$G_n^{RG} = \frac{\partial S_{ij}}{\partial U_n} J_0^{-1}, \tag{10}$$

where $\frac{\partial S_{ij}}{\partial U_n}$ denotes the partial derivative of the power flow of branches $i-j$ with respect to the voltage variation at node n of the critical generating unit.

3) Sensitivity of non-critical generating units to provincial transmission lines

Since the power system operator usually does not give additional instructions to non-critical generating units when the line is congested, it can be assumed that the power output of non-critical generating units no longer changes. Therefore, the non-critical generating units in the province can be weighted and aggregated into an equivalent generating node, which has the following sensitivity G_x^{PG} to the provincial transmission line:

$$G_x^{PG} = \sum_{g=1}^G \lambda_x^g \cdot \frac{\partial S_{ij}}{\partial U_x} J_0^{-1}, \tag{11}$$

$$\lambda_x^g = \frac{G_x^g}{\sum_{x=1}^X G_x^g}, \tag{12}$$

$$\sum_{x=1}^X \lambda_x^g = 1, \tag{13}$$

where x denotes the number of the non-critical generating units, λ_x^g denotes the weight of the non-critical unit, $\frac{\partial S_{ij}}{\partial U_x}$ denotes the partial derivative of the power flow of branches $i-j$ with respect to the voltage variation of the non-critical unit x , and G_x^g is the capacity of each generating unit.

3.2 Coupling relationship between the trading network and provincial transmission lines

The generation and consumption balance relationship of the provincial grid can be expressed as follows:

$$\sum_{m=1}^M \Delta P_m^L + \sum_{n=1}^N \Delta P_n^{RG} + \Delta P^{PG} = 0, \tag{14}$$

where ΔP_m^L , ΔP_n^{RG} , and ΔP^{PG} denote the trading channel transaction volume, critical generating unit output in the province, and non-critical generating unit output in the province, respectively.

Based on the above equation, the sensitivity of the inter-provincial physical link and the critical generating units within the province after considering the non-critical generating units is expressed as follows:

$$G_l^{L,c} = G_l^L - G_x^{PG}, \tag{15}$$

$$G_n^{RG,c} = G_n^{RG} - G_x^{PG}, \tag{16}$$

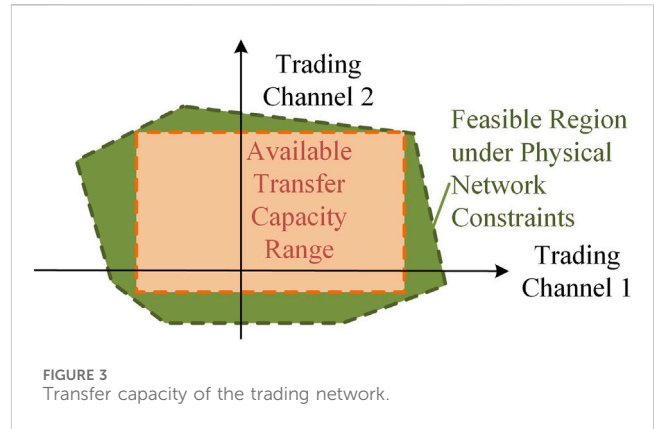
where $G_l^{L,c}$ and $G_n^{RG,c}$ are the sensitivities of the inter-provincial physical contact line and the critical generating units in the province after considering the non-critical generating units, respectively.

The coupling relationship between the trading network and the provincial transmission lines can be expressed as follows:

$$\Delta P_i^{SC} = \sum_{l=1}^L \sum_{m=1}^M G_l^{L,c} \Delta P_m^L + \sum_{n=1}^N G_n^{RG,c} \Delta P_n^{RG}, \tag{17}$$

$$\Delta P_i^{SC, \min} \leq \Delta P_i^{SC} \leq \Delta P_i^{SC, \max}, \tag{18}$$

where ΔP_i^{SC} is the power change of the provincial transmission line, i is the number of provincial transmission lines selected by the



gradient boosting tree prediction model in Section 2, and $\Delta P_i^{SC, \max}$ and $\Delta P_i^{SC, \min}$ denote the upper and lower limits of the provincial transmission line, respectively.

