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Original Research Paper

Identifying accident black spots based on the accident spacing distribution

Hongjun Cui, Jianguo Dong, Minqing Zhu, Xia Li, Qingzhou Wang*

School of Civil and Transportation Engineering, Hebei University of Technology, Tianjin 300401, China

HIGHLIGHTS

- Reviews and summarizes the identification methods of accident black spots.
- Uses the Poisson distribution to avoid the division of road sections.
- Introduces the concept of quality control management -3σ principle provide basis for the method.
- Compared with other methods, the accuracy of the method proposed in the paper is higher.

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ABSTRACT

The identification of accident black spots is of great significance for the prevention of traffic accidents. Commonly used accident black spot identification methods divide road sections for the analysis of accident data, the direct result of which is the splitting of accident black spots, which affects the results. This paper is based on three years of traffic accident data from the Beijing–Harbin Expressway, including the time and location of traffic accidents, form of the accident fatalities, severe injuries, slight injuries, and property damage only (PDO). To avoid road division effects, an identification method based on the accident spacing distribution is established by using quality control theory. The results show that the average number of accidents per kilometer by the method proposed in this paper is 42, which is much higher than 10, identified by other identification methods. The method proposed in this paper improves the accuracy of the identification results. This method avoids the problem of road segmentation found in other common methods and can more accurately reflect the spatial distribution of traffic accidents. Thus making the identification of accidents more scientific and accurate.

* *Corresponding author*. Tel.: +86 13785938762.
E-mail addresses: cuihj1974@126.com (H. Cui), djg898@163.com (J. Dong), 898041107@qq.com (M. Zhu), 64406435@qq.com (X. Li), 2006126@hebut.edu.cn (Q. Wang).

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1. Introduction

In recent years, road traffic accidents around the world have been increasing. This phenomenon is especially prominent in developing countries. China has traditionally been the hardest hit by road traffic accidents. According to a research report released by the Ministry of Transport, the number of deaths caused by traffic accidents in 2017 was approximately 63,000, which was the second-highest in the world (Qian, 2018). In 2018, the number of road traffic accidents in the country dropped by 0.9%. According to the National Bureau of Statistics, the number of deaths in road traffic accidents per 10 thousand vehicles in recent two years (2018 and 2019) was 1.93 and 1.80, respectively. It is estimated that death by traffic accidents is currently the eighth leading cause of death and is expected to be the third leading cause of death by 2030, which is also a reason to concentrate on traffic accident prevention (WHO, 2013). Accidents can be studied in two stages: prevention and treatment (Vistisen, 2002). The main purpose of prevention stage is to prevent accidents by identifying potential high hazardous road sections (Farnsworth, 2013; Gutierrez-Osorio and Pedraza, 2020; Noland and Adediji, 2018). In contrast, the main goal of treatment stage is to implement corrective measures for reducing the losses involved in and the severity of accidents by emergency rescue. Through the rectification of high-risk road sections, the number of traffic accidents in China has recently decreased, although the numbers of accidents and deaths are still high. The number of deaths from accidents is high, and the situation is not optimistic. Strengthening research on traffic accidents and concentrated road sections by improving the accuracy of black spot identification has a multiplier effect that prevents traffic accidents, reduces traffic accident rates also the losses caused by traffic accidents, and improves the overall safety level of roads.

The identification of black spots in accidents is an active area of research (Debrabant et al., 2018; De Pauw et al., 2014; Vandenbulcke et al., 2014). Road traffic accident black spots are also referred to as hazardous road locations, high-risk locations, accident-prone locations, hotspots, sites with promise, and prioritize investigation locations (Haghighi and Maskooni, 2018). They are defined as points where the number and characteristics of traffic accidents are prominent or where there are potential safety risks compared with other normal points over a long period time (usually 1–3 years) due to the influence of the road conditions, traffic conditions, climate and environment (Cheng and Washington, 2005; Elvik, 2007). The distribution of road traffic on expressways is usually uneven. The road section where accidents are concentrated affects and even determines the safety level of the entire road to some extent. Focusing on eliminating safety hazards in concentrated road sections is the most effective and economical way to improve the overall safety of roads. Aiming at the identification method of accidents, many experienced scholars have done a substantial amount of work. There are two types of methods used to identify black spots in traffic accidents, direct and indirect methods. The direct methods are based on the analysis of historical traffic accident data and include the accident frequency method, the accident rate method, the accident frequency-accident rate method (AF-AR), the quality control method, the cumulative frequency method, the matrix method, the grey theory method, and the regression model method. In the indirect methods, such as traffic conflict techniques and safety factor methods (Zhu et al., 2009), another type of intermediary is used instead of historical data on traffic accidents. Table 1 summarizes the two types of black spot identification methods.

