Study on the BL Early Warning Model of Transmission Line Tower Based on KNN-SVM Algorithm

Huawei Hong¹, Kaibin Wu²,3,,* and Yunfeng Zhang⁴

¹Marketing Department, State Grid Fujian Electric Power Co., Ltd., Fuzhou, Fujian, China, 350003
²State Grid Electric Power Research Institute, Wuhan Efficiency Evaluation Co., Ltd., Wuhan, Hubei, China, 430074
³NARI Group Co., Ltd. (State Grid Electric Power Research Institute Co., Ltd.), Nanjing, Jiangsu, China, 210003
⁴Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science & Technology, Nanjing, China, 210044

*Corresponding author e-mail: 002336@nuist.edu.cn

Abstract. With the expansion of China's power grid construction scale, the transmission line span are gradually improved, which also increases the risk of BL stroke on the transmission line. However, the traditional passive BL protection has many problems, such as weak pertinence and high investment cost, which can not meet the needs of social development. KNN can well describe the similarity measure between the two, which can effectively reduce the training samples. SVM can find the best compromise between model complexity and learning ability in small samples, which is a good sample training method. Through KNN - in-depth learning of the historical data of BL activities accumulated in the power grid, a supervised BL early warning model (hereinafter referred to as EWM) of transmission line can be trained. At the same time, the BL strike of transmission line tower (hereinafter referred to as TLT) has complex meteorological conditions, which requires comprehensive confirmation of various monitoring point parameters. Therefore, it is of great significance to study the BL EWM of TLT based on KNN-SVM algorithm. Firstly, this paper analyzes the KNN-SVM algorithm. Then, this paper establishes an EWM. Finally, this paper is verified.

Keywords: KNN, SVM, Transmission Line Tower, BL EWM

1. Introduction
The scale of power construction in China is further increased. The frequency of power grid faults or accidents caused by meteorological factors increases gradually, among which the tripping accidents caused by lightning (hereinafter referred to as BL) strike occur frequently [1]. Once the transmission line is struck BL, the insulator flashover accident of supporting conductor and preventing...
current from returning to ground will often be caused. The disasters caused BL strike account for about 60% ~ 80% of all natural disasters of transmission line [2]. Therefore, we must carry out effective monitoring and early warning of BL strikes on transmission lines, which can effectively prevent the damage caused by BL activities to transmission lines [3-6]. At present, the BL monitoring of transmission line mainly depends on the networking of BL location base stations evenly distributed all over the country, which can realize the BL location monitoring of transmission line [7]. Therefore, we must use advanced intelligent technology to warn the BL stroke of transmission line, which can reduce the probability of line fault. Therefore, the intelligent prediction of transmission line BL stroke has basic conditions, which is also an important problem to be solved by China's power grid [8].

2. BL fault mechanism of transmission line

2.1. Direct BL over tower voltage

Direct BL strike over the tower is mainly on the top of the tower, which is mainly due to the highest relative position of the top of the tower. Moreover, the tower has good contact with the earth, which is the best excitation point for BL [9]. Therefore, the tower is easy to generate head-on leader on the top structure to intercept the downward leader of thunderstorm, which will lead to counter flashover trip. Take negative thunderstorm discharge as an example. Before the thunder cloud discharges, the potential on the conductor, BL conductor and tower is zero. Therefore, the potential difference between the two ends of the line insulator string is also zero. When the negative BL strikes the top of the tower, part of the BL current propagates to the earth along the tower, and the other part propagates to the adjacent tower along the BL wires on both sides of the tower top [10]. Due to the existence of tower wave impedance and grounding resistance, the BL current propagating along the earth will produce high potential to the ground at the top of the tower and the cross arm, which will cause mutual inductance and capacitance between the conductor and the BL conductor. The BL current propagating along the BL conductor will induce a combined current on the conductor, which will lead to the increase of the potential of the conductor. The movement of the upward leader to the thunder cloud along the main discharge channel will cause the change of space magnetic field, which will induce positive Overvoltage on the conductor. Therefore, the potential of conductor, BL conductor and tower has changed. When this potential difference exceeds the impulse discharge voltage on the insulator string, the line insulation will be broken down, and the flashover trip will occur immediately [11].

