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DOI
10.1016/j.physa.2024.129498

Publication date
2024

Document Version
Final published version

Published in
Physica A: Statistical Mechanics and its Applications

Physica A 635 (2024) 129498

Contents lists available at ScienceDirect

Physica A: Statistical Mechanics and its Applications

journal homepage: www.elsevier.com/locate/physa

Development and experiment of an intelligent connected cooperative vehicle infrastructure system based on multiple V2I modes and BWM-IGR method

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ARTICLE INFO

Key words:
Intelligent connected cooperative vehicle infrastructure system
Abnormal data recognition
Effectiveness testing
Comprehensive evaluation

ABSTRACT

To increase the efficiency and safety of expressway, this paper constructed a new intelligent connected cooperative vehicle infrastructure system and its effectiveness was verifid from both data and practical applications. Firstly, considering the convenience of using intelligent networking systems for public transportation, a new intelligent connected cooperative vehicle infrastructure system architecture was proposed by incorporating mobile communication methods. Then, the new system was illustrated from road side unit (RSU), on board unit (OBU) and data interaction. Additionally, to verify the effectiveness of the system, this paper proposes a two-stage model named Transformer Embedded Clustering- Hierarchical Density-Based Spatial Clustering of Applications with Noise (TEC-HDBSCAN) model to identify outliers in the trajectory data of vehicles collected by the system and obtain the speed sequence of the vehicle. Finally, data from actual testing scenarios was collected and a Best Worst Method-Improved Gray Relational (BWM-IGR) model was built to verify the effectiveness of the system. The results show that the established intelligent networked transportation system can effectively guide vehicles and collect data with high accuracy.

1. Introduction

In recent years, China has experienced a rapid increase in urbanization, leading to a surge in the number of vehicles. This has resulted in mounting pressure on urban transportation systems [1]. As we step into the information age and witness advancements in science and technology, the idea of utilizing advanced technology to revamp existing road traffic and management systems has gained significant attention. This transformation aims to substantially enhance the capacity and service quality of transportation networks. Connected automated vehicles (CAVs) [2], cooperative vehicle infrastructure systems and other intelligent connected transportation systems have emerged as promising solutions to boost traffic efficiency and safety [3]. These technologies provide new approaches to address the current transportation challenges. However, it's crucial to note that the effectiveness and precision of the data they rely on can profoundly influence both vehicle operations and overall traffic flow [4]. Hence, a comprehensive evaluation of the effectiveness of intelligent connected cooperative vehicle infrastructure system holds great theoretical and practical significance.

With the rise and development of technologies such as AI and the Internet of Things (IoT), an increasing number of cities have

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https://doi.org/10.1016/j.physa.2024.129498
Received 27 September 2023; Received in revised form 14 November 2023; Accepted 3 January 2024
Available online 6 January 2024
0378-4371/

begun to explore the establishment of intelligent transportation systems. This trend is particularly emphasized in many advanced countries such as the United States, Japan, and the European Union, a where it's regarded as an effective means to enhance road reliability, safety, and reduce environmental pollution. However, intelligent connected transportation systems in various Chinese cities currently face challenges, including issues related to low data collection accuracy, susceptibility to environmental interference, limited real-time communication with users, and uncertain system evaluation methods.窗体顶端.

Therefore, in this paper, we focus on the development of a new intelligent connected cooperative vehicle infrastructure system and the assessment algorithms. A crucial element in establishing such an intelligent connected system involves the smart transformation of existing roadside infrastructure to enhance data accuracy and real-time perception of highway traffic conditions. This transformation enables the timely dissemination of effective guidance information to travelers, ultimately enhancing residents' satisfaction with their travel experiences.

As a result, the innovative intelligent connected system developed in this paper enhances the existing high-latency roadside data collection infrastructure. This is achieved through roadside units or base stations that employ DSRC/LTE or similar technologies for interacting with onboard vehicle units. By doing so, it streamlines the collection of road vehicle data while minimizing data transmission latency. Furthermore, the road management center utilizes 4 G/5 G networks to communicate with travelers' mobile devices, providing them with more timely and precise guidance messages.

Another issue is how to evaluate the effectiveness of the intelligent transportation system once it is established. Most existing research predominantly relies on subjective methods to assess the overall performance of the system, which can be somewhat one-sided and may overlook the impact of objective data. This paper delineates the system validation into two aspects: data validity and system utility. In assessing data validity, to accommodate the variations in driving styles among different drivers, a two-stage clustering model is proposed. It initially classifies drivers based on their styles and then, for different driver categories, identifies outliers in vehicle trajectories while utilizing smoothing algorithms to present these trajectories effectively.

