Early Warning Model of Power Grid Meteorological Disaster Based on Machine Learning

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Abstract: In order to solve the problem of early warning of meteorological disasters in power grid, this paper uses random forest model modeling to construct an efficient early warning system based on the analysis of the correlation between meteorological factors and power grid faults. In the process of research, this paper collects the power grid operation data and meteorological records of a province for 5 years, and uses a data-driven method to train and optimize the model. The experimental data show that the prediction accuracy of the model is 88.7%, which is significantly better than the traditional method and has a strong application prospect. The research results show that the early warning model of power grid meteorological disasters based on machine learning can effectively improve the early warning ability of the power grid under complex meteorological conditions after being constructed by using the random forest algorithm, and provide stable and strong support for the safe operation of the power grid.

1 INTRODUCTION

Power grid meteorological disaster early warning is one of the research directions to make the stable operation of the power grid, due to the intensification of climate change, so extreme weather is frequent, which is easy to cause threats to the power system. Previously, methods based on statistical analysis were proposed to predict the impact of meteorological disasters on power grids, but these methods were unable to cope with complex meteorological conditions due to the strong dependence and inflexibility of data. Some researchers have emphasized that this can be handled by physical modeling, but it cannot be applied on a large scale because it requires a large number of practical parameters. The reason why this paper uses the random forest model to carry out the research on power grid meteorological disaster early warning is that, as a machine learning algorithm, the random forest algorithm can process high-dimensional data, and in addition, it has a strong generalization ability, which can effectively reduce false alarms and false negatives in power grid meteorological disaster early warning. It is hoped that the research in this paper can effectively improve the disaster prevention ability of the power grid system and ensure the stability and security of power supply.

2 RELATED WORKS

2.1 Machine Learning Theory

Machine learning theory is one of the core theories of the power grid meteorological disaster early warning model in this paper. Machine learning is based on building mathematical models, learning patterns from data (Chen, Huang et al. 2023), and does not rely on explicit programming instructions. Based on the ensemble learning theory, the random forest algorithm can be effectively used in the early warning of meteorological disasters in power grids, and the results can be effectively combined through the training of multiple decision trees, so as to improve its overall prediction performance (Chen and Srivastava, 2023). Random forests can reduce variance and prevent overfitting, which is suitable for fault prediction under complex meteorological conditions of power grids.

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2.2 Theory of Meteorological Disasters in Power Grids

The theory of power grid meteorological disasters is the basic theory for the study of the influence of meteorological conditions on the operation of power grid. The operation of grid equipment can be affected by various meteorological factors, such as wind speed and precipitation, temperature changes, etc. (Hu, Qu et al. 2024). For example, strong winds can cause power lines to break or collapse, and ice, snow and freezing rain can cause transmission lines to freeze and cause equipment failure. The theory of power grid meteorological disasters is based on the analysis of power grid failure modes under different meteorological conditions (Ling, Chen, et al. 2023), which provides guidance for the input feature selection and data preparation of machine learning models.

2.3 Data-Driven Modeling Theory

Data-driven modeling theory emphasizes that big data and advanced analytics techniques can be used to perform model construction and provide decision support. In the early warning of power grid meteorological disasters, data-driven modeling relies on historical meteorological data and power grid fault records, and based on the analysis of these data, a correlation model between meteorological factors and power grid faults can be established. This approach does not rely too heavily on traditional physical modeling, but uses a combination of data pattern discovery and machine learning algorithms (Liu and Chen, 2023) to improve the accuracy and timeliness of its early warnings. For the early warning of power grid meteorological disasters, the Random Forest algorithm is used to construct the model. The model is based on the integration of multiple decision trees to effectively predict the risk of grid failure under different meteorological conditions (McLoughlin, Gifkins et al. 2023). The power grid system is affected by a variety of meteorological factors, such as strong winds and heavy rains, drastic temperature changes, etc., which may cause potential risks to power grid lines, substations, and power equipment. Therefore, the early warning accuracy of the model should be improved based on reasonable parameter setting and optimization methods (Pandey, and Basnet, 2023).