Identifying road traffic black spots is the first and most crucial step in improving road traffic safety. There are various methods for identifying accident-prone points, and one of the most important steps in identification is road segmentation (Boroujerdian et al., 2014). However, due to the randomness of the road segment division when calculating the accident rate, accident-prone points are often split into different sections, resulting in the omission of accident-prone points, which affects the final determination of the accident black spots (Ghadi and Torok, 2019). The road segment division method can be roughly divided into two categories. In one of them, the road section is divided according to the road mileage. The required length was proposed like 500 m (Wang, 2018), 1000 m (Hu et al., 2007) and 2000 m (Hauer, 1997). Accidents from the same black spot are easy to divide into two adjacent road sections in this method, resulting in the omission of accident black spots. The other method is dividing the road sections according to the road geometric line type (Geng and Peng, 2018), including the characteristics of straight lines, circular curves, and transition curves (Kwon et al., 2013; Ma, 2020), etc. Accidents are not concentrated on the geometric feature sections but changes in the continuity of the road, especially the road geometry. In the road section where a change occurs, the section where the accident is concentrated is not consistent with a geometric feature section. Additionally, some geometric features are relatively short, but the accident rate of a road section is very high. As shown in Fig. 1, R is radius of curve, RS is round straight point, SR is straight round point. It is obvious that there are many accidents at mileage from K102+000 to K104+000. The vicinity of the mileage may be an accident-prone point. Regardless of whether the road section is divided according to the station number or the road geometry, the accident will be split, which will affect the identification results of the aforementioned methods.

Due to the current dangerous conditions, an increasing number of scholars are studying accident black spots. To improve the accuracy of identification, accident black spot identification methods considering the distribution of accident spacing based on Bayesian technology (Dong et al., 2016), spatial clustering (Ding, 2019; Fan and Dong, 2019) and GIS technology (Dereli and Erdogan, 2017; Harirforoush and Bellalite, 2016; Wang and Li, 2019) are proposed by researchers.

To avoid road segmentation, this paper takes from the perspective of accident spacing distribution. As mentioned in the paper, the number of accidents per kilometre of Expressway obeys Poisson distribution, based on which we proved that the accident interval follows negative exponential distribution. Then based on the results obtained from the certification, the upper limit of the abnormal accident spacing and the number of consecutive abnormal accident spacings

Table 1 – Different black spot identification methods.

Method	Type	Description	Advantage	Disadvantage
Accident number method (ANM) or accident frequency method (AFM)	Direct method	If the number of accidents on a road section is greater than the critical value, it is considered to be an accident black spot.	It is easy to calculate and select, and the result is clear.	When the numbers of accidents in different locations are almost the same, it is difficult to make an objective judgment.
Accident rate method (ARM)	Direct method	When the accident rate of a road section exceeds the critical value, it is considered to be an accident black spot.	It is convenient and fast and considers the impact of related factors.	It does not consider the effects of random fluctuations, and the criteria are subjective.
Matrix method (MM)	Direct method	Each segment is represented by a matrix unit in the matrix, and the position of the matrix unit represents the degree of danger of the segment (Wang, 2018).	The size of the matrix may be determined by the needs of users, taking the frequency of accidents method and the accident rate into account.	The determination of black spots is simple and does not consider severity and thresholds.
Quality control method (QCM)	Direct method	Compare the accident rate of the road section with the average accident rate of similar road sections (Xue, 2013).	It is objective, fair and able to solve the problem of random fluctuations.	Heavy workload, insufficient consideration for large-scale transportation systems.
Cumulative frequency method (CFM)	Direct method	The method is based on statistical theory and plotting the cumulative frequency accident rate curve of the cumulative frequency and accident rate (Chen, 2020; Zhang, 2019).	It is an economic discrimination method with a high practical value.	Abnormal sections are not considered.
Equivalent accident total number method (EATNM)	Direct method	The severity of the accident is calculated by giving a certain weight to injury and death, and the critical indicator is determined to identify the accident black spot.	Intuitive, easy to understand, easy to operate, fast.	The process of identification is rough.
Grey theory method	Direct method	Find the law from the road traffic accident itself and establish a prediction model.	It is suitable for processing small samples and easy to operate.	The system must be a grey system.
Regression model method	Direct method	Determine the correlation between dependent variable and independent variable, and establish regression equation with better correlation.	It shows the significant relationship and influence intensity between independent variable and dependent variable.	The model is simple, and the algorithm is low-level.
Traffic conflict technique	Indirect method	Quantitatively measure and determine the process and severity of conflicts (Zheng et al., 2014).	Little dependence on accident statistics.	The investigation workload is large, the modelling is difficult, and the operability is not strong.
Safety factor method	Indirect method	Use the relationship between vehicle speed changes and traffic accidents to identify dangerous sections.	Little dependence on accident statistics.	The investigation workload is large, the modelling is difficult, and the operability is not strong.