3.3 Calculation of the available transfer capability of the trading channel

China's inter-provincial power spot market uses the ATC model, so power system operators need to calculate the upper and lower limits for each trading channel. Different trading channels have different sensitivities to the intra-provincial transmission lines, and it is necessary to make the calculated channel ATC as close as possible to the maximum transmission limit and appropriately adjust the ATC of certain inter-provincial channels in order to avoid the congestion of intra-provincial lines. As shown in Figure 3, the outer green portion indicates the feasible region under physical network constraints, and the inner orange portion indicates the available transfer capacity range. It is worth noting that each ATC is determined by the upper and lower limits filled in by the scheduler, and therefore, the available transfer capacity range can only be represented as a rectangle in the two-dimensional plane formed by the two trading channels.

In this regard, the objective function shown in Eq. 19 can be designed to normalize the inter-provincial trading channels according to their capacities and then sum up the squares, which can not only guarantee the utilization rate of the trading channels but also make the distribution of the ratio of the ATC of the inter-provincial trading channels to the corresponding maximum limit nearly uniform.

$$\min \sum_{t=1}^T \sum_{m=1}^M \left(\frac{\Delta P_{m,t}^{TL,I} - \Delta P_{m,t}^{TL, \max}}{\Delta P_{m,t}^{TL,I}} \right)^2 + \sum_{t=1}^T \sum_{m=1}^M \left(\frac{\Delta P_{m,t}^{TL,O} - \Delta P_{m,t}^{TL, \min}}{\Delta P_{m,t}^{TL,O}} \right)^2, \tag{19}$$

where $\Delta P_{m,t}^{TL,I}$ and $\Delta P_{m,t}^{TL,O}$ are the upper and lower limits of the inter-provincial trading channel required by the stabilization regulations, respectively.

The constraints on the trading channel power are shown as follows:

$$0 \leq \Delta P_{m,t}^{TL, \max} \leq \Delta P_{m,t}^{TL,I}, \tag{20}$$

$$\Delta P_{m,t}^{TL,O} \leq \Delta P_{m,t}^{TL, \min} \leq 0. \tag{21}$$

TABLE 1 Power network transmission congestion severity categories.

LLF	<50%	50%–60%	60%–70%	>70%
Severity categories	0	1	2	3

The critical generating unit output is also required to meet the following equations:

$$\Delta P_{n,t}^{RG, \min} \leq \Delta P_{s,n,t}^{RG} \leq \Delta P_{n,t}^{RG, \max}, \quad (22)$$

$$\left| P_{n,t}^{RG, \text{plan}} + \Delta P_{s,n,t}^{RG} - P_{n,t-1}^{RG, \text{plan}} - \Delta P_{s,n,t-1}^{RG} \right| \leq \Delta P_{n,t}^{RG, \text{ramp}}, \quad (23)$$

where $\Delta P_{n,t}^{RG, \max}$ and $\Delta P_{n,t}^{RG, \min}$ are the maximum and minimum values of critical generating unit output changes, respectively, $\Delta P_{n,t}^{RG, \text{ramp}}$ is the critical generating unit output climbing capacity, and $P_{n,t}^{RG, \text{plan}}$ is the critical generating unit day-ahead planned output.

4 Example and result

4.1 Description of the example

The study is based on a provincial grid H with the highest load level in central China, focusing on 12 intra-provincial transmission lines, 5 key power plants, and 2 trading corridors. The data time starting point is 1 March 2021, and the end point is 31 December 2022. In the process of resampling, the resampling frequency is set to 5 min/time, considering that the time scale of the forecast is within hours. The data content includes not only electrical variables but also non-electrical variables. It includes the output of the whole network units (thermal power units, hydropower units, and new energy units), the transmission power and transmission limit of critical generating units, the total power generation, the total power receiving, the new energy generation in each region, the critical bus voltages of 500 kV and above, and the six elements of meteorology at each meteorological station in the region.

Power network transmission congestion is defined as the transmission of power by a line in excess of the specified capacity that the line can carry. A measure of power network transmission congestion can be expressed in terms of line loading factor (LLF), which is calculated as follows:

$$LLF = \frac{S_n}{S_{n, \max}}, \quad (24)$$

where S_n is the transmission power of line n , and $S_{n, \max}$ is the transmission power limit of line n set in accordance with the relevant power system security and stability regulations, and the transmission power limit in this paper is given by the dispatching department.

The categorization of congestion events is defined as shown in Table 1, where category 0 denotes no congestion and 1, 2, and 3 denote minor, moderate, and severe congestion, respectively.

