# Research on The Qualitative Evaluation and Quantitative Evaluation Transformation System of Autonomous Driving Closed Site of Intelligent Networked Heavy-duty Vehicles


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## Abstract

To address the limitations of qualitative evaluation in closed site testing for autonomous driving, this study investigates the correlation between qualitative and quantitative assessments of intelligent connected heavy-duty vehicles during closed site autonomous driving tests. Taking intelligent connected heavy-duty vehicles as the research subject, a thorough analysis of the requirements for qualitative assessment in automated driving scenario testing is conducted. Scientifically reasonable parameter indicators are selected based on expert experience for quantitative evaluation, leading to the establishment of a transformation system between qualitative and quantitative evaluations for closed site testing in autonomous driving. Real-world trials involving five heavy-duty vehicles are performed to obtain critical driving strategy data for heavy-duty trucks in an autonomous driving state, ultimately determining the threshold ranges for quantitative indicators under various conditions such as following, braking, and lane changing.

**Keywords:** heavy-duty vehicles, autonomous driving, quantitative evaluation system, closed field test

## 1. Introduction

At present, intelligent networked heavy-duty trucks are evaluated for autonomous driving capabilities with "scenario test + qualitative evaluation" as the main feature. However, the qualitative evaluation of autonomous driving is mainly based on the concept of language, which inevitably has uncertainty in the process of describing objective things. Therefore, the establishment of a qualitative and quantitative uncertainty transformation model for autonomous driving and the realization of the exchange of language values and numerical values are urgent problems to be solved in the research of complex systems for autonomous driving evaluation [1].

In the late 20th century, Qian Xuesen proposed the "comprehensive integration method from qualitative to quantitative" for open complex giant systems, advocating human-oriented, human-machine integration, and comprehensive integration from qualitative to quantitative [2]. In 1995, Li Deyi proposed the concept of cloud for the uncertainty transformation model of qualitative and quantitative transformation of complex systems, and in 2003, the cloud model theory was upgraded to the generalization theory of cloud model, and the data model of qualitative and quantitative transformation was further improved [3][4]. In 2006, Chen Zhonglin et al. used the generalized Weber-Fiscler law to link qualitative and quantitative problems in lighting engineering [5]. In 2009, Li Xin researched a qualitative and quantitative information fusion method based on the principle of graph representation, and established a comprehensive evaluation algorithm for train comfort [6]. In 2013, Lin Yongxin et al. proposed a nonlinear mutual prediction algorithm for the correlation between the behaviors of the seed system of complex dynamic giant systems, which provides a nonlinear mutual prediction measure for the theoretical analysis of the financial crisis [7]. In 2023, Wang Pei et al. used the chaotic scalable analytic hierarchy process to quantitatively evaluate the comprehensive intelligence level of autonomous vehicles, and established a quantitative analysis model based on environmental complexity, task complexity, and the degree of human intervention [8].

The above qualitative and quantitative transformation model focuses on the establishment of a scoring system, that is, the establishment of a score evaluation system through quantitative language concepts and mathematical models. Since this paper focuses on the establishment and determination of objective indicators of autonomous vehicles, the above methods are not suitable for the qualitative and quantitative conversion system in the testing methods of autonomous driving scenarios. Based on the experience of 20 experts in the field of automobile testing, this paper deeply analyzes the qualitative evaluation requirements of autonomous driving scenario testing, systematically classifies the qualitative evaluation indicators, selects scientific and reasonable parameter indicators for quantitative evaluation, obtains the key data of the driving strategy of heavy-duty trucks in the state of autonomous driving through real vehicle tests, and finally determines the threshold range of quantitative indicators of heavy-duty trucks in the states of following, braking, and lane change, so as to establish a set of qualitative evaluation and quantitative evaluation transformation system for autonomous driving closed field testing.

## 2. Qualitative And Quantitative Evaluation Index Evaluation And Transformation System

### 2.1 Qualitative Evaluation Indicators for Autonomous Driving of Intelligent Networked Heavy-Duty Vehicles

In recent years, various provinces, municipalities and districts in China have successively issued a series of test specifications for autonomous driving such as passenger cars, heavy-duty trucks, passenger buses, unmanned delivery vehicles, and sweepers. The above-mentioned specifications take scenario testing as the main body, and use qualitative indicators for passing evaluation, because the specifications are not open to the public, so it is impossible to directly conduct qualitative index research. In 2022, China released an autonomous driving test standard, namely GB/T 41798-2022 "Intelligent and connected vehicles – Track testing methods and requirements for automated driving functions". This standard is applicable to Class M and N vehicles with autonomous driving functions, and proposes corresponding test scenarios, test methods, and approval requirements for closed sites to verify the ability of autonomous driving functions to cope with typical scenarios [9].