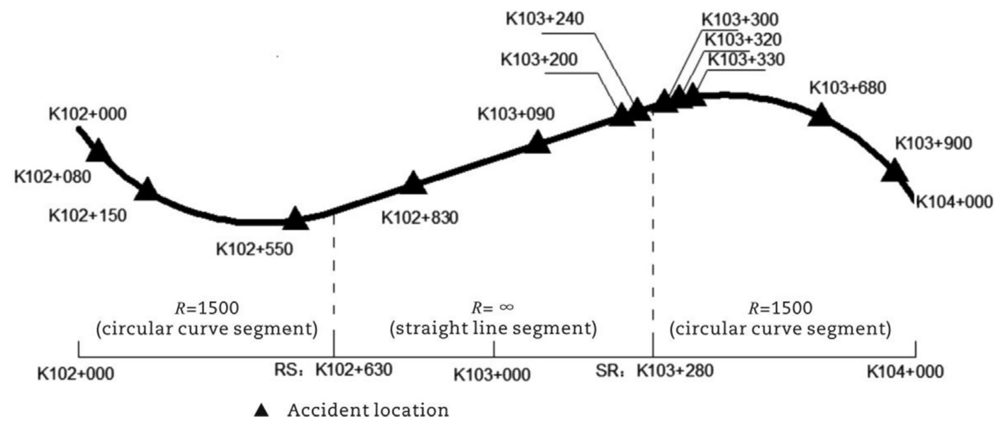

Fig. 1 – Distribution of traffic accidents on a certain section.

are calculated to determine the accident black spots. Although the accident rate hasn't been considered in the method proposed, the distribution of accidents is reflected in the length of accident spacing. The average number of accidents determined by identifying black spots based on the spacing of abnormal accidents is much larger than other methods, which proves the accuracy of the method. The method avoids road segmentation, reflecting the distribution of accident spacing more accurately and objectively, thus determining the location of accident black spots with more accuracy.

The paper is organized as follows. First, literature and related work are reviewed. Next, an overview of the method is presented, along with the theoretical basis of the method. Subsequently, based on the collected data, the results of an analysis are presented to describe the different black spot identification methods for accidents. Finally, conclusions are drawn based on the results of the analysis.

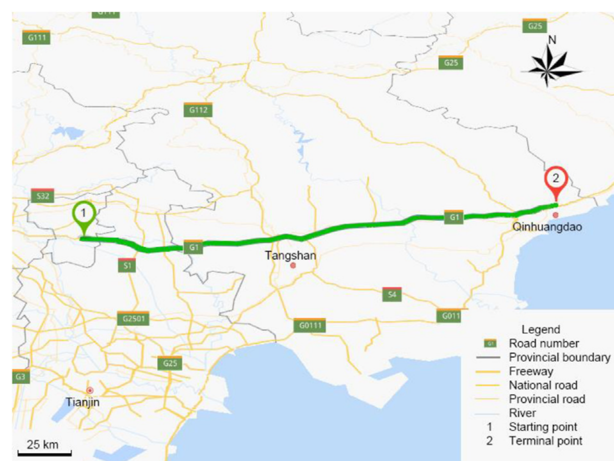

Fig. 2 – The study area (https://map.baidu.com/).

2. Description of data

The Beijing–Harbin Expressway forms a new fast-track entry and exit link to the three north-eastern provinces, linking Beijing–Shanghai Expressway, Beijing–Zhuhai Expressway and other national highway trunk lines into one. It is the transportation artery that connects the Northeast and North China. The data in this article were provided by the Beijing–Qinhuangdao Expressway Management Office in Hebei Province.

In the paper, the data are extracted from the information management system of the Hebei–Qinhuangdao Expressway Management Office of Hebei Province. This study used the records of 333 traffic accidents from the Tangshan section (K102+000–K16+850) of the Beijing–Harbin Expressway (road number G1) on the Jing–Harbin Expressway in Hebei Province (Fig. 2). This study is based on the road loss account of the Beijing–Qinhuangdao Expressway from 2016 to 2018, which includes various types of information, such as the basic information of the driver, the time and location of traffic accidents, severe injuries, slight injuries and property damage only (PDO).

