Research on Dynamic Evaluation of Metro Passenger Credit

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Abstract: With the expansion of metro network, the large passenger flow in peak hours has brought great challenges to metro operation. While upgrading the security inspection, the traffic efficiency of passengers in metro stations has also been affected. Considering public security and security inspection efficiency, using the method of passenger credit rating to establish a differentiated security inspection mode has become the development direction of intelligent security inspection in the future. It is necessary to study the passenger credit evaluation system due to a lack of research on metro passenger credit scoring. However, previous research focused on static credit evaluation rather than dynamic credit evaluation. This paper introduces motivation factor, time weight and night safety reduction coefficient to conduct dynamic passenger credit evaluation.

1. INTRODUCTION

The large passenger flow in peak hour has brought great challenges to metro operation and management. Faced with this dilemma, the metro operation department intends to use the metro passenger safety credit evaluation system to divide passengers into different levels and take different security check measures for passengers of different levels. The establishment of passenger credit system is instrumental to achieve the integration mode between security check and ticket check.

However, the majority of previous research on credit system focused on static credit evaluation, which ignored the trend of passenger credit. Li et al. [1] proposed the logistic regression model with elastic net penalty to conduct personal credit scoring. Support vector machine (SVM) classifiers are applied to evaluate the bank credits of the applicants [2]. Luo et al. [3] used deep learning algorithm for corporate credit scoring. Abellán and Castellano [4] combined logistic regression, support vector machine, multi-layer perceptron and decision tree to establish a credit evaluation model with higher prediction accuracy. Liberati et al. [5] conducted credit scoring via linear regression.

The rest of this manuscript is organized as follows: In "Methodology" section, we introduce the dynamic evaluation method applied to passenger credit scoring. "Case Study" section presents the case of dynamic credit evaluation of passengers. Our summary and conclusions are presented in "Conclusion".

2. METHODOLOGY

The static credit scores are obtained from credit evaluation at an isolated time point. However, the passengers' credit evaluation should be a dynamic change process rather than static credit evaluation. To reduce the impact of sudden change of passenger's credit evaluation value on the credit evaluation results at a certain time, the overall credit condition and the trend of passenger credit in multiple time points should be comprehensively considered. Based on the passenger static safety credit evaluation, the passenger safety credit is adjusted through the dynamic evaluation method considering the following factors： motivation factor, time weight, and night safety reduction coefficient.

2.1. Motivation factor

In this paper, motivation factor is introduced into the dynamic evaluation of the passenger credit, in which the concept of speed and acceleration in physics are used [6]. Considering the trend of the credit value during different periods, the values of passenger credit are adjusted through motivation factors. Therefore, it encourages passengers to attach more importance to maintaining excellent personal credit, through credit incentive and discredit punishment mechanism brought by motivation factor.

Each passenger will obtain a static credit evaluation value at a different time point. The static credit evaluation matrix ($Y = [y_i(t_k)]_{s \times t}$) is obtained from passenger credit results.

$$Y = \begin{bmatrix} y_1(t_1) & y_1(t_2) & \cdots & y_1(t_T) \\ y_2(t_1) & y_2(t_2) & \cdots & y_2(t_T) \\ \vdots & \vdots & \ddots & \vdots \\ y_s(t_1) & y_s(t_2) & \cdots & y_s(t_T) \end{bmatrix} \quad (1)$$

Where t_k is the time point, $y_i(t_k)$ is the credit evaluation value of the passenger i at time point t_k.

The variation of static credit value of the passenger i

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from t_k to t_{k+1} is shown in Formula (2), which represents the velocity of static credit evaluation value.

$$v_{ik} = \frac{y_i(t_{k+1}) - y_i(t_k)}{t_{k+1} - t_k} \tag{2}$$

The change rate of the variation of static credit value of the passenger i from t_k to t_{k+1} is shown in Formula (3), which represents the acceleration of static credit evaluation value.

$$a_{ik} = \frac{v_i(t_{k+1}) - v_i(t_k)}{t_{k+1} - t_k} \tag{3}$$

The motivation factor (g) is defined to quantify the reward and punishment measure to reflect the change trend of passenger credit evaluation value in a certain period. The motivation factors are determined according to Formula (4).

$$g = \begin{cases} \dfrac{2v_{ik}}{1 + e^{\frac{-a_{ik}v_{ik}}{10|v_{ik}|}}}, & v \neq 0 \\ a_{ik}, & v = 0 \end{cases} \tag{4}$$

The passenger credit change trend is mainly divided into three types: growth, decline and steadiness. The analysis is as follows.

When $v > 0$, $g = \frac{2v}{1+e^{-\frac{a}{10}}}$. It is necessary to reward for the increase of the credit evaluation value. If $a > 0$, g will increases with the accelerated growth trend of the credit evaluation value. More rewards will be given for the increase of credit evaluation value, and the reward value will increase with the increase of a; If $a < 0$, g will decreases in which the growth trend of the credit evaluation value will slow down. The reward for the rise of the credit evaluation value will be reduced, and the reducing value will increase with the decrease of a; If $a = 0$, a certain reward will be given for the increase of the evaluation value.