In this paper, GB/T 41798-2022 is taken as the research object, and three typical driving conditions of lane change, following and braking are selected for research, and three corresponding autonomous driving test scenarios are selected to refine the qualitative evaluation index of autonomous driving of heavy-duty trucks.

### 2.2 Quantitative Evaluation Indicators

Combined with expert experience and industry needs, a quantitative evaluation system was constructed, and automotive parameters that could fully reflect the performance of autonomous driving were preliminarily selected. These indicators include following speed, following distance, braking distance, yaw angle velocity, etc., which can directly reflect the performance of the autonomous driving system in various scenarios. Through the quantitative analysis of performance indicators, the advantages and disadvantages of autonomous driving technology can be objectively evaluated.

### 2.3 Transformation System

After preliminarily determining the quantitative evaluation parameters, this paper conducted a questionnaire survey of 20 professional engineers in the field of automotive testing, used the Delphi method for questionnaire analysis, and arranged the quantitative indicators in order according to their importance, and constructed a transformation system between qualitative and quantitative evaluation, as shown in Table 1[10].

**Table 1 - Qualitative and quantitative evaluation index transformation system for autonomous driving of intelligent networked heavy vehicles**

| Num. | operating conditions | Autonomous driving test scenarios | Qualitative indicators | Quantitative indicators |
|---|---|---|---|---|
| 1 | Lane change | Roadworks | Do not collide with obstacles | Lateral acceleration, yaw rate, detour distance |
| 2 | | Expressway lane signal lights | Drive into an adjacent lane in front of a signal | |

| Num. | operating conditions | Autonomous driving test scenarios | Qualitative indicators | Quantitative indicators |
|---|---|---|---|---|
| 3 | | Motorcycles travel in the same lane | Do not collide with motorcycles | |
| 4 | | the vanished car | Do not collide with the target vehicle | |
| 5 | | Minimal risk maneuver | Do not collide with the target | |
| 6 | | Pedestrians crossing | Do not collide with pedestrians | |
| 7 | following | Cut-in | Do not collide with the target vehicle | Following speed, following speed difference, following distance, following deceleration, time gap |
| 8 | Braking | Emergency braking of the target vehicle | Do not collide with the target vehicle | Braking deceleration, relative distance after braking, reaction time |
| 9 | | Stationary vehicles occupy part of the lane | Do not collide with the target vehicle | |
| 10 | | the target vehicle stops and goes | Do not collide with the target vehicle | |
| 11 | speed limit | Speed limit signs | The speed shall not be higher than the value of the speed limit mark, and shall not be less than 0.75 times the value of the speed limit mark | Speed, braking deceleration, acceleration |
| 12 | | Corners | The speed of the vehicle shall not be less than 0.5 times the speed limit | |
| 13 | | Ramp | The speed is not less than 15km/h | |

## 3. Vehicle Test

### 3.1 Test Vehicles

In this test, five intelligent networked heavy-duty trucks were selected for the autonomous driving closed-field actual vehicle test, which were recorded as V1, V2, V3, V4 and V5 respectively. All five vehicles are capable of Level 4 autonomous driving, as shown in Table 2. Before the test, the tire pressure is adjusted to the manufacturer's required value, and the load state is adjusted to the full load state.

**Table 2 - Basic parameters of tested vehicle**

| Basic parameters | V1 | V2 | V3 | V4 | V5 |
|---|---|---|---|---|---|
| Self-driving level | L4 | L4 | L4 | L4 | L4 |
| type | $N_3$ | $N_3$ | $N_3$ | $N_3$ | $N_3$ |
| Overall dimensions L×W ×H(mm) | 7480×2550×3950 | 7075×2550×3950 | 6880×2550×4000 | 7220×2550×3000 | 7270×2550×4000 |
| Curb weight (kg) | 9400 | 9500 | 8870 | 10650 | 8870 |
| Maximum permissible towing mass (kg) | 39400 | 33370 | 40000 | 38220 | 40000 |
| Power form | diesel engine | drive motors | diesel engine | drive motors | diesel engine |
| Tire model | 295/80R22.5 18PR | 12R22.5 18PR | 12R22.5 18PR | 12R22.5 | 295/80R22.5 18PR |
| Tire pressure (kPa) | 900/900/900 | 930/930 | 930/930/930 | 930/930/930 | 860/860/860 |
| Train quality (no-load) (kg) | 18060 | 16755 | 15240 | 19885 | 17865 |
| Train quality (fully loaded) | 48545 | 42895 | 48210 | 48385 | 48930 |
| maximum speed in autonomous driving mode (km/h) | 89 | 89 | 89 | 80 | 80 |