As for the evaluation of system utility, this paper combines subjective and objective methods to determine the weightage of various indicators, considering factors such as traffic efficiency, safety, and environmental impact. These assessments result in a comprehensive evaluation of the system. The main contribution of this paper can be summarized as follows:

(1) A novel intelligent connected cooperative vehicle infrastructure system was constructed.

(2) A two-stage clustering method for abnormal data detection named Transformer Embedded Clustering- Hierarchical Density-Based Spatial Clustering of Applications with Noise (TEC-HDBSCAN) was proposed.

(3) A system effectiveness evaluation method named Best Worst Method-Improved Gray Relational (BWM-IGR) model was built.

2. Literature review

The evaluation methods for intelligent transportation systems (ITS) can be categorized into two aspects: subjective judgment-based methods and data-driven methods.

Subjective judgment-based methods have been used earlier, capable of reflecting people's opinions within the sampling scope, with relatively low data requirements. However, it's challenging to achieve consensus among individuals, resulting in lower persuasiveness of the outcomes. Lo et al. [5] proposed an evaluation framework for cooperative vehicle infrastructure systems from three aspects: system architecture, operating environment, and their impact on the traffic system. Wei et al. [6] utilizing the Analytic Hierarchy Process (AHP) and Gray Relational Analysis Process (GRAP), presented the AHP-GRAP model, considering technical feasibility, economic benefits, and social advantages. Peng and Beimbomn [7] assessed intelligent transportation systems using a benefit tree and a novel evaluation approach. They identified key variables in the evaluation of intelligent transportation projects, facilitating their screening, ranking, and selection. Longo et al. [8] applied multi-objective analysis to analyze the application effectiveness of intelligent transportation systems. Mattingly et al. [9] employed an integrated multi-objective-multi-attribute evaluation method to assess the SCOOT traffic control system in Anaheim, California. Levine and Underwood [10] evaluated the traffic planning objectives of FAST-TRAC using the Analytic Hierarchy Process, determining the weights for each traffic objective.

In recent years, there has been a vast accumulation of traffic data, and the development of deep learning has propelled the advancement of intelligent transportation. The use of machine learning models in the field of transportation has become increasingly common [11]. Such methods are capable of fully exploiting the spatiotemporal correlations among data but typically require a substantial amount of data for model training. Du et al. [12] proposed a lifelong framework for roadside sensor data quality detection based on the Longest Common Subsequence Considering Time and Relative Position Sequences (LCSS-TRPS). This framework matched the perception data of Connected Automated Vehicles (CAVs) with roadside-collected data and was verified for performance and feasibility through Prescan and experiments at the Donghai Bridge. Zhao et al. [13] analyzed the positioning accuracy of roadside millimeter-wave radar, considering the impact of both the radar itself and vehicle attitudes. Wang et al. [14] used a probabilistic graphical model to assess the trustworthiness of sensor nodes based on collected data and communication behaviors. They also scheduled nodes to reduce mobility distances. Zhang et al. [15] introduced a software-defined trust-based VANET architecture and used deep Q-learning methods to obtain optimal communication link strategies. They modeled the joint optimization problem of trust levels and reverse delivery rates for vehicles using Markov Decision Processes and ultimately solved it with machine learning techniques. Wang et al. [16] first transformed the credit evaluation problem into an optimization problem and proposed a heuristic mobility strategy. This strategy utilizes the maximum neighbor-to-vehicle ratio for scheduling vehicles, thereby enhancing the efficiency of trust assessment.

In conclusion, the current research on intelligent connected transportation systems has the following shortcomings: Firstly, concerning evaluation methods, subjective approaches lack strong persuasiveness, while data-driven methods often rely on comparing data collected from vehicle-road cooperative systems with data from other sources to validate data collection, requiring a substantial amount of data. Additionally, in terms of testing and verification of vehicle-road cooperative systems, simulation-based methods are commonly employed. While simulation environments are relatively ideal, they may deviate to some extent from real-world applications.

In this paper, a novel intelligent connected transportation system was constructed. To validate the effectiveness of the collected data, an assessment of communication latency was conducted. Additionally, a tow stage model for abnormal data detection named TEC-HDBSCAN was proposed to identify outliers in vehicle trajectory data, enabling an assessment of the accuracy of the system's data. According to this foundation, an evaluation of the impact of the intelligent connected transportation system was carried out in response to two experiments, Decentralized Environmental Notification Message (DENM) and In-Vehicle Infotainment (IVI). Through practical experiments, the effectiveness of the system was verified by BWM-IGR model and it has been demonstrated that this system can significantly enhance the safety and efficiency of vehicle operations.