The statistics show that more than 150 congestion events occurred in the fourth quarter of 2021, and more than 50% of the critical lines have congestion events. Among them, the HX line had more than 20 power network transmission congestion events in 3 months, as shown in Figure 4. Therefore, the HX line was chosen as the test object for the subsequent prediction part of the calculus.

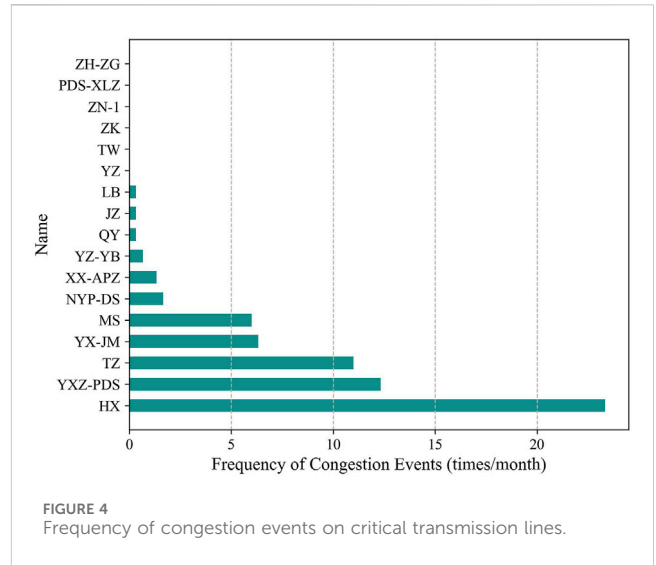


FIGURE 4 Frequency of congestion events on critical transmission lines.