### 3.2 Test Methods

Before the test, a set of data acquisition equipment, gyroscope, GPS positioning antenna, communication module, video acquisition system, surveillance camera, power supply and other instruments and equipment are installed in the test vehicle and the target vehicle respectively, so as to obtain high-precision vehicle parameters and relative data, and the equipment installation scheme is shown in Figure 1. During the test, according to GB/T 41798-2022, typical scenarios in the real road environment are simulated, and the test vehicle completes the above scenarios in an autonomous driving state, as shown in Figure 3~Figure 14.

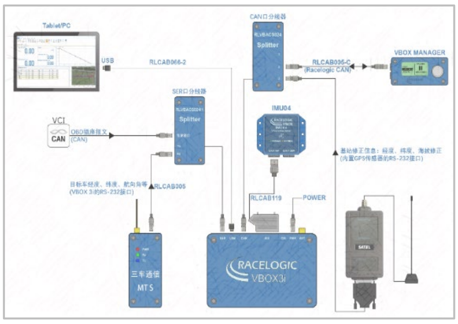


**Figure 1 - Schematic diagram of the installation**

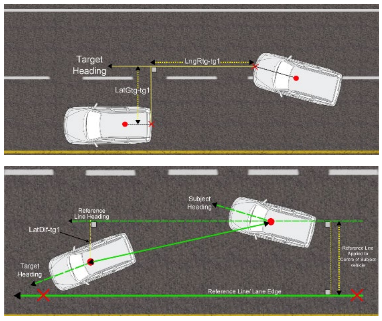


**Figure 2 - Instrument testing principle**

### 3.3 Test Scenario

Taking V1 as an example, three typical driving behaviors, such as lane changing, following and braking, and their corresponding autonomous driving test scenarios, were selected for closed-field testing. To ensure the accuracy of the test results, the test was repeated 3 times for each scenario.

***Lane Change Behavior – Roadworks***

The test road is at least a long straight with a one-way two-lane road, and the middle lane line is a white dotted line. The outer lane is equipped with traffic cones and traffic signs according to the traffic control requirements of the long-term operation area of road construction. The test vehicle drove ahead of an obstacle in the roadworks.

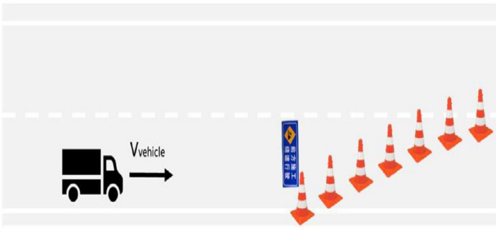


**Figure 3 - Schematic diagram of the roadworks**

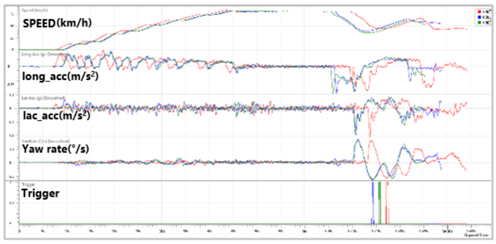


**Figure 4 - Test data curve of roadworks**

**Figure 5 - the test scenario of roadworks**

**Figure 6 - Interior view of the roadworks testing**

***Following Behavior - Cut-in***

The test road is a long straight road with at least two lanes in one direction, and the middle lane line is a white dotted line. The target vehicle is traveling at a constant speed of 40 km/h. The test vehicle was driven in the inside lane. When the test vehicle reaches more than 85% of $V_{max}$ and the pre-collision time of the two vehicles reaches [4,5]s for the first time, the target vehicle cuts into the inner lane from the outer lane and completes the lane change, and the lane change time is not more than 3s, and the longitudinal speed of the target vehicle is equal to 40km/h during and after the completion of the cut-in.