When $v < 0$, $g = \frac{2v}{1+e^{\frac{a}{10}}}$. It is necessary to punish for the decline of the credit evaluation value. If $a > 0$, g will decreases in which decline trend of the credit evaluation value will slow down. The penalty for the decrease of credit evaluation value will be reduced, and the reduction value will increase with the increase of a; If $a < 0$, the decline of the credit evaluation value accelerates, and g decreases with the decrease of a, the penalty for the decline of the credit evaluation value is increased, and the penalty value increases with the decrease of a; If $a = 0$, a certain punishment will be given for the decline of evaluation value.

When $v < 0$, $g = a$. The reward and punishment results should be determined according to the acceleration of the credit change value. If $a > 0$, rewards will be given for the rising trend of the credit evaluation value; If $a < 0$, punishment will be given to the downward trend of the credit evaluation value; If $a = 0$, there will be neither reward nor punishment.

We define the attention attached to the motivation factor (β). The credit motivation value of the passenger i adjusted, as is shown in Formula (5).

$$y_i(t_k)' = y_i(t_k) + \beta g_{ik} \tag{5}$$

Where g_{ik} is the motivation factor of the passenger i from t_k to t_{k+1}, β indicates the importance attached to credit motivation factors.

2.2. Time weight

In previous studies, personal credit evaluation pays more attention to the regularity of historical data rather than adds historical data to the future credit forecasting process. Therefore, considering the dynamic characteristics of passenger credit evaluation over time, time weight is applied to the comprehensive credit evaluation.

Compared with old information, recent information can better reflect the future development characteristics of things. The time weight also contains the idea of "emphasizing the present but neglecting the past", which indicates the importance attached to the relevant evaluation results at different time points in the dynamic evaluation process.

We define time degree (γ) as preference for the importance of information at different time points. The closer the time point is to the current moment, the bigger γ. The relationship between the time degree (γ) and time weight (τ_t) is define in Formula (6).

$$\gamma = \sum_{t=1}^{s} \frac{s-t}{s-1}\tau_t \tag{6}$$

If γ tends to 0, it means that the evaluator lay more emphasis on the old information of passenger credit. If γ tends to 1, it means that the evaluator pays more attention the new information rather than old information. If γ= 0.5, it means that the evaluator assume that the new information and the old information are equally important to the evaluation process of passenger credit. The meaning of time degree is shown in the Table 1.

Table 1. The Value of Time Degree

γ	characteristic
0.1	Extreme emphasis on old information
0.3	Great emphasis on old information
0.5	Equal importance
0.7	Great emphasis on new information
0.9	Extreme emphasis on new information
0.2, 0.4,0.6,0.8	Intermediate values

Set the sample variance of time weight γ is:

$$D^2 = \frac{1}{s}\sum_{t=1}^{s}(\tau_t - \overline{\tau_t})^2 = \frac{1}{s}\sum_{t=1}^{s}{\tau_t}^2 - \frac{1}{s^2} \tag{7}$$

Objective function:

$$min\left(\frac{1}{s}\sum_{t=1}^{s}{\tau_t}^2 - \frac{1}{s^2}\right) \tag{8}$$

Constraints:

$$\begin{cases} \gamma = \sum_{t=1}^{s} \dfrac{s-t}{s-1}\tau_t \\ \sum_{t=1}^{s} \tau_t = 1 \\ \tau_t \in (0,1) \end{cases} \tag{9}$$

The minimum variance method is used to transform the calculation of the time weight into a nonlinear programming [7]. The aim of the minimum variance method is to find a set of time weight coefficients with the least fluctuation. According to Formula (9), the constraint conditions are linear, and the optimal solution of the time weight vector can be calculated by determining the value of the time degree.

2.3. Night safety reduction coefficient

When a safety incident occurs, it will threaten the life and property safety of passengers due to the limited confined space and entrance and exit of metro, which may cause great social impact. Man-made accidents such as property invasion, violent crimes and terrorist attacks are important factors threatening the safe operation of urban metro. Wang et al. [8] investigated safety accidents in Guangzhou, Beijing and Shanghai, and found that the threat of violence and terrorist attacks accounted for about 40% of all metro safety accidents. Although the occurrence of man-made safety threats in urban metro is random, some inherent laws can be discovered from the statistical data of historical metro safety accidents.

Ceccato [9] analysed the temporal patterns of the crime and disorder in Stockholm Metro. The Stockholm Metro operates from five o'clock to one o'clock tomorrow on weekdays and operates 24 hours a day on weekends. Most man-made safety accidents usually occur at night. From 4:00 o'clock, the safety accident index in the station began to increase, and reached the peak at midnight, as shown in Figure 1.