2.2. Induced BL over tower voltage

According to the survey data, about 75% of the BL accidents of low-voltage distribution lines are caused by induced BL overvoltage, and about 25% are caused by direct BL overvoltage [12]. Therefore, induced BL overvoltage has become the main cause of BL failure of low-voltage distribution lines. Induced BL overvoltage consists of two components: the electromagnetic component caused by the charge in the BL pilot channel and the electromagnetic component caused by the BL current magnetic field. Take negative thunderstorm discharge as an example. At the initial stage of the negative thunderstorm discharging to the earth, the transmission conductor is in the electric field of the thunderstorm and the pilot channel. Under the action of electrostatic induction, the positive charges at both ends of the conductor are attracted to a section of conductor near the pilot channel by the electric field strength tile along the line, which will accumulate into positive bound charges. The negative charge on the transmission line flows into the earth through the grounding device on the line because of the repulsion. The charge on the wire moves slowly, which fails to form a significant current. When the negative thunderstorm discharges to the earth near the transmission line, the negative charge in the pilot channel is neutralized rapidly. Therefore, the electric field intensity generated by the channel decreases rapidly, which will release the positive bound charge accumulated on the transmission line immediately.
3. Research on related algorithms

3.1. KNN algorithms
KNN is based on the input and output of known training data sets. When inputting test data, we can compare the input features of the test data with the corresponding input features in the training set, which can find k data with the smallest Euclidean distance or Manhattan distance between the training set and the test data. In KNN, we often use Euclidean distance or Manhattan distance to calculate the distance between two samples, which can be used as a measure of similarity between them. The Euclidean distance is shown in Formula 1.

\[ d(x, y) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2} \]  

(1)

Manhattan distance is shown in Formula 2.

\[ d(x, y) = \sqrt{\sum_{k=1}^{n} |x_k - y_k|} \]  

(2)

3.2. SVM algorithms
SVM has some limitations in large sample classification and regression, but it shows many unique advantages in small sample problem. SVM can find the best compromise between the complexity of the model and learning ability according to the limited sample information, which can obtain the best generalization ability. Therefore, SVM has the remarkable characteristics of structural risk minimization and strong generalization ability. The regression function is shown in Formula 3.

\[ f(x) = (w, \varphi(x)) + b \]  

(3)

The structural risk formula is shown in formula 4.

\[ R_{\text{reg}} = \lambda \|w\|^2 + R_{\text{emp}}[f] = \sum_{i=1}^{S} C(e_i) + \lambda \|w\|^2 \]  

(4)

Among them, \( \|w\|^2 \) is the confidence risk, \( R_{\text{emp}}[f] \) is the empirical risk, \( \lambda \) is the constant, \( C(e_i) \) is the empirical loss of the model, \( e_i \) is the error value of the sample.

We can get the Figure 5.

\[ \max u = -\frac{1}{2} \sum_{i,j=1}^{S} (\alpha_i - \alpha_i^*) (\alpha_j^* - \alpha_j) (\phi(x_i), \phi(x_j)) + \sum_{i=1}^{S} \alpha_i^* (Y_i + \varepsilon) - \sum_{i=1}^{S} \alpha_i (Y_i + \varepsilon) \]

\[ \sum_{i=1}^{S} \alpha_i^* = \sum_{i=1}^{S} \alpha_i \]

\( s.t., 0 \leq \alpha_i \leq C \)
\( 0 \leq \alpha_i^* \leq C \)  

(5)

The optimal weight vector and optimal offset are shown in formula 6:
Finally, we can get the formula 7.

\[ f(x) = \sum_{i=1}^{S} (\alpha_i - \alpha_i^*)(\phi(x_i), \phi(x)) + b \]