3. Methodology

This section presents the method for identifying accident black spots. First, we prove that the accident spacing follows a negative binomial distribution and then calculates the upper limit value of the abnormal accident spacing and the number of abnormal spacing according to the distribution density function of the negative binomial distribution. Finally, we identify the location of the accident black spots.

3.1. *Road traffic accident spacing distribution rule*

In the identification of accident black spots, the quality control law assumes that the number of accidents in each road section follows a Poisson distribution (Chen, 2007; Cui et al., 2001; Hiroshi, 1997; Hu et al., 2004; Xing and Li, 2015). Poisson regression is often the first choice to explore the relationship between the number of accident and other factors (Dereli and Erdogan, 2017). Therefore, this paper assumes that the number of accidents per unit road section on the expressway follows the Poisson distribution. According to the statistical principle, if the number of traffic accidents per unit road section follows the Poisson distribution, the following assumptions should be met: (1) the characteristics of a Poisson distribution is that the expectation and variance are basically equal; (2) the numbers of accidents in different road sections are independent of each other; (3) the probability of two or more accidents is extremely small and can be ignored in a sufficiently small road section; and (4) on any small road segment, the probability of an accident depends on the length of the road segment.

Traffic accident spacing is a continuous variable that requires a large number of traffic accident spacing samples for statistical analysis. So, it is difficult to directly analyzes the distribution characteristics of traffic accidents. Therefore, statistical knowledge can be used to derive the distribution characteristics of the accident spacing. Assuming that the number of traffic accidents on a unit road section follows a Poisson distribution, the equation is as below.

$$P(k)=\frac{y^k}{k!}e^{-y} \quad k=0,\ 1,\ 2,\ \cdots \tag{1}$$

where $P(k)$ is the probability of occurrence of k accidents on a unit road segment and y is the expected value of the accident rate on a unit road segment.

Eq. (1) is converted into the general form, and the probability of the number of accidents k on the l-segment is as below.

$$P_k(l)=\frac{(yl)^k}{k!}e^{-yl} \quad l>0,\ k=0,\ 1,\ 2,\ \cdots \tag{2}$$

where $P_k(l)$ is the probability that the number of accidents on the l-segment is k, l is the length of the road.

The probability of a road segment with a length of l without accidents is as below.

$$P_0(l)=\frac{(yl)^0}{0!}e^{-yl}=e^{-yl} \quad l>0 \tag{3}$$

Then, the probability of at least one accident on the l-long road segment is as below.

$$P_k(l)=1-P_0(l)=1-e^{-yl} \quad k\geq 1,\ l>0 \tag{4}$$

Assuming that the accident spacing is L, the probability of at least one accident occurring on the l-long road segment is equivalent to the probability of the accident spacing $L\leq 1$, and Eq. (4) can be expressed as below.

$$P\{L\leq 1\}=1-e^{-yl} \quad l>0 \tag{5}$$

Obviously, Eq. (5) is the distribution function of the accident spacing, which is a common negative exponential distribution that can be abbreviated as Eq. (6)

$$F_L(l)=\begin{cases}1-e^{-yl} & l\geq 0\\ 0 & l<0\end{cases} \tag{6}$$

Its distribution density function is Eq. (7).

$$f_L(l)=d(F_L(l))=\begin{cases}ye^{-yl} & l\geq 0\\ 0 & l<0\end{cases} \tag{7}$$

3.2. *Accident black spot identification method*

3.2.1. *Determination of the abnormal spacing of the accident*

As far as the entire road is concerned, the overall traffic safety level of different roads is different, and the proportions of traffic accidents (α) directly affected by road conditions are different. Referring to the experience of relevant experts, under normal circumstances, the road safety level is relatively high when the average annual traffic accident rate is less than 1 time/km and the corresponding α is relatively low. When the average annual traffic accident rate on the road is 1–2.5 times/km, the traffic safety level is average and α is approximately 30%. When the average annual traffic accident rate is more than 2.5 times/km, the traffic safety level is relatively low and α is relatively high (Yu, 2007).

It is assumed that an abnormal accident spacing indicates that the road condition has a direct impact on the corresponding accidents. The upper limit of the abnormal accident spacing is L^+, the expected number of accidents per kilometre is y, and the proportion of accident spacing abnormality caused by the road conditions is α. According to Eq. (6), accident spacing follows a negative exponential distribution, L^+ can be obtained by the following equation.

$$\int_0^{L^+} f_L(l)dl=\alpha \Rightarrow L^+=\frac{-\ln(1-\alpha)}{y} \tag{8}$$

It can be seen that when the accident spacing is less than L^+, bad road conditions may play a direct role in traffic safety (Yang, 2020), and the area may be an accident black spot.