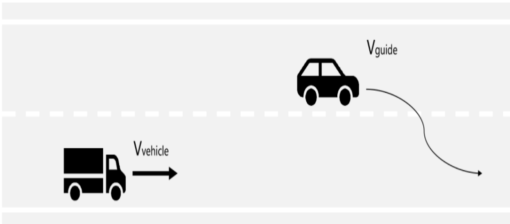


**Figure 7 - schematic diagram of cut-in**

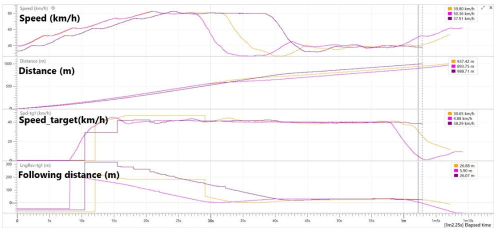


**Figure 8 - Test data curve of cut-in**

**Figure 9 - the test scenario of cut-in**

**Figure 10 - the interior view of cut-in testing**

***Braking Behavior - Emergency Braking of the Target Vehicle***

The test vehicle and the target vehicle are in the same lane, and the target vehicle is traveling at a constant speed of 75% of Vmax. The test vehicle steadily follows the target vehicle. The target vehicle achieves a deceleration of 6 m/s2 within 1 second and decelerates to a stop.

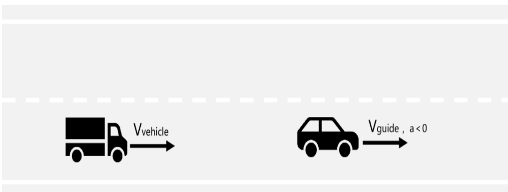


**Figure 11 - Schematic diagram of the emergency braking of the target vehicle**

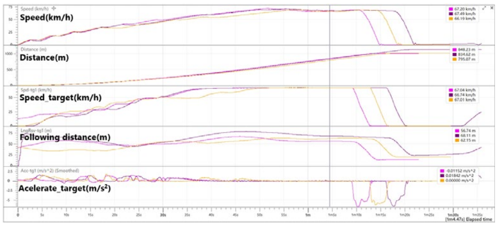


**Figure 12 - Test data curve of the Emergency braking of the target vehicle**

**Figure 13 - the test scenario of the emergency braking of the target vehicle**


**Figure 14 - Interior view of the emergency braking test**

## 4. Key Data Analysis of Autonomous Driving Strategies

Characterization of lane changes, following and braking behaviors. Affected by the driving strategy, the intelligent networked heavy-duty truck basically has good driving consistency under lane change, following and braking conditions, so the parameter characteristics of the autonomous driving strategy can be effectively studied through objective performance indicators such as lateral acceleration, following distance, and braking deceleration.

### 4.1 Analysis of Lane Change Behavior Characteristics

***Lateral Acceleration***

Lateral acceleration is the acceleration caused by the centrifugal force generated when the vehicle is driving in a corner, reflecting the safety and comfort of autonomous vehicles when changing lanes. It can be seen that the distribution curve of lateral acceleration is shown in Figure 15 under the condition of obstacle avoidance and lane change. The mean value of the lateral acceleration is 3.14 $m/s^2$ with a standard deviation of 0.65, a maximum of 3.60 $m/s^2$, and a minimum of 2.00 $m/s^2$.

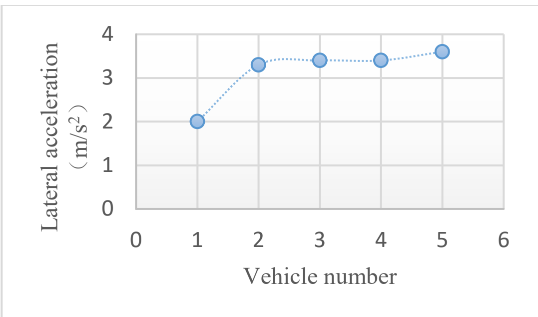


**Figure 15 - Distribution curve of Lateral acceleration**

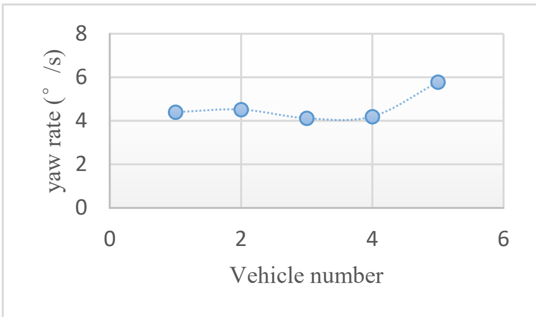


**Figure 16 - Distribution curve of yaw rate**

***Yaw Rate***

Yaw rate is an important parameter of lateral motion during lane changes, which characterizes the stability and handling of autonomous vehicles when changing lanes. The distribution curve of yaw rate is shown in Figure 16 under the condition of obstacle avoidance and lane change. The mean value of yaw rate is 4.60°/s, the standard deviation is 0.68, the maximum is 5.78°/s, and the minimum is 4.12°/s.