3.3. Data normalization processing

Before the application of CNN model, we need to normalize the sample data, which can avoid many problems caused by the influence of dimension and unit. In this paper, dispersion standardization is used for data normalization, as shown in formula 8.

\[ y_i = \frac{x_i - \min_{1 \leq i \leq k} \{x_i\}}{\max_{1 \leq i \leq k} \{x_i\} - \min_{1 \leq i \leq k} \{x_i\}} \]

4. Modeling of BL early warning based on KNN-SVM algorithm

Based on the power Internet of things, we can obtain a variety of parameters of the transmission line corridor, including micro meteorology, micro terrain and TLT ontology information. Through KNN-SVM, we can learn and train the training samples, which can obtain a supervised BL disaster EWM. The transmission line BL early warning system based on KNN-SVM algorithm is shown in Figure 1.

5. Analysis of simulation results

In this paper, 500 test data are simulated, and the experimental results are shown in Table 1.
Table 1. Analysis of simulation results

| Algorithm | No. of training samples | No. of test samples | Test accuracy | Training time (s) |
|-----------|-------------------------|---------------------|---------------|------------------|
| SVM       | 1500                    | 500                 | 89.25%        | 4.1254           |
| KNN-SVM   | 1500                    | 500                 | 93.05%        | 0.3518           |

6. Conclusion
Through the power grid monitoring system, we can obtain real-time data, which can improve the stability and reliability of data processing. Through KNN-SVM algorithm, we can better train the data set model, which will improve the accuracy of fault prediction. By establishing a meteorological disaster EWM suitable for complex meteorological conditions, we can more scientifically early warning the BL strike of TLTs.

References
[1] Tong ruining, Nie Haifu, Li Peng. TLT BL EWM based on KNN-SVM algorithm [J]. Yunnan electric power technology, 2020, 48 (02): 8-11 + 16.
[2] Zhang Linshan. Special column of "Research on power application of Internet of things technology" [J]. Yunnan power technology, 2020, 48 (02): 1.
[3] Zhao Jiankun. Development and application of power meteorological disaster monitoring and early warning system [J]. Inner Mongolia power technology, 2020, 38 (04): 9-12.
[4] Zhou Xiangxian, Zhang Yi. Study on BL risk early warning method of Zhejiang Power Grid [J]. Zhejiang electric power, 2021, 40 (04): 89-93.
[5] Zhou Xiangxian, Liu Li. Overview of natural disaster characteristics, trends and prediction technology of Zhejiang Power Grid [J]. Zhejiang electric power, 2021, 40 (05): 20-29.
[6] Gao Honghui, Lv Liang, Liu Zhiyong. Design of transmission line fault EWM based on big data [J]. China Southern Power Grid technology, 2017, 11 (04): 30-37.
[7] Zheng Shiling, Liu Jing, Guo Juntian. BL early warning system of Anhui Power Grid [J]. Rural electrification, 2017 (08): 37-40.
[8] Gu Chengyu. Research and application of meteorological environment risk early warning for 500kV transmission line of East China Power Grid [J]. East China power, 2010, 38 (08): 1220-1225.
[9] Xiong Yu, Gou Anning, Ruan Ling. Application of BL proximity prediction method in BL early warning of transmission line [J]. Rainstorm disaster, 2015, 34 (03): 275-280.
[10] Wang Xudong. Research and implementation of transmission line disaster prediction and early warning system based on integrated intelligent auxiliary support [J]. Journal of electric power, 2013, 28 (05): 425-428 + 432.
[11] Tang Ju. Basic research on preventing power grid outage caused by power transmission and transformation equipment failure [J]. China basic science, 2013, 15 (06): 3-10 + 62 + 2.
[12] Yang Xiaoyu, Zhang Sheng. Meteorological disaster risk intelligent analysis and early warning system [J]. Shandong electric power technology, 2016, 43 (07): 21-24.