3 METHODS

3.1 Design of Meteorological Disaster Early Warning Model

In the early warning of power grid meteorological disasters, the setting of the number of decision trees directly affects the robustness and performance of the model. The random forest model is based on the integration of multiple decision trees to reduce the risk of overfitting a single tree. If the number of decision trees is too small, the model may not be able to fully capture its complex meteorological characteristics, which may cause false alarms or false negatives. If the number of trees is too large, the computation cost will increase, which in turn will affect the real-time performance. For this, see Eq. (1).

$$y = \frac{1}{n}\sum_{i=1}^{n} T_i\,(X) \tag{1}$$

In equation (1), $y$is represents the final prediction value of the power grid meteorological disaster warning, which$n$is refers to the number of decision trees. $T_i(X)$ is the prediction made by the ith decision tree on various input characteristics X, including wind speed or precipitation, temperature, etc. By increasing the number of decision trees, the model can effectively capture the relationship between meteorological variables and power grid fault risk, and improve the accuracy of early warning.

The maximum depth of the tree controls the complexity of each decision tree. In the early warning of power grid meteorological disasters, the shallow tree depth may lead to the underfitting of the model and the inability to capture the complex meteorological disaster model. Too deep tree depth may lead to overfitting of the model, which will be too adaptable to historical meteorological data, and perform poorly in the face of new meteorological conditions (Wang, Wen, et al. 2023). Therefore, when constructing the power grid meteorological disaster early warning model, the depth of the tree should be reasonably set according to the complexity of the data. For this, see Eq. (2).

$$T_i(X) = \sum_{j=1}^{m} \omega_j\, h_j(X) \tag{2}$$

In this formula, $T_i(X)$ is the first tree to predict$i$is the power grid fault under specific meteorological conditions, and $h_j(X)$ is the division planning of the first node in$i$is the tree. Itm is the depth of the tree. After setting the depth of the tree reasonably, the model can better balance the different impacts of complex meteorological conditions on power grid equipment.

In the power grid meteorological disaster early warning model, only a part of the meteorological features are selected from the meteorological features each time the decision tree nodes are divided to perform the division. For example, a random selection of meteorological variables such as wind speed and temperature, humidity, and precipitation prevents a specific meteorological variable, such as wind speed, from dominating model decisions. This random selection will enhance the diversity of the model and thus avoid early warning errors due to fluctuations in a variable. In this regard, Eq. (3) can be seen.

$$G(X) = \sum_{i=1}^{k} \omega_i f_i(X) \tag{3}$$

In Eq. (3), $G(X)$ is the final predicted value, the $f_i(X)$ is contribution of each selected meteorological feature to its model decision. In the early warning of power grid meteorological disasters, the random combination of factors such as strong winds, heavy rains, and drastic temperature changes, their contribution to the final prediction of power grid faults by the model needs to be stratified, which can ensure that the stochastic algorithm model can make accurate early warnings for a variety of meteorological disasters.

3.2 Training and optimization of Power Meteorological Disaster Early Warning Model

During the model training process, the random forest uses bootstrap sampling to generate multiple sub-datasets. Specifically, each decision tree performs training on a different subset. The advantage is that the generalization ability of the model can be improved, especially in the power grid meteorological disasters, where the complexity of meteorological factors is high, and each decision tree needs to be trained based on a different subset of data, under which the potential risks to the power grid operation under different meteorological conditions can be better captured (Zhang, and Song, 2023). After the training is completed, the model can effectively predict the impact of future meteorological disasters on the power grid, such as the probability of power grid failure under extreme weather in a certain area.