3.2.2. *Determination of accident black points*

The "3σ principle" (Li and Zhou, 2012) is applied to the statistical process control (SPC) theory, and a control chart for real-time quality control (Cai et al., 2020) during production is proposed, as shown in Fig. 3.

In the control chart for real-time quality control during production, the centre line (CL) is u, the upper control line (UCL) is $u+3\sigma$, and the lower control line (LCL) is $u-3\sigma$. When the control chart is applied to actual production, the most basic judgment standard is: if the characteristic value of the sample is outside the upper and lower limits, the production process can be considered unstable, and the production process is considered to be abnormal.

From the perspective of quality control theory, the process characteristic value or its statistics should be a qualified state, and the production equipment is normal. The control process does not allow unqualified products to appear. Due to system factors and random factors, the occurrence of substandard products cannot indicate that the production equipment has problems. From a statistical point of view, continuous

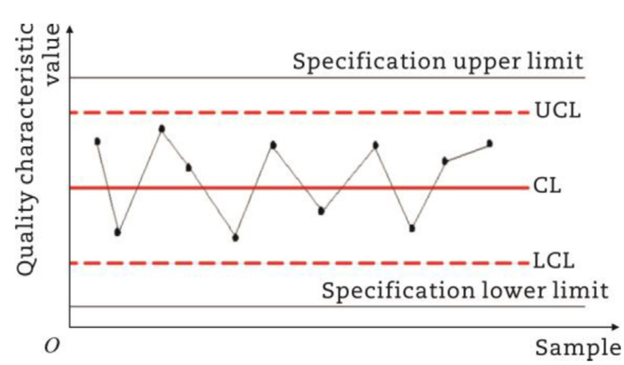

Fig. 3 – Schematic diagram of quality control.

unqualified products can identify the existence of production equipment.

If the road is regarded as the production equipment and the accident distance is regarded as the product, due to the great randomness in the occurrence of traffic accidents, the occurrence of abnormal accident spacing can only indicate that a location may be an accident black spot. It is easy to determine that the adverse event indicating the existence of problems in a production system is the continuous output of unqualified products (the continuous output of abnormal accident spacing). With significant levels of β, when the abnormal accident spacing is less than L^+ and the accident abnormal spacing number is greater than n, as shown in Fig. 4, the road segment may be determined to be an accident black spot.

Assuming that the probability that the device will produce a defective product (accident abnormal spacing) is P, the significance level of the problem in the production system is β. According to the "3σ" principle, β is generally taken as 0.05. It is assumed that the condition is satisfied when n abnormal accident spacings occur continuously and n can be obtained by the following equation

$$P = F_L(L^+) = 1 - e^{-yL^+} \tag{9}$$

$$P^n \le \beta \Rightarrow n \ge \frac{\ln(\beta)}{\ln(P)} \quad P<1,\ \beta<1 \tag{10}$$

Therefore, when more than n abnormal accident spacings appear continuously, there are obvious traffic safety hazards in road conditions, which can be identified as accident-prone road points.

4. Case study

4.1. *Road traffic accident spacing distribution rule*

In general, the occurrence of road traffic accidents is random and meets the above assumptions. To further verify whether

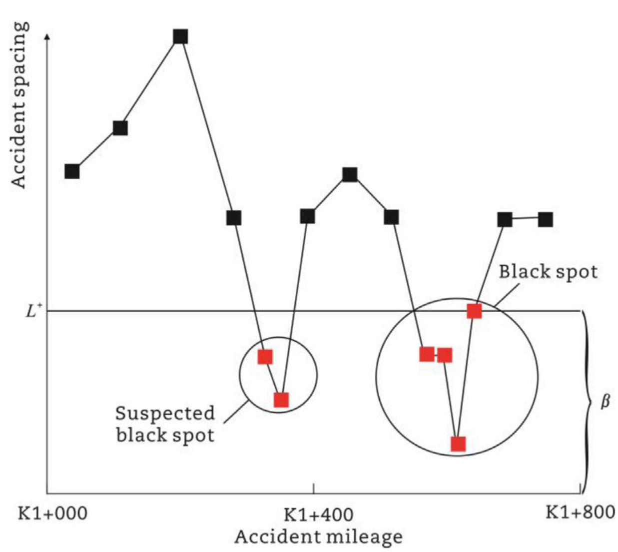

Fig. 4 – Idea diagram of accident black point identification based on abnormal accident spacing.

the unit road accidents obey a Poisson distribution, the contingent impact of accident statistics and the statistical period of accident black spots are taken into account in the definition (the statistical period is generally 1–3 years). If the statistical period is too long, the road traffic conditions and the surrounding environment change greatly, and it is difficult to correctly reflect the actual conditions of the accident distribution. Conversely, if the statistical period is too short, the accidents are more sporadic and fail to indicate the universal law. Therefore, this paper analyses the distribution of traffic accidents in a section of the Beijing–Harbin Expressway in 2016–2018. The statistics of the accidents are shown in Table 2.