3. Construction of the intelligent connected cooperative vehicle infrastructure system

3.1. Overall architecture

The previously established intelligent transportation system primarily centered on communication between roadside facilities and on-board units[17]. However, it's important to note that not all vehicles are currently equipped with OBUs. To fully leverage the benefits of intelligent transportation systems, enhance road capacity, and boost safety, this paper introduces a new intelligent connected cooperative vehicle infrastructure system. The overall architecture is depicted in Fig. 1, featuring roadside units, intelligent on-board units, the Road Management Center - Data Exchange Center, smartphones, and traffic incident detection facilities.

The information exchange of the system is orchestrated through the central services, which delivers traffic control information to onboard applications and drivers in the form of alerts and messages.

The RSU (Roadside Unit) as part of the roadside equipment for vehicle-road collaboration, and the OBU (On-Board Unit) within the vehicle-road collaboration vehicle terminal system, serve as the foundational hardware components for vehicle-road collaboration. They establish a low-latency C-ITS (Cooperative Intelligent Transport Systems) information exchange via the appropriate communication protocol stack, and relay it to the central services for coordination.

The original roadside collection system includes roadside monitors and coils, as well as microwave detection and control systems. These facilities detect traffic status and events, and transmit information to the central service platform, which has high transmission delay. In order to real-time grasp information such as unexpected situations on highways, the central services in this paper also interacts with roadside units or base stations, and road management centers, which have low latency, able to publish and implement traffic measures, warnings, and information more quickly. It is worth noting that the roadside unit can interact with the vehicle unit through technologies such as DSRC/LTE, and the road management center can transmit information to the driver's smartphone based on 4 G/5 G. The vehicle unit can also correspond to the user's smartphone, thus achieving more efficient road control.

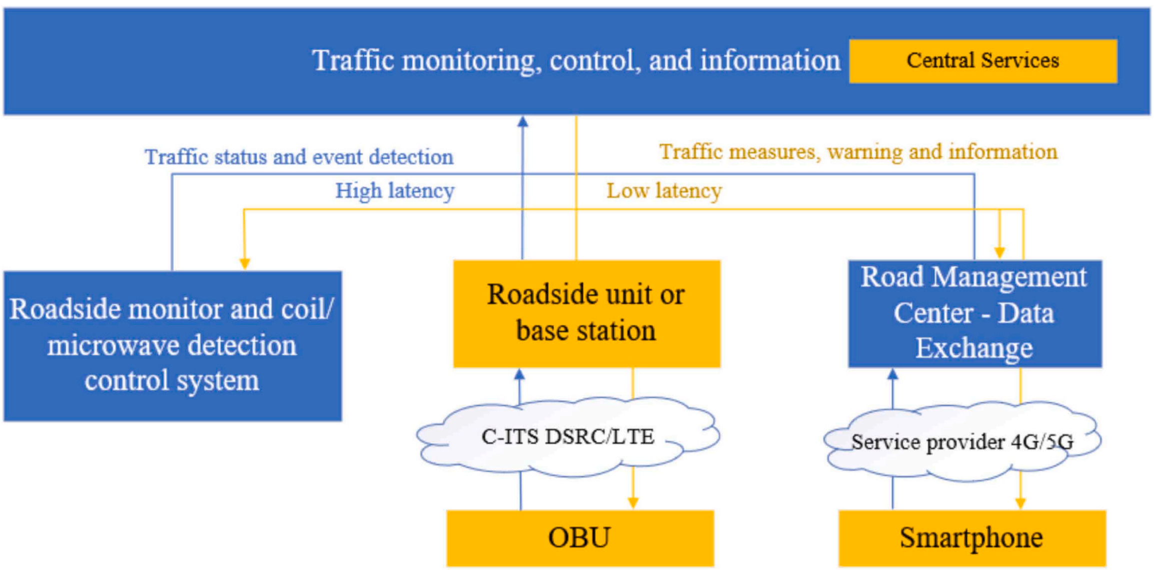

Fig. 1. The technical architecture for the intelligent connected cooperative vehicle infrastructure system.

3.2. Intelligent RSU

Intelligent RSUs primarily handle tasks such as gathering and processing road traffic data, along with sharing traffic management information. They acquire data related to traffic conditions (including vehicles, non-motorized vehicles, pedestrians, etc.), road conditions, and traffic signal control status through the roadside information subsystem. Leveraging the capabilities of the roadside communication subsystem and traffic control and information distribution subsystem, these RSUs communicate driving plans to drivers, thus aiding them in making informed decisions.