4.2 Example results

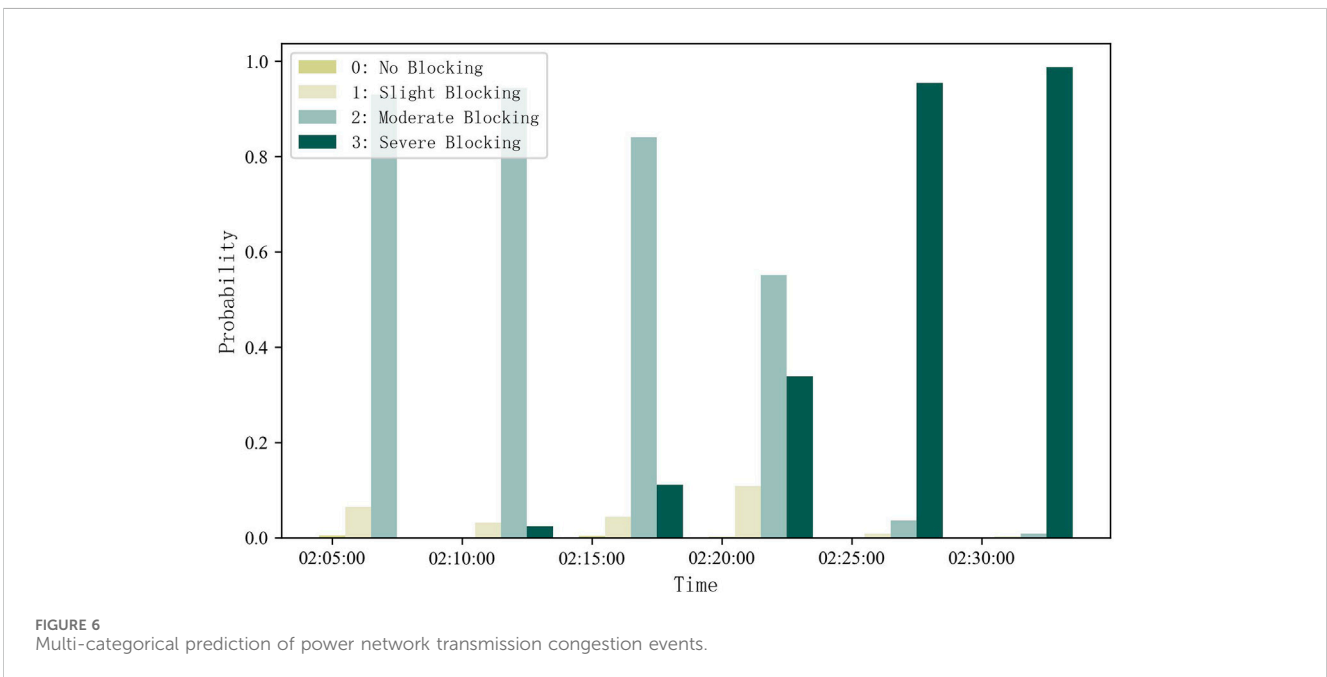
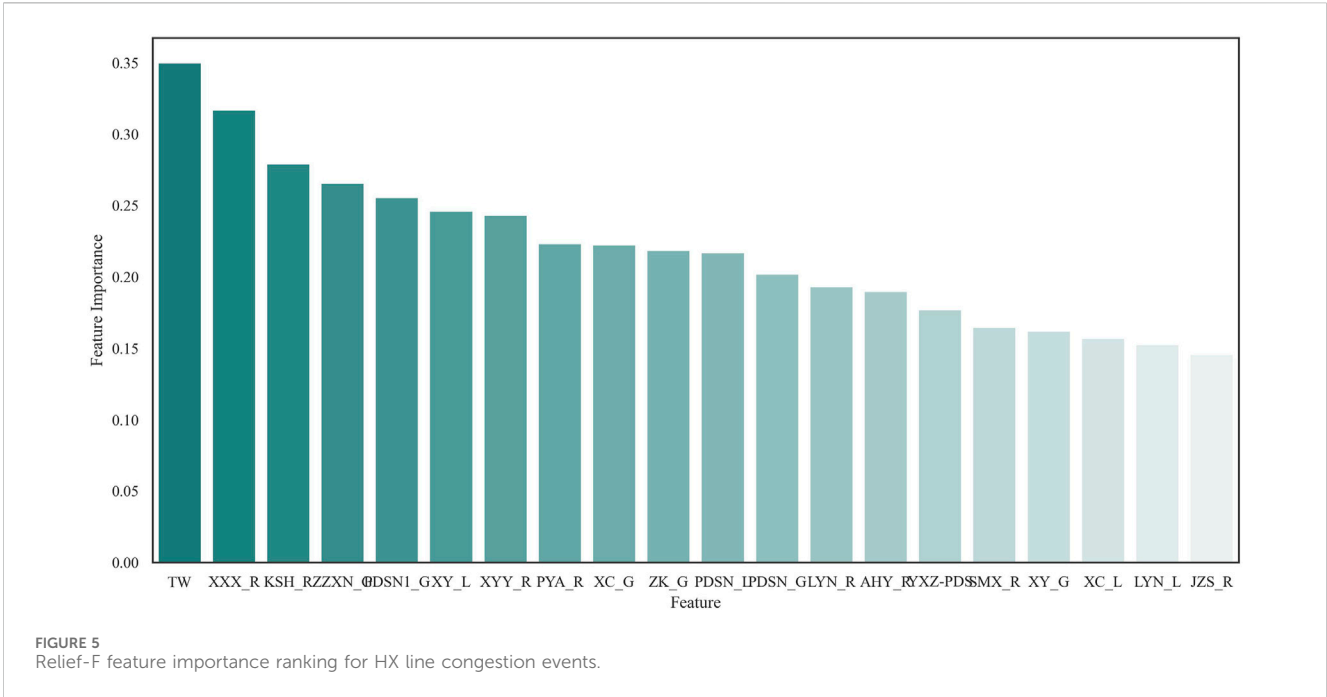
The data of feature variables are preprocessed, interpolated, corrected, and then normalized. The HX line power is selected as the target variable, and feature selection is performed by the Relief-F algorithm.

As shown in Figure 5, the importance ranking of some power system feature variables is demonstrated, with the name of each feature in the horizontal coordinate and the importance score of the corresponding feature in the vertical coordinate. Here, “_R” denotes new energy, “_L” denotes load, and “_G” denotes total regional generation. If a feature is not underlined “_,” it means it is a line power variable. TW, XXX_R, and KSH_R are the most important features, followed by ZZZXN_G and PDSN1_G, and the more the features at the top of the list, the more the impact on the target variable. There are some features with lower importance scores, and these features have less impact on the target variable and can be considered eliminated. In this case, the 100 variables with the highest importance scores are selected as the feature variables to be subsequently used for categorical prediction.