According to the characteristics of a Poisson distribution, the expectation and variance of the number of accidents k should be equal. The calculated results of the data in Table 2 are $y = E(k) = 5.23$ and $\mathrm{Var}(k) = 5.34$. The expectation and variance are basically equal, which conforms to the characteristics of a Poisson distribution. Then, the cumulative probability of k accidents occurring on each kilometre of road in 3 years is as in Eq. (11).

$$P(k) = \frac{5.23^k}{k!} e^{-5.23} \qquad k = 0,\ 1,\ 2,\ \cdots \tag{11}$$

The theoretical frequency of the number of accidents per unit road section can be calculated. The results are shown in Fig. 5.

Fig. 5 shows that the maximum error of the theoretical frequency and the actual frequency is 3.66 and the minimum error is 0.46. The actual frequency drifts around the theoretical frequency. The theoretical frequency is considered to be very close to the actual frequency. The fitting test of the distribution is performed using the Pearson χ^2 test.

$$\chi^2 = \sum_{r=1}^{7} \frac{(\upsilon_k - np_k)^2}{np_k} \tag{12}$$

where υ_k is the actual frequency of the accident and np_k is the theoretical frequency of the accident.

Substituting the data in Table 2 into Eq. (12) gives $\chi^2 = 6.422$. The degree of freedom of χ^2 in Eq. (12) is 7−1−1 = 5. With a significance level of 0.01, the expression is as below.

$$\chi_5^2(0.99) = 15.086 > \chi^2 = 6.422 \tag{13}$$

Therefore, the number of accidents on a unit road section can be considered to obey the Poisson distribution. It is known from the probability information that the average number of accidents per unit road segment also follows the Poisson distribution. Eventually, the distance between road traffic accidents can be shown to obey the negative exponential distribution, and the distribution density function is in Eq. (14).

$$f_L(l) = d(F_L(l)) = \begin{cases} 5.23e^{-5.23l} & l \ge 0 \\ 0 & l < 0 \end{cases} \tag{14}$$

4.2. *Accident black spot identification method*

According to the new method for identifying black spots of highway accidents proposed in this paper, the data of the accidents on the Beijing–Harbin Expressway from 2016 to

Table 2 – Distribution of traffic accidents on the Beijing–Harbin Expressway in 2016–2018.

Mileage	Accident quantity	Mileage	Accident quantity	Mileage	Accident quantity	Mileage	Accident quantity
102	1	118	5	134	6	150	7
103	4	119	4	135	7	151	1
104	6	120	8	136	5	152	5
105	3	121	4	137	5	153	3
106	1	122	5	138	3	154	5
107	4	123	4	139	7	155	3
108	6	124	13	140	6	156	5
109	5	125	5	141	8	157	2
110	6	126	5	142	5	158	6
111	4	127	3	143	10	159	7
112	7	128	7	144	8	160	12
113	4	129	4	145	5	161	5
114	8	130	7	146	4	162	3
115	1	131	3	147	6	163	7
116	4	132	4	148	7	164	4
117	4	133	6	149	4	165	7

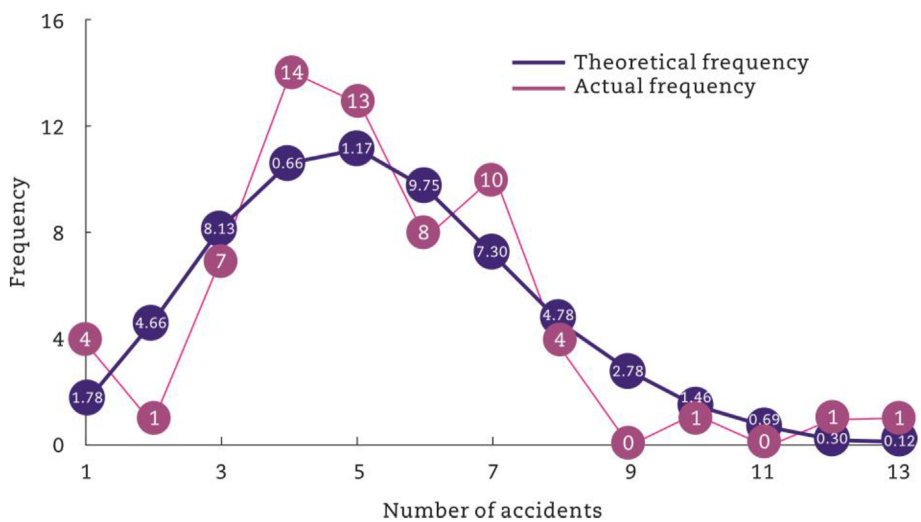

Fig. 5 – Comparison of the theoretical frequency and actual frequency of the number of accidents per unit kilometer.