In the power grid meteorological disaster early warning model, the hyperparameters of the model need to be tuned, which is also part of the optimization process. For example, the number and maximum depth of decision trees need to be tuned. The tuning process can be based on grid search or random search, and the optimal combination of parameters can be found based on the minimization of the loss function on the validation set. See Eq. (4) for details.

$$\theta^* = argmin_{\theta} L_{\text{val}}(\theta) \quad (\tag{4}$$

In this equation, (θ^*) is the optimal combination of parameters is represented, $L_{\text{val}}(\theta)$ is refers to the loss function on its validation set. Through the method of tuning these parameters, the efficiency and accuracy of the model in the early warning of power grid meteorological disasters will be ensured, especially in the face of extreme weather conditions. To effectively prevent the model from overfitting on specific meteorological data, it would be very effective to introduce regularization. In the case of power grid meteorological disasters, some extreme meteorological conditions may occur less frequently in historical data, which can easily make the model have problems or perform poorly in the face of these conditions. Based on regularization, it will be possible to effectively constrain the complexity of the model and thus avoid overfitting. For this, see Eq. (5).

$$L_{reg} = L(y, \hat{y}) + \lambda \sum_{j=1}^{M} w_j^2 \tag{5}$$

In equation (5), $L_{\text{reg}}$is represents the loss function after adding regularization, but $\lambda$is the regularization intensity, which can effectively improve the generalization ability of the model in the early warning of power grid meteorological disasters, especially in the face of rare extreme weather.

In order to further improve the robustness of its power grid meteorological disaster early warning model, random forests can be integrated with other model executions, such as gradient boosting decision trees. This ensemble strategy can improve the prediction accuracy of the model under complex meteorological conditions based on the advantages of integrating multiple algorithms. See Eq. (6) for this.

$$y = \alpha \times y_{RF} + (1 - \alpha) \times y_{GBoost} \tag{6}$$

In Eq. (6), $y_{RF}$is the random forest prediction value, $y_{GBoost}$is the prediction value of the gradient boosting tree, andα is the weight parameter. Based on the ensemble learning method, the prediction ability of the power grid meteorological disaster early warning model under a variety of meteorological disasters will be effectively improved. The application of the power grid meteorological disaster early warning model based on random forest can effectively capture the complex relationship between meteorological factors and power grid faults. The model uses reasonable parameter setting and optimization methods to ensure the accuracy and robustness of the early warning system, and provides the best guarantee for the safe operation of the power grid system.

4 RESULTS AND DISCUSSION

4.1 Case introduction of Meteorological Disaster Early Warning Model

The operation data and meteorological disaster records of a provincial power grid in the past five years are a case study in this paper. The region's power grid covers a variety of terrain and climate zones, and the meteorological conditions are complex and changeable, often affected by various extreme weather such as storms, thunder, lightning, and freezing. These meteorological disasters frequently cause damage to power equipment, interruption of transmission lines, and disruption of power supply. Therefore, the provincial power grid company hopes to identify some potential risks in advance based on the meteorological disaster early warning model constructed this time, and then improve the disaster prevention and resilience of the provincial power grid, and then ensure the safety and stability of its power supply, the warning range is shown in Figure 1.

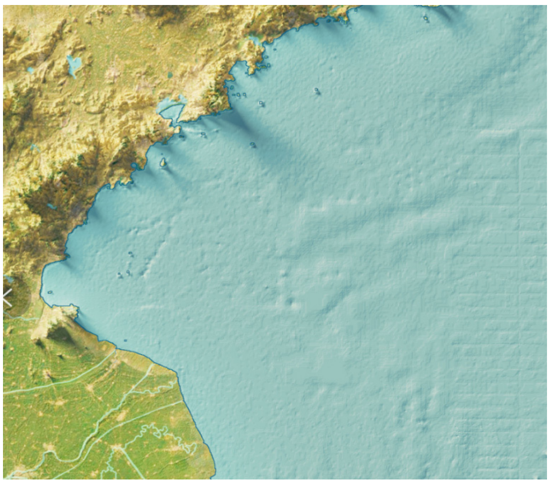

Figure 1 Scope of meteorological disaster warning for power grid.