***Detour Distance***

The detour distance refers to the longitudinal distance from the obstacle when the autonomous vehicle starts to change lanes, which can effectively reflect the urgency of the autonomous vehicle when avoiding obstacles. The distribution curve of the detour distance is shown in Figure 17 under the condition of obstacle avoidance and lane change. The mean detour distance is 50.26m, the standard deviation is 5.20, the maximum is 58.34m, and the minimum is 44.68m.

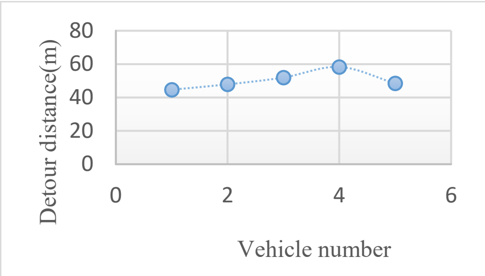


**Figure 17 - Distribution curve of detour distance**

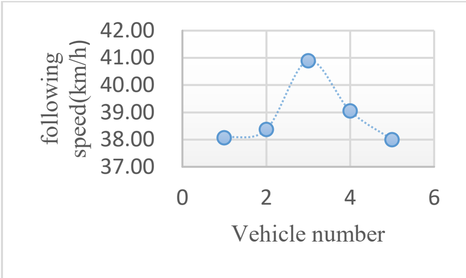


**Figure 18 - Distribution curve of following speed**

### 4.2 Analysis of the Following Behavior Characteristics

***Following Speed***

Following speed reflects the speed stability of an autonomous vehicle during the following process[11]. When the target vehicle travels at a constant speed of 40km/h and cuts in, the heavy-duty truck slows down and steadily follows the target vehicle. In the steady following state, the distribution curve of the following speed is shown in Figure 18. The average value of the steady following speed is 38.88 km/h, the standard deviation is 1.2, the maximum value is 40.9 km/h, and the minimum value is 38.00 km/h.

Stabilizing the following speed difference during the following process can intuitively reflect the following speed accuracy of the autonomous vehicle. In the steady following state, the distribution curve of the following speed difference is shown in Figure 19. After analysis, the average value of the following speed difference is -0.84 km/h, the standard deviation is 1.37, the maximum value is 1.50 km/h, and the minimum value is -1.83 km/h.

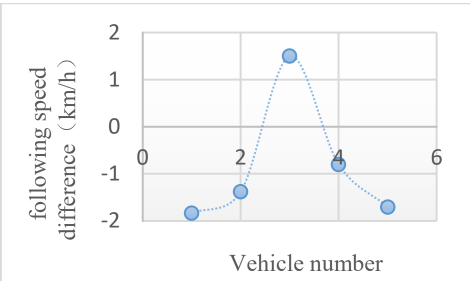


**Figure 19 - Distribution curve of following speed difference**

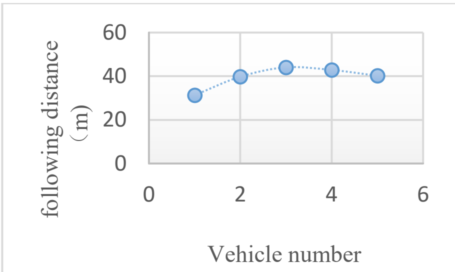


**Figure 20 - Distribution curve of following distance**

***Following Distance***

The following distance is the safe distance maintained by the autonomous vehicle according to the driving strategy during the stable following process. The distribution of the following distance is shown in Figure 20 in the stable following state. After analysis, the average following distance is 39.65m, the standard deviation is 4.99, the maximum is 44.06m, and the minimum is 31.31m.

***Following Deceleration***

Following deceleration is a characteristic indicator of deceleration generated by the deceleration of an autonomous vehicle when it encounters the vehicle in front, which can effectively reflect the driving strategy of the vehicle when the vehicle in front of it cuts in. In the stable following state, the distribution of the following distance is shown in Figure 21. After analysis, the average value of following deceleration is 2.92 m/s$^2$, the standard deviation is 1.65, the maximum value is 5.50 m/s$^2$, and the minimum value is 1.10 m/s$^2$.