After selecting the feature variables, the HGTTB algorithm is used to classify the power prediction of the line. As shown in Figure 6, the HZ line has a high probability of moderate congestion before 02:20 on 10 November 2021. After 02:20, the power network transmission congestion will be transformed into severe congestion.

Table 2 gives the multi-classification prediction accuracies of the different algorithms for different time scales over a 30-min period, as well as the time taken for training and prediction.

For the power network transmission congestion multi-classification problem, this paper compares the computational efficiency and accuracy of HGTTB with other machine learning algorithms. The compared algorithms include logistic regression (LR), support vector machine (SVM), k neighbors (KN), Gaussian Naïve Bayes (GNB), and decision tree (DT). HGTTB is a robust integration algorithm. This paper also compares different integration ideas: bagging and random forest (RF). The accuracy rate in the table is the ratio of the number of samples correctly classified by the classification model in the test dataset to



the number of all samples in the test dataset. The value outside the parentheses denotes the mean of the accuracy rate of each validation in the cross-validation process, and the brackets denote the variance.

It can be seen that HGTTB has the highest accuracy, and its predictions are the most stable compared to the other algorithms, with an average accuracy of 0.87 and a variance of only 0.04 in 10-fold cross-validation.

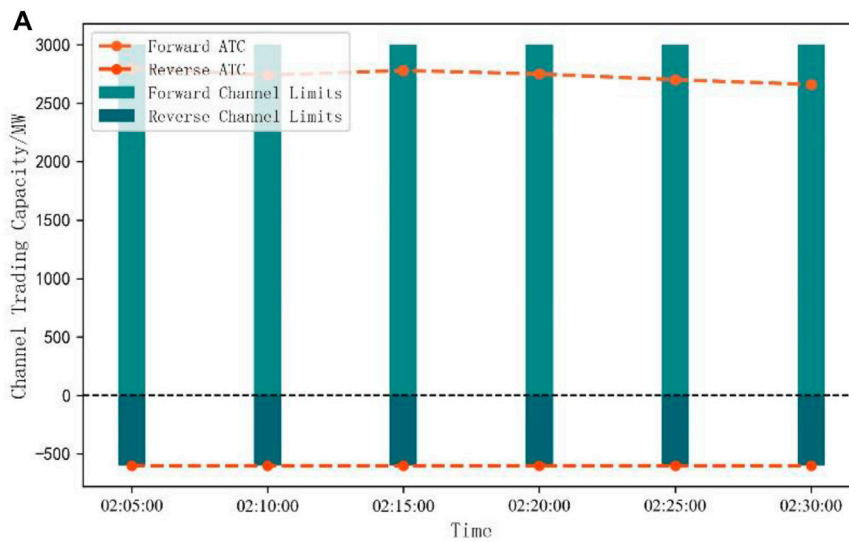
We select the data before 02:00 on 10 November 2021 for simulation and calculate the available transfer capability of the

two trading channels in the next half hour, where channel 1 is an AC line and channel 2 is a DC line. The direction of power sink into province A is specified as the positive direction. Using the HGTTB algorithm, 12 lines with a high probability of severe congestion are selected as constraints, shown in Eq. 18. Equation 19 is used as the optimization objective, and Eq. 18 and Eqs 20–23 are used as constraints. YALMIP/GUROBI is chosen to solve the problem.

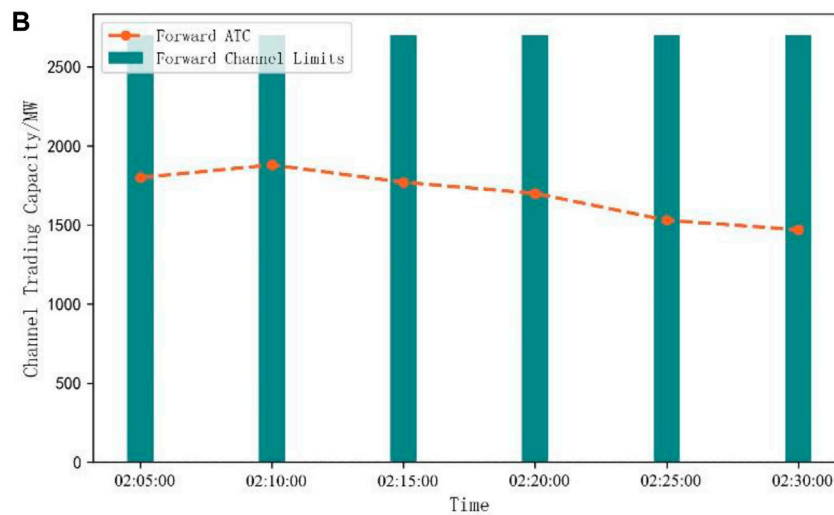
Figure 7 illustrates the available transfer capability of the two trading channels. By analyzing the calculation results of channel 1, we can learn that, regardless of the positive or negative

TABLE 2 Comparison of accuracy and computational efficiency.