Undoubtedly, the main focus is on predicting the power grid of coastal cities in areas with frequent meteorological occurrences, and tracking and analyzing meteorological disasters in the region.

4.2 The Overall Effectiveness of Disaster Warning

In the research and development process of the power grid meteorological disaster early warning model, in order to verify the effectiveness and stability of the model, it is necessary to carry out multiple rounds of simulation experiments. The purpose of the simulation is to test the iterative performance of the model in a simulated environment, evaluate the predictive ability of the model based on a large number of historical meteorological data and grid fault data (Zhang, Xie et al. 2023), and observe its performance under different parameter configurations. During the simulation process, the model gradually improves its prediction accuracy based on continuous optimization, and finally lays the foundation for the next practical application verification. Table I shows the iterative results of the model during the simulation process, including the training set, the validation set, the accuracy of the test set, and the time required for each iteration. After 60 iterations, it can be seen that the prediction performance of the model has gradually improved and tends to be stable. The simulation test iteration was 60 times, 600 verifications, 40 days of testing, 200 people participated, referring to 5 years of meteorological data, 5 types of meteorological disasters.

Table 1: Results of the simulation of this model

The number of iterations	Training set accuracy	Validation set accuracy	Test set accuracy	Time per iteration (seconds)
Wind disasters.	0.754	0.733	0.7225	5.2
Tsunami disaster.	0.758	0.736	0.7250	5.4
Earthquake disasters.	0.762	0.739	0.7275	5.6
Random disasters.	0.766	0.742	0.7300	5.8
Sudden disasters.	0.770	0.745	0.7325	6.0
...	...	...	...	...
Overall disaster situation.	0.905	0.887	0.8730	9.2

Based on the simulation process, it can be seen: Its accuracy is significantly improved. Under the continuous iteration of the model, its accuracy on the training set, verification set and test set is gradually improved, which shows that the power grid meteorological disaster early warning model can effectively capture the complex relationship between meteorological conditions and power grid faults through the random forest algorithm, one of the machine learning methods,The degree of meteorological disaster prediction within the green range is shown in Figure 2.

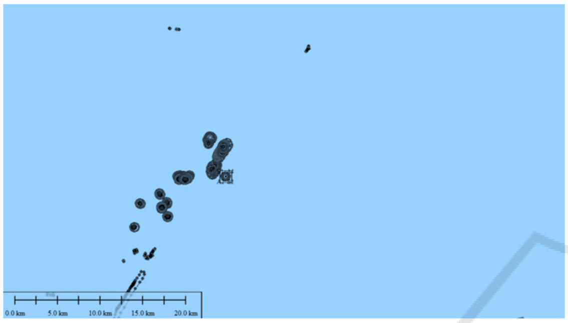

Figure 2: Predicted degree of meteorological disasters in the power grid.

As analyzed in Figure 2, it can be seen that the prediction level of power grid component disasters is relatively high, but its prediction range needs to be further determined. The specific results are shown in Figure 3.

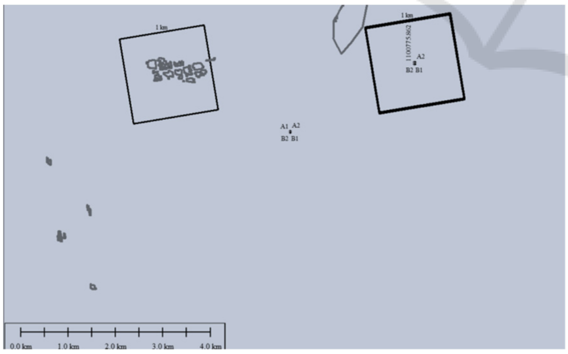

Figure 3: The predicted range of meteorological disasters.

The measurement range of meteorological disaster prediction was found to be relatively good.

