Evolution characteristics of the spatiotemporal pattern of alarm of electric power transmission line monitoring system

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ABSTRACT

Revealing the dynamic characteristics of the temporal and spatial evolution of false alarms is of great significance for decision support to reduce the high false alarm rate of the transmission line monitoring systems. Therefore, based on the alarm data extracted from the transmission line monitoring system, various methods such as coefficient of variation, Kernel density analysis, and spatial correlation were utilized in this study. The evolution characteristics of the spatiotemporal pattern of alarm at the city and district levels were analyzed. The results show that: (1) Through the coefficient of variation (CV), we found that the coefficient of variation (CV) of alarm showed an upward trend at the city levels. (2) Through the kernel density analysis, the median of the false alarm increased. The largest rate of false alarms is minhang, baoshan, and fengxian. The maximum rate of the false alarm changed from baoshan to minhang. (3) Through the rank-scale rule, it is found that the numbers of districts in HH and LL regions are larger than the other two regions, and they remain unchanged. The districts in HH are mainly concentrated in the western region and the districts in LL are mainly concentrated in the middle region.

Keywords: Electric power transmission line, monitoring system, alarm warning, spatiotemporal dynamics.

1. INTRODUCTION

The Power tube pole is a kind of important facility for carrying the power supply. Its fault-free operation is of great significance to ensure industrial development, resident life along the line, traffic safety, etc [1,2].

Through the operation practice, the transmission line monitoring system can better identify all kinds of monitoring images. However, affected by the installation of sensors, this way can result in lower monitoring accuracy, higher false alarm rate, and high failure rate of equipment. Numerous studies have analyzed and explored these problems[3-8]. However, the literature relevant to the evolution characteristics of the spatiotemporal pattern of alarm of electric power transmission line monitoring systems is very scarce. The purpose of this study is to find the spatio-temporal dynamics and evolution patterns of false alarms of transmission line monitoring systems at the city and district levels. The research results of this paper will enrich the current academic research on false alarms of transmission line monitoring systems to a certain extent.

2. DATA DESCRIPTION

The data is collected from a branch office of State Grid Electric Power Company. According to the alarm data from June 2023 to November 2023, the number of intelligent monitoring alarms received every day is about 30,000. It is equivalent to processing more than 1000 pieces of data per hour and dealing with more than 10 channel alarms every minute. It is obviously beyond the limits of conventional manpower can be dealt with.

3. METHODOLOGY

3.1 Coefficient of variation

The coefficient of variation is commonly used to evaluate the degree of dispersion of each observation. This coefficient, CV, means the ratio of standard deviation to average. Based on the values of different districts in the alarm warning data,

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the coefficient of variation can measure and reveal the relative differences in the alarm warning at the district levels. The calculation equation is as follows:

$$CV = \frac{\alpha}{\mu} \tag{1}$$

where, α is the standard deviation of observations, and μ is the average value of the observations. The larger the value of CV is, the greater the relative difference in regional alarm warning will be.

3.2 Kernel density analysis

The principle of Kernel estimation is to take point p as the center of the circle and threshold h as the radius.

$$p(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left[\frac{d(x,x_i)}{h}\right] \tag{2}$$

In the formula, n represents the number of administrative units included in the distance scale; k represents the kernel density function; h represents the distance threshold, which is the scale of the kernel density estimation method; $d(x, x_i)$ represents the Euclidean distance between two points[9].

3.3 Spatial Correlation

The spatial autocorrelation of Moran's I can be expressed as:

$$I = \frac{n\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i \sum_j w_{ij} \sum_i (x_i - \bar{x})^2} \tag{3}$$

Where, n represents number of district, x_i, x_j represents the number of alarm warning in district i, j. $\bar{x}$ represents the average number of alarms in each month. w_{ij} is the spatial weight between the district i and j.

When I > 0, district false alarms in the electric power transmission line monitoring system are spatially positively correlated, the occurrence of false alarms tends to be spatially clustered, and there is a certain spatial correlation effect of false alarms in different districts. when I < 0, the spatial correlation of district false alarms is negative, the occurrence of false alarms tends to be spatially discrete, and the false alarms in different districts have greater heterogeneity. when I = 0, the district false alarms are randomly distributed.