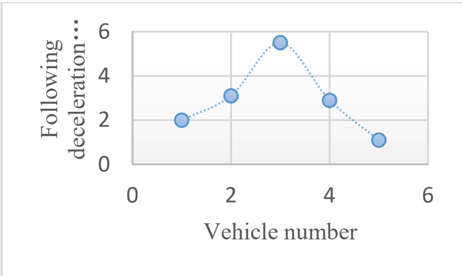


**Figure 21 - Distribution curve of following deceleration**

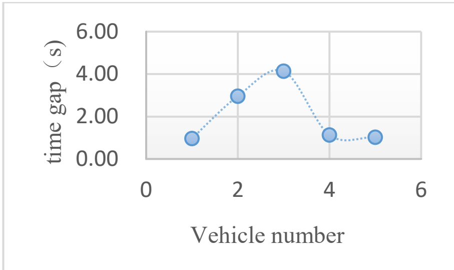


**Figure 22 - Distribution curve of time gap**

***Time Gap***

The time gap refers to the time interval required for the vehicle distance between the vehicle that the vehicle passes through the continuous vehicle, that is, the time interval between the rear vehicle and the target vehicle in the process of following [12]. In the stable following state, the distribution of the time gap is shown in Figure 22. After analysis, the average value of the time gap was 2.05 s, the standard deviation was 1.43, the maximum value was 4.13 s, and the minimum value was 0.97 s.

## 4.3 Analysis of Braking Behavior Characteristics

***Braking Deceleration***

Braking deceleration refers to the rate of change in the speed during braking, which can effectively characterize the safety strategy of the vehicle during emergency braking of the target vehicle. In the case of emergency braking, the braking deceleration distribution curve is shown in Figure 23. After analysis, the average value of braking deceleration is 5.90 m/s$^2$, the standard deviation is 0.07, the maximum value is 6.00 m/s$^2$, and the minimum value is 5.84 m/s$^2$.

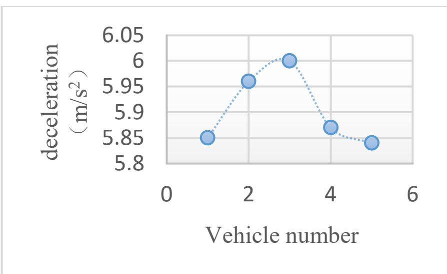


**Figure 23 - Distribution curve of**

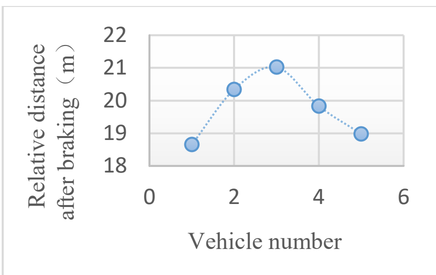


**Figure 24 - Distribution curve**

**braking deceleration** **of relative vehicle distance after braking**

***Relative Distance after Braking***

The relative distance after braking means the relative longitudinal distance between the vehicles after emergency braking, which can intuitively reflect the safety obstacle avoidance effect of the autonomous vehicle. In the emergency braking state, the relative distance distribution curve after braking is shown in Figure 24. After analysis, the average relative distance is 19.76m, the standard deviation is 0.97, the maximum value is 21.02m, and the minimum value is 18.65m.

***Reaction Time***

Reaction time refers to the time it takes for an autonomous vehicle to start emergency braking after detecting emergency braking from the vehicle in front of it. This indicator can effectively characterize the responsiveness of autonomous vehicles in emergency situations. In the case of emergency braking, the reaction time distribution curve is shown in Figure 25. After analysis, the mean reaction time was 1.15 s, the standard deviation was 0.06, the maximum was 1.21 s, and the minimum was 1.05. The reaction time here includes the braking coordination time of the vehicle's braking structure.

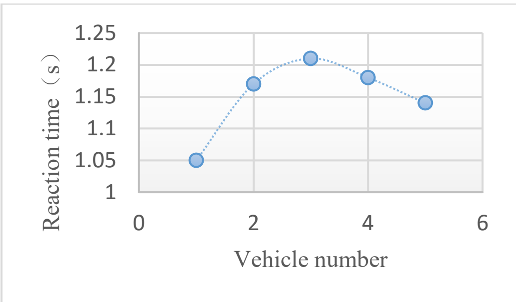


**Figure 25 - Reaction time distribution curve**

## 5. Correlation between qualitative and quantitative indicators

In order to further study the correlation between qualitative and quantitative indicators, the entropy method was used to determine the weight coefficient of quantitative indicators, and the influence of quantitative and qualitative indicators was indirectly reflected through the weight coefficients, and the evaluation system of autonomous driving function of intelligent networked heavy-duty trucks could be preliminarily established, so as to realize the accurate analysis and evaluation of the safety and efficiency of autonomous driving behavior.