4.3 Prediction and Effectiveness Assessment of Meteorological Disasters in the Power Grid

Its stability is significantly enhanced, which indicates that the performance indicators of the model tend to be stable during the simulation process. In other words, it is proved that the model has a strong generalization ability after a period of optimization. Moreover, the time consumption is moderate, and the time of each iteration increases under the increasing complexity of the model, but it is still within the acceptable range, so as to meet the real-time requirements of power grid early warning, as shown in Table 2.

Table 2: Grid operation data and meteorological disaster record data of the province in the past five years.

year	Number of meteorological disasters	The number of power equipment failures	The number of transmission line interruptions	Hours of power supply interruptions
2018	15	10	8	12
2019	20	14	10	18
2020	18	13	9	16
2021	22	16	11	20
2022	19	12	10	15

The table shows the number of meteorological disasters in the province's power grid over the past five years, the corresponding power equipment failures, transmission line interruptions, and the number of hours of power supply interruptions. It can be seen that the annual meteorological disasters have different degrees of impact on the operation of the power grid in the province, which provides rich historical data for the application of the model, The results are shown in Table 3.

Table 3: The failure risk identified by the model and the actual situation.

Meteorological type	Wind speed (m/s)	Precipitation (mm)	Temperature (°C)	Risks of failures identified (number of times)	The actual number of failures that occurred
Storm	25	150	18	17	16
Thunderstorm	18	55	23	12	12
Freezing rain	7	30	-3	22	20
High temperature	0	0	36	9	8
Heavy rain	10	90	21	10	9

Table 3 shows the prediction results given by the grid meteorological disaster early warning model in identifying the risk of grid failure under different meteorological conditions, and comparing it with the actual fault situation. The table shows that the model has a high degree of accuracy under extreme meteorological conditions, especially in storms, freezing rain and other weather, and its prediction results are quite close to the actual failure situation.

4.4 Effect of Meteorological Disaster Early Warning Model

The early warning effect is remarkable. This can be seen in combination with the data. Specifically, the accuracy of the model provides a very effective decision-making basis for power grid management, which can accurately and advance the risk caused by extreme weather, which is conducive to the provincial power grid to take early protective measures and reduce power interruptions and equipment damage, The overall change result is shown in Figure 4.

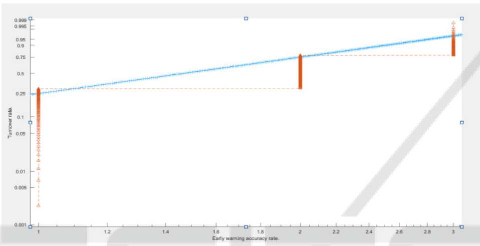

Figure 4: Overall prediction effect of meteorological disasters.

This can be seen through a comprehensive analysis of the key data from Table 2 and Table 3. Storms and freezing rain are the meteorological conditions that have the most significant impact on the grid, and the gap between the model prediction and the actual failure is very small. For example, in storm conditions, there are 17 predicted failures and 16 actual occurrences. Freezing rain was predicted 22 times and actually occurred 20 times, indicating that the model is effective in dealing with the risk of extreme weather. The model still shows high accuracy under relatively low-risk weather conditions such as thunderstorms and high temperatures. There were 12 predicted failures in thunderstorms, which was consistent with the actual failures, and in hot weather, there were 9 predictions, but the actual number was 8.

5 CONCLUSIONS

This paper constructs a random forest-based power grid meteorological disaster early warning model to prove the effectiveness and applicability of the model under complex meteorological conditions. Based on the comprehensive analysis of the correlation between meteorological factors and power grid faults, the model can accurately identify potential power grid risks and warn in advance of the possible impact of various extreme meteorological events. Compared with the traditional method, the proposed model has stronger prediction ability, which can reduce false positives and false negatives, and provide scientific and effective decision support for power grid managers. At the same time, the application of this model can effectively improve the disaster prevention and resilience of the power grid, and provide a strong guarantee for the safe operation of the power system. To a certain extent, the research in this paper has been very complete, but its data content still has certain limitations and needs to be expanded in the future.

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