4. EMPIRICAL RESULTS

4.1 Spatio-temporal evolution characteristics of alarm warning at different scales

Figure 1 shows that during the study period from June 2023 to November 2023, the coefficient of variation (CV) of the false alarm in the electric power transmission line monitoring system arose at the city level. The coefficient of variation (CV) of the alarm shows a different trend and maintains stability at the district level. These findings indicate the difference in false alarms at the city level is greater than at the district level. The change trend increased from 2.91 to 3.38. Specifically, in the 27th five days, the CV is 3.35, which is the maximum value at the two scales. The average change every five days in the CV of the false alarm in the electric power transmission line monitoring system at the city level is 1.34%.

4.2 Spatio structure evolution characteristics of alarm warning at different scales

Figure 2 shows that the median of the kernel density distribution of the false alarm in the electric power transmission line monitoring system increased during the study period from June 2023 to November 2023.

To explore the spatial structure of false alarms in the electric power transmission line monitoring system at the district level, the occurrence per square kilometer is utilized.

$$rate_i = \frac{m_i}{R_i} \tag{4}$$

Where m_i is the number of false alarm at ith district, R_i is the area of the ith district.

The districts with high rates indicate a high degree of concentration, while areas with low rates indicate a low degree of concentration.

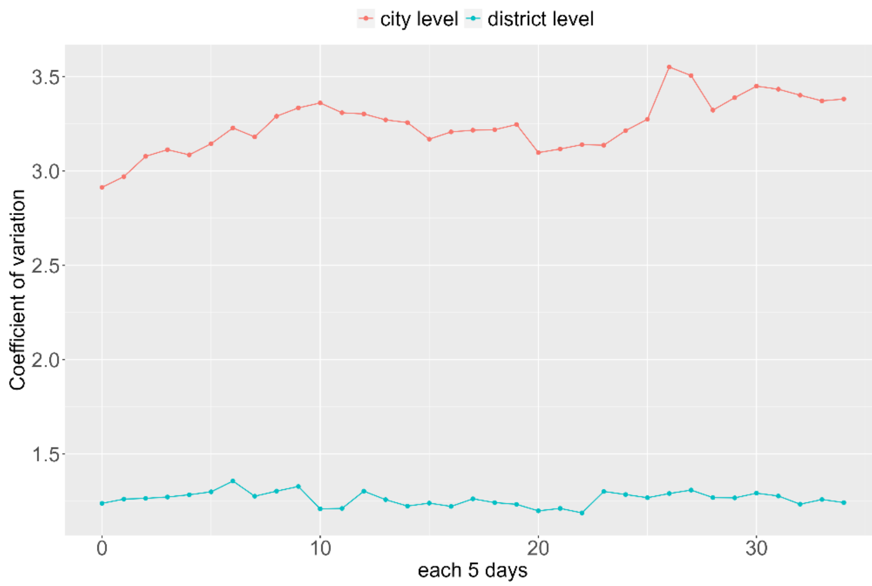

Figure 1. Dynamic evolution of the coefficient of variation of alarm's CV at different scales every five days