### 5.1 Introduction to the entropy method

The entropy method was used to determine the weight coefficient between qualitative and quantitative indicators. The basic idea of the entropy method is that the larger the amount of information in the system, the smaller the uncertainty, the smaller the entropy, and the greater the weight. The smaller the amount of information, the greater the uncertainty, the greater the entropy, and the smaller the weight [13]. There are m schemes to be evaluated, n evaluation indicators, and the original index data matrix is formed $X = (X_{ij})_{m\times n}$，$0 \le i \le m$，$0 \le j \le n$. For the jth indicator, the larger the difference between the index values $X_{ij}$, the greater the role of the indicator in the comprehensive evaluation. If all the values of an indicator are equal, the indicator does not work in the overall evaluation.

### 5.2 Entropy and weights of qualitative and quantitative indicators

Based on the experimental data, the hierarchical structure model was established according to the entropy method analysis method, and the weight, entropy and difference coefficient of the ith scheme index value under the jth index were calculated, and the weight coefficient was finally calculated, as shown in Table 3.

**Table 3 - Entropy value, difference coefficient and weight of quantitative evaluation indexes of autonomous driving capability of heavy-duty trucks**

| Nom. | Target layer | Criterion layer | Scenario layer | Entropy | Coefficient of variability | weight |
|---|---|---|---|---|---|---|
| 1 | Autonomous driving capabilities for heavy-duty trucks | Lane Change Behavior / Following Behavior / Braking Behavior（Do not collide with the target） | Lateral acceleration（$m/s^2$） | 0.9883 | 0.0117 | 0.0488 |
| 2 | | | Yaw rate（°/s） | 0.9949 | 0.0051 | 0.0213 |
| 3 | | | Detour distance（m） | 0.9974 | 0.0026 | 0.0110 |
| 4 | | | Following speed（km/h） | 0.9791 | 0.0209 | 0.0876 |
| 5 | | | Following speed difference（km/h） | 0.9998 | 0.0002 | 0.0010 |
| 6 | | | Following distance（m） | 0.9959 | 0.0041 | 0.0172 |
| 7 | | | Following deceleration（$m/s^2$） | 0.9227 | 0.0773 | 0.3235 |
| 8 | | | Time gap（s） | 0.8843 | 0.1157 | 0.4839 |
| 9 | | | Braking deceleration（$m/s^2$） | 1.0000 | 0.0000 | 0.0002 |
| 10 | | | Relative distance after braking（m） | 0.9994 | 0.0006 | 0.0025 |
| 11 | | | Reaction time（s） | 0.9993 | 0.0007 | 0.0030 |

### 5.3 Analysis of results

As can be seen from Table 3, the established quantitative indicators can reflect the autonomous driving capability of heavy-duty trucks to a certain extent. From the perspective of the influence of indicators, the following time distance and following deceleration have the greatest impact on the autonomous driving ability of heavy trucks, while the influence of other indicators is small. The main reason for the above phenomenon is that qualitative indicators only focus on whether there is a collision with the target (target car, pedestrian, motorcycle, etc.), so the following time distance and following deceleration can most intuitively reflect the potential collision risk (near miss).

## 6. Conclusions And Recommendations

### 6.1 Conclusions

The main conclusions of the study are as follows:

1) A set of qualitative evaluation and quantitative evaluation and transformation system for closed field test of autonomous driving of heavy-duty trucks was established, including 13 scenarios and 14 qualitative and quantitative evaluation indicators.

2) In the case of lane change, the autonomous driving strategy of heavy-duty trucks can be quantitatively evaluated by lateral acceleration, yaw rate and detour distance, in which the threshold range of lateral acceleration is [2,3.6]m/s$^2$, the threshold range of yaw rate is [4.12,5.78]°/s, and the threshold range of detour distance is [44.68,58.34]m.

3) In the following condition, the autonomous driving strategy of heavy-duty trucks can be quantitatively evaluated by following speed, following speed difference, following distance, following deceleration and time gap, in which the threshold range of following speed is [38.00, 40.90] km/h, the threshold range of following speed difference is [-1.83, 1.50] km/h, the threshold range of following distance is [31.31, 44.06] m, and the threshold range of following deceleration is [1.10, 5.50] m/ s$^2$, the threshold range of the time gap is [0.97, 4.13]s.

4) Under the emergency braking condition, the autonomous driving strategy of heavy-duty trucks can be used through braking deceleration, relative distance after braking, and reaction time, where the threshold range of braking deceleration is [5.84, 6.00]m/s$^2$, the threshold range of relative distance after braking is [18.65, 21.02]m, and the threshold range of reaction time is [1.05, 1.21]s.

5) The following time distance and following deceleration have the greatest impact on the autonomous driving ability of heavy-duty trucks, while other indicators have less impact.