2018 in Table 2 are processed and analysed. The cumulative number of traffic accidents occurred in the three years between K102 and K165. The expected number of accidents per kilometre is $y = 5.23$. The average accident rate is 1.74 times/km, so α is 0.3, and β is generally taken as 0.05.

According to the obtained distribution function, the upper limit value of the spacing between accidents can be calculated in Eq. (15).

$$\int_0^{L^+} f_L(l)\mathrm{d}l = \alpha \Rightarrow L^+ = \frac{-\ln(1-\alpha)}{y} = \frac{-\ln(1-0.3)}{5.23} = 0.068\ \text{km} \tag{15}$$

The number of abnormal accident spacings is in Eq. (16).

$$n \geq \frac{\ln(\beta)}{\ln(\mathrm{P})} = \frac{\ln(\beta)}{\ln(1-\mathrm{e}^{-yL^+})} = \frac{\ln(0.05)}{\ln(1-\mathrm{e}^{-5.23\times 0.068})} = 2.48 \tag{16}$$

According to the calculation results and combined with the actual condition, n should be an integer, $n \geq 3$.

4.3. *Result analysis*

Based on the above calculation results, the black spots of traffic accidents on the Beijing–Harbin Expressway in 2016–2018 are identified and compared with the results calculated by other methods, as shown in Figs. 6 and 7.

It is known from Fig. 6 that the accident black spots are concentrated in the second half of the selected section, and there are at most five black spots of accidents in the section where accidents are concentrated, indicating that the accident risk is large, and efforts should be made to strengthen the management in this location.

The results obtained by the method identified in this paper are compared with the results of several other methods. The identification results are shown in Fig. 7. The abscissa axis represents various methods of identifying black spots in accidents. The last method (abnormal spacing method) is the method studied in this article. The ordinate axis represents the relevant indicators of the identified accident black spots,

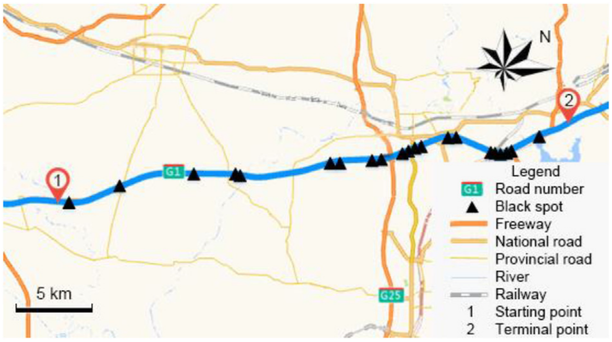

Fig. 6 – Location of identified accident black spots.

including number of accident black spots, contains the number of accidents, accumulated accident mileage and average number of accidents. It can be seen from Fig. 7(a) that the accident black spot identification method based on abnormal accident spacing (ASM) proposed in this paper identifies 20 accident black spots, and the number of black points identified is overall not much different from those of other methods. However, the accident black spots determined by other methods include more accidents. As shown in Fig. 7(b), the total number of accidents in the selected section is 333 in the paper, and the number of accident black spots determined by the cumulative frequency method (CFM) is 249. This accounts for 74.7% of the total number of accidents, which means that most accidents on the road are concentrated at the black spots, and is inconsistent with the actual conditions. The number of accidents identified by the method proposed in this paper accounts for 29.7%, which is in line with the actual conditions. It can be seen from Fig. 7(c) that the accident mileage covered by accident black spots of other methods is much higher than that of the method in this paper. When road management is carried out, road managers need to focus on roads with higher risks. Due to the longer accident mileage covered by the accident black spots, it is not possible to accurately identify the locations that need to be addressed. It is more difficult to identify specific short-distance road sections, which is not conducive to the improvement of roads by road managers and is not targeted. Finally, we calculated the number of accidents per kilometre from the data in Fig. 7(b) and (c). As shown in Fig. 7(d), in the method proposed in this paper, the number of accidents per kilometre is 42, which is much higher than those of other identification methods. The identification results fully reflect the concentration of the accident black spots and show that the method proposed in this paper avoids the segmentation of road, can more accurately identify the locations of accident black spots and provides targeted road sections with more dangerous to management department for road improvement.