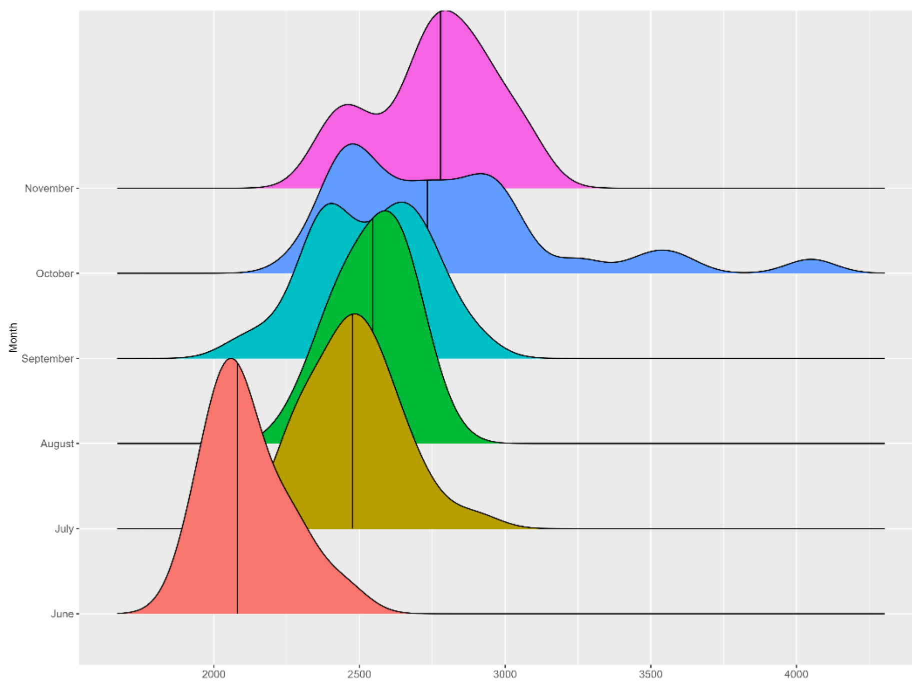

Figure 2. Kernel density estimation of the false alarm from June 2023 to November 2023

Figure 3 shows that the largest rate of false alarms is minhang, baoshan, and fengxian. The maximum rate of the false alarm in the electric power transmission line monitoring system changed from baoshan to minhang from June 2023 to November 2023.

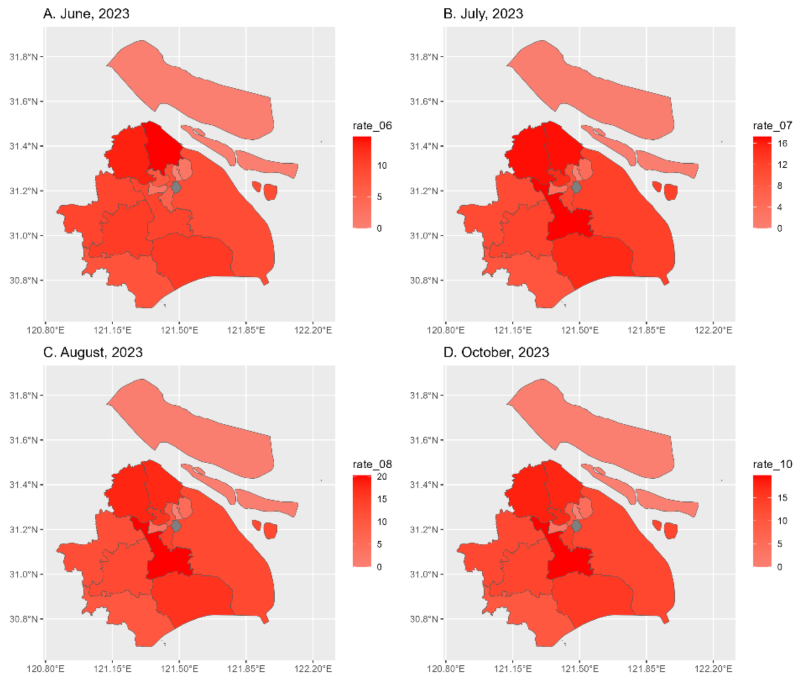

Figure 3. Spatio distribution of the false alarm from June 2023 to November 2023 at district level

4.3 Spatio autocorrelation characteristics of alarm warning at different scales

The Moran scatter diagram describes the correlation between variables and their spatial lag vectors, reflects the degree of correlation and difference between observations of spatial units, and consists of four quadrants, namely, high-high (HH), high-low (HL), low-high (LH) and low-low (LL). They represent four kinds of relationships between false alarms in a district and its neighboring districts: HH represents that the number of false alarms in itself and its neighboring districts is high, HL represents that the number of its own false alarms is high, while the number of its neighborhood false alarms is low. LH means that its own false alarms are low, while the neighbourhood false alarms value is high, and LL means that both its own and the neighborhood false alarms value are low.