### 6.2 Recommendations

The research results of this paper provide support for the extraction of key parameters of autonomous driving, test scheme and data analysis for the quantitative evaluation of intelligent networked heavy-duty trucks, which provide strong support for the closed field test of autonomous driving. However, there are still some limitations in this paper, which are mainly reflected in:

1) In the research process of qualitative evaluation and quantitative evaluation transformation system of closed-field test of autonomous driving of heavy-duty trucks, the quantitative evaluation index is extracted only based on expert knowledge, which is deeply affected by expert experience and has great subjectivity. It is suggested that the mathematical model should be further added to the research process of qualitative and quantitative system transformation in the future, so as to improve the objectivity of the transformation system.

2) The research object of this paper is limited to the lane change, following and emergency braking behaviors of heavy-duty trucks, and the data sample size is small, which cannot fully reflect the threshold of quantitative evaluation indicators for autonomous driving of intelligent networked heavy-duty trucks.

3) In the future, when revising GB/T 41798-2022, relevant indicators of near miss events should be introduced in the qualitative evaluation. Studies have shown that near-miss is very similar to the mechanism of accidents and is a prerequisite for the occurrence of accidents, so

in-depth research on near-miss is of great significance to reduce the occurrence of accidents [14].

4) In terms of relevance, the interaction between quantitative and qualitative indicators should be discussed in more detail, and the correlation between quantitative and qualitative indicators should be further fully studied.

5) This paper determines the weight of quantitative evaluation indicators, and suggests that a scientific evaluation system for autonomous driving functions of intelligent networked heavy-duty trucks should be established on this basis in the future, so as to achieve accurate analysis and evaluation of the safety and efficiency of autonomous driving behavior.

## 7. References

[1] Chen Guilin. (2010), Uncertain model of qualitative/ quantitative information transformation-cloud model[J]. Application Research of Computers, 27(6): 2006-2010.
[2] Dai Ruwei. (1990), The formation and modern development of the integrated method from qualitative to quantitative[J]. Chinese Journal of Nature, 31(6):311-326.
[3] Li Deyi, Meng Haijun, Shi Xuemei. (1995), Subordinate cloud and subordinate cloud generator[J].Computer Research and Development, 32(6):15-20.
[4] Lv Huijun, Wang Ye, Li Deyi, et al. (2003), Application of reverse cloud in qualitative evaluation[J].Chinese Journal of Computers, 26(8):1009-1014.
[5]Chen Zhonglin, Weng Ji, Hu Yingkui. (2006), Study of transform between qualitative analysis and quantitative analysis in lighting engineering. Journal of Chongqing Jianzhu University, 28（4）:1-3.
[6]Li Xin. ( 2009), Research of the theory and application of fuzzy theory and chart expression principle qualitative and quantitative transformation[D]. Yanshan University.
[7]Lin Yongxin, Chen Yushu, Wang Dan. (2013), New approach to the correlation measurement for subsystems in a complex giant system[J]. Applied Mathematics and Mechanics, 34（9）,917-928.
[8] Wang Pei, Zhang Jiefei. (2023), Quantitative analysis of comprehensive intelligent evaluation for autonomous vehicles[J]. Internal Combustion Engines & Accessories, (10):29-31.
[9] National Automotive Standardization Technical Committee. (2022), Field test methods and requirements for autonomous driving functions of intelligent networked vehicles: GB/T 41798-2022[S]. Beijing: Standards Press of China, 1-28.
[10] Wang Chunzhi, Si Qin. (2011), A study of data statistical processing method of Delphi method and its application[J]. Journal of Inner Mongolia University of Finance and Economics (Comprehensive Edition), 9(4):92-96.
[11] Yu Peng, Ren Guichao, Lin Qiang. (2023), An evaluation model of autonomous vehicle car-following intelligence based on expressway natural driving data[J]. Transport Research, 9(6):44-54.
[12] National Technical Committee for Standardization of Intelligent Transportation Systems. (2006), Intelligent transportation system adaptive cruise control performance requirements and testing methods: GB/T 20608-2006[S].Beijing: China Standards Press, 1-19.
[13] Xian Yanling, Liu Xiaojing, Liu Jian-bo. (2005), The Method of Giving Weight for Performance Indicator Based on Entropy Method[J]. Journal of Daqing Petroleum Institute,29(1):107-109,127.
[14] Zhang Yuming, Tang Yanjuan, Du Haibo, et. (2022), Visual analysis on evolution path and development frontiers of Near-miss underknowledge map[J]. Journal of Safety Science and Technology,18(7).