Arithmetic	Accuracy	Training time/s	Prediction time/s
LR	0.75 (± 0.25)	36.20	0.10
SVM	0.80 (± 0.12)	98.57	3.26
KN	0.72 (± 0.20)	1.20	2.66
GNB	0.76 (± 0.15)	1.24	0.10
DT	0.83 (± 0.17)	3.65	0.09
Bagging	0.75 (± 0.16)	1.29	9.30
RF	0.84 (± 0.12)	23.49	0.17
GTB	0.86 (± 0.05)	185.67	0.10
HGTB	0.87 (± 0.04)	11.09	0.20



Transaction channel 1



Transaction channel 2

FIGURE 7 Available transfer capability for trading channels. The text "Trading Channel 1" and "Trading Channel 2" at the bottom of the image corresponds to the titles of images (A) and (B), respectively.

direction, even if a large number of transactions are carried out in this trading channel, it does not exacerbate the congestion on the provincial lines. The calculation results of channel 2 show that although there is a large amount of tradable space in this channel, the calculated available transfer capability does not reach its upper limit value after taking into account the congestion of the transmission lines in the province. Specifically, since the sensitivity of trading channel 1 to congestion lines in the positive direction is small, the trades generated by this channel in the positive direction do not adversely affect the provincial lines. Therefore, more flexible trading arrangements can be made on this basis. At the same time, the transactions of transaction channel 1 in the opposite direction can also alleviate congestion on the transmission lines in the province. Therefore, in the event of congestion of the provincial lines, the outward transmission of electricity through trading channel 2 can be used to alleviate the congestion of the provincial lines. Channel 2, on the other hand, has ample tradable space in the forward direction, but the available transfer capability is limited due to the congestion of the transmission lines in the province. It is worth noting that this channel is a DC line and only exists to trade in the positive direction, hence the absence of negative values on the histogram for channel 2. These limitations need to be fully considered before market clearing in order to avoid the overloading of provincial lines during actual implementation. Therefore, in order to ensure the stable operation of the system, it is recommended to refine the analysis of provincial transmission lines prone to congestion in the market operation so as to better reflect the actual situation and formulate a reasonable trading strategy.

5 Conclusion

In this paper, a method for calculating the available transfer capability of trading channels based on power network congestion prediction is proposed. First, this study conducted feature selection based on the Relief-F algorithm to extract effective information for predicting power network transmission congestion from redundant data and features, and the input variables of the prediction model were dimensionally reduced. Next, the severity and probability of power network congestion were calculated using the HGTD prediction model. Then, considering the impact of the trading volume of the trading channel on the congestion line, the sensitivity of the power trading channel as well as the generating units to the transmission line was calculated, and the model of the coupling relationship between the trading network and the transmission line in the province was clarified, while the normalized quadratic objective function was established for taking into account the congestion control and the balance of supply and demand. Finally, a simulation was carried out using actual data from central China, comparing this paper's prediction algorithm with other algorithms to verify the accuracy of the prediction algorithm. The ATC results calculated in the simulation illustrate that the consideration of intra-provincial congestion lines will lead to the decrease in some of the available

transfer capability of the trading corridor, and the analysis of intra-provincial congestion-prone transmission lines should be taken into account in the operation of the market. On the basis of the research in this paper, the uncertainty brought by the new energy output can be further considered to assess the risk of the deviation of the trading volume in the power market.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

CW: funding acquisition, project administration, and writing–review and editing. LJ: conceptualization, methodology, and writing–review and editing. XW: data curation, investigation, and writing–review and editing. YC: formal analysis, methodology, validation, and writing–original draft. YiH: visualization and writing–review and editing. YaH: software and writing–review and editing. SL: methodology and writing–review and editing.

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Conflict of interest

Authors CW, XW, YC, YiH, and YaH were employed by the Central China Branch of the State Grid Corporation of China.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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