Figure 4 shows that the numbers of districts in the HH and LL regions are larger than the other two regions, and they remain unchanged. The value of districts in the HH region is 5 and unchanged from June 2023 to November 2023, indicating that the spatial agglomeration ability of local false alarms is stable. The local false alarms were concentrated in the western region of Shanghai, including fengxian, qingpu, songjiang, jinshan, and minhang. The value of districts in the LL region is 6 and remains the same from June 2023 to November 2023. The local false alarms were concentrated in the middle region of Shanghai, including huangpu, hongkou, changning, xuhui, jingan, putuo.

The number of districts in the HL and LH regions is small and shows different characteristics. The values of districts in the LH region increased in July 2023 and then remained stable. The number of districts in the HL region decreased in July 2023and then remained unchanged.

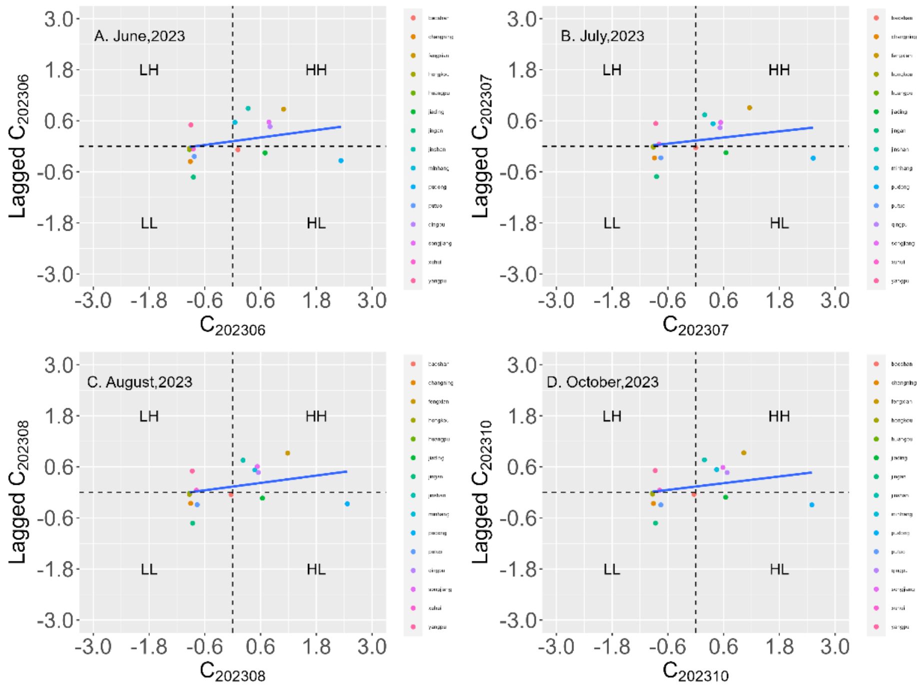

Figure 4. Moran scatter plot of false alarms in Shanghai, June,2023-November,2023

5. CONCLUSIONS

Exploring the dynamic characteristics of the temporal and spatial evolution of alarms is significant for decision support to reduce the high false alarm rate of the transmission line monitoring system. Therefore, based on the alarm data extracted from the transmission line monitoring system, various methods such as coefficient of variation, Kernel density analysis, and spatial correlation were utilized. The evolution characteristics of the spatiotemporal pattern of alarm at the city and district levels were analyzed. The main findings are:

a. The coefficient of variation (CV) of alarm showed an upward trend at the city levels.

b. The median of the kernel density distribution of the false alarm increased. The largest rate of false alarms is minhang, baoshan, and fengxian. The maximum rate of the false alarm changed from baoshan to minhang.

c. The numbers of districts in HH and LL regions are larger than the other two regions, and they remain unchanged. The districts in HH are mainly concentrated in the western region and the districts in LL are mainly concentrated in the middle region.

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