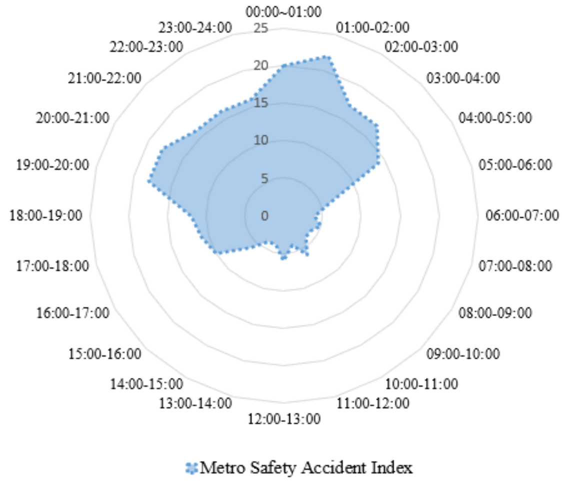

Figure 1. Time Distribution of Metro Safety Accidents

Violence and terrorist attacks often occurs at night within metro stations. On the one hand, the light as well as regular patrol at night is poor. On the other hand, people are generally tired at night, and their defence psychology is weak, which gives criminals opportunities. All passengers entering the subway station should receive a dynamic adjustment of credit value in different time periods of the day, making the safety credit rating of passengers whose safety credit rating is at the edge of decline will be temporarily lowered. Therefore, the adoption of night safety reduction coefficient can strengthen the identification of some passengers to better cope with the security situation of rail transit in different time periods. The operation time of metro in most cities is from 6:00 o'clock to 24:00 o'clock in China.

As shown in Table 2, the value of night safety reduction coefficient (θ) is set in different time periods.

Table 2. The Value of Night Safety Reduction Coefficient

Time	6:00-18:00	18:00~19:30	19:30-22:00	22:00-24:00
θ	1	0.95	0.85	0.75

2.4. Multi-step dynamic Evaluation

Step 1: β, the attention attached to the motivation factor, is assumed to be 1. Based on the passenger's static credit evaluation value, the velocity value and the acceleration of static credit evaluation value can be obtained according to formula (2) and formula (3). Then, the motivation factor g_{ik} at time point t_k can be found according to formula (4). Finally, $y_i(t_k)'$, the incentive credit score, can be found according to formula (5).

Step 2: The time scale is determined to be 0.25, which indicates that more attention is paid to the new information in the process of dynamic credit evaluation. According to formulas (8) and (9), the weight vector can be obtained through LINGO software. The credit evaluation values at each time point. By aggregating the credit evaluation values at each time point from time dimension, the dynamic evaluation value of passenger (Y) is obtained.

Step 3: Through the night safety reduction coefficient, the dynamic evaluation the values of passenger credit are adjusted in different time periods.

3. CASE STUDY

Some passengers who often travel by metro are selected to test the effectiveness of the proposed dynamic credit evaluation method. With 3 months as a time point, passengers were observed for four points (t_1, t_2, t_3, t_4). The static credit value ranging from 0 to 100 is obtained from the credit evaluation at a certain time point. Passenger A is selected as a case.

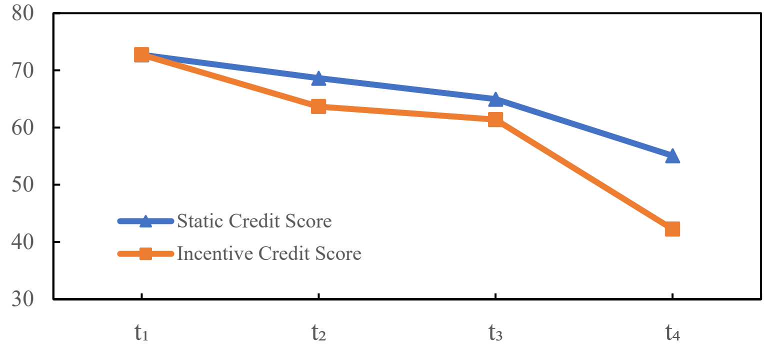

Figure 2. The Trend of Credit Score of Passenger A

The credit score of Passenger A has present a rapid decline because of repeated misbehaviour. The trend of credit score is shown in Figure 2 and the credit scores at different time points are shown in Table 3.

Table 3. The Dynamic Credit Score of Passenger A

Passenger A	t_1	t_2	t_3	t_4
$y_i(t_k)$	72.74	68.62	64.96	55.09
v	0	-4.12	-9.86	-9.87
a	0	-4.12	0.45	-6.21
$y_i(t_k)'$	72.74	63.66	61.38	42.25
Y				52.98

Adjusted by the night safety reduction coefficient, the dynamic evaluation value of passenger A is lowered at night, which means he should receive more attention from the security system.

4. CONCLUSION

Considering the trend of passenger credit in multiple time points, this paper adopts the dynamic evaluation method. Motivation factor is introduced to promote awareness of keeping excellent credit scores. In addition, the time weight can be used to aggregate incentive credit score from the time dimension to obtain the dynamic credit score. Though the night safety reduction coefficient, the dynamic credit scores is adjusted to identify potential risk passengers.

In the future, a further exploration of this research is worthwhile. The repair mechanism of passenger credit can be discussed in the process of dynamic credit evaluation. Furthermore, dynamic evaluation method can be applied to personal credit evaluations.

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