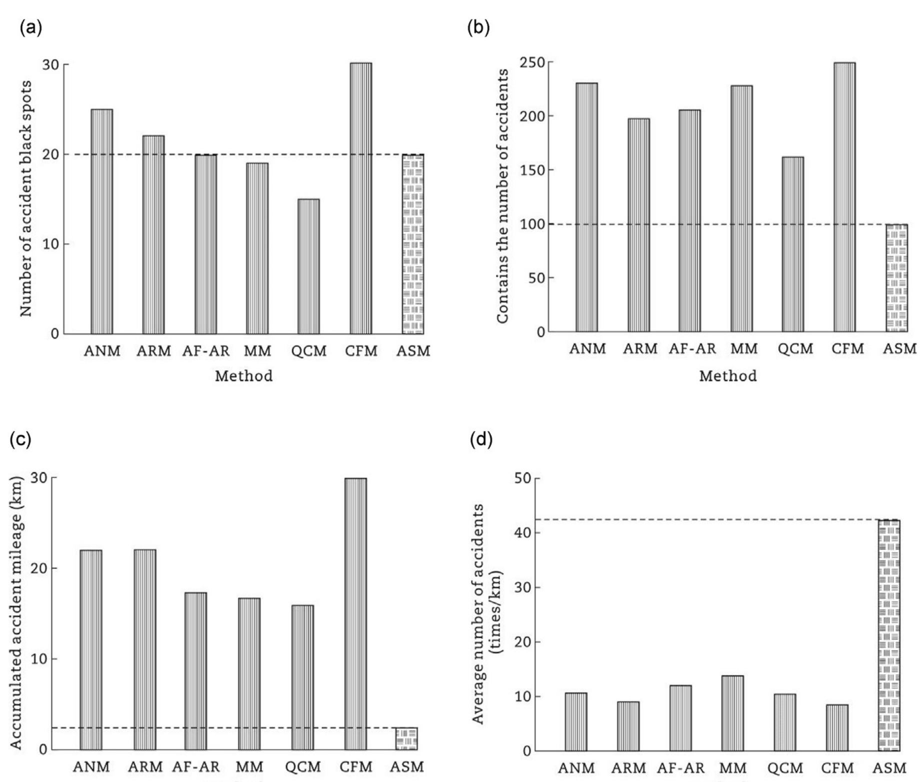

Fig. 7 – Comparison of the results of different methods. (a) Number of accident black spots. (b) Contains the number of accidents. (c) Accumulated accident mileage. (d) Average number of accidents.

5. Conclusions

This paper analyses the black spots of highway traffic accidents by analysing the spacing characteristics of traffic accidents. Based on the results obtained from the certification, the upper limit of the abnormal accident spacing and the number of consecutive abnormal accident spacings are calculated to determine the accident black spots. Although the concept of the accident rate is not mentioned, the length of the accident spacing also reflects the distribution of accidents. The average number of accidents determined by identifying black spots based on abnormal accident spacings is much larger than those of other methods, which proves the accuracy of the proposed method. The method avoids road segmentation, fully reflects the concentration on the accident-prone segments and improves the accuracy of the identification results. To avoid bias from the accident statistics, this method proposes the analysis of traffic accident data from many years, which fully reflects the rationality and accuracy of the method.

There are several limitations to our study. First, the results obtained in this article depend on the initial data selected (distribution of accidents on the Beijing–Harbin Expressway from 2016 to 2018) and the method used. If relevant data about accidents on different highways are obtained, we can compare and analyze the discrimination results of different roads. Second, the accident data used in the calculation do not take into account the severity of the accidents, such as injury, death, and property damage. Only the data of the accident location is analysed.

The results of this article can be further studied. In this paper, relatively few parameters are used to calculate the anomalous distances of accidents. In the later period, the relationship between the anomalous distances of accidents and the service life of the road can be studied. In the paper, the expectation and variance of the number of accidents are equal only checked with χ^2 test and further analysis can be used to verify scientifically. The adaptability could be better verified if we get the data of other expressway in the future.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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Hongjun Cui, professor, graduated from Southeast University with a PhD in transportation planning and management. He has published more than 70 papers in core journals such as China Journal of Highway and Transport, 3 academic monographs, and obtained 4 national invention patents and 4 utility model patents. He chaired 23 scientific research projects, including 2 projects of the National Natural Science Foundation of China and 2 provincial and ministerial projects.