3.3. Intelligent OBU

The intelligent OBU (On-Board Unit) serves as a critical interface for human-vehicle interaction. OBUs employ sensors within the onboard information subsystem to gather data regarding vehicle movements and the surrounding environment. After processing this information, they relay the results to the driver for decision-making through the on-board communication subsystem and on-board control subsystem. Furthermore, the onboard system can offer path guidance and collision avoidance features from a vehicle operation perspective.

3.4. Information interaction

3.4.1. Data fusion technology

Data fusion technology facilitates telecommunications and information interaction across various sources, making use of diverse infrastructure such as highways, vehicles, mobile phones, and various communication methods. It enables robust data storage capabilities, intricate task computation and processing, along with seamless cross-layer data interactions, ensuring efficient and high-speed information transmission.

3.4.2. Edge-cloud information computing technology

The expressway makes use of cloud-edge computing technology, harnessing a network of edge computing nodes, including various vehicles and roadside components, such as multiple types of video systems, event monitoring tools, information systems, computing terminals, and sensors. This setup shifts the computational workload from the cloud to the edge layer, where the majority of calculations take place at Edge Computing Nodes (ECN). Using transmission methods like LTE-V/5 G RSU, the results are transmitted in real-time to the On-Board Unit (OBU) in vehicles, effectively meeting the ultra-low latency requirements of vehicle-road collaboration. The key system components are visually represented in Fig. 2.

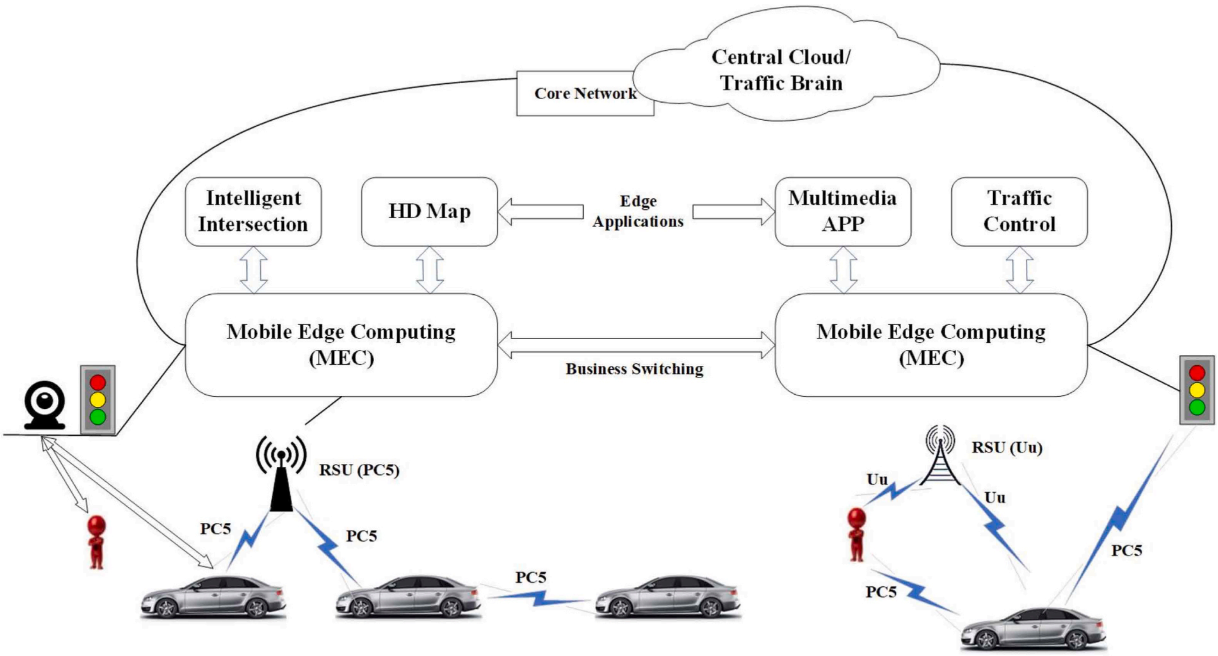

Fig. 2. Overview of Edge Computing and Edge-Cloud Collaboration in V2X Communication.

4. Data collection and analysis

4.1. Data collection

To valid the new intelligent connected cooperative vehicle infrastructure system proposed in the paper, an experiment was conducted on Xinyuan Expressway. During the experiment, the system interacted with intelligent connected vehicles through devices such as RSU and OBU, and collected vehicle trajectory data (log data). The format of log data is specified in the log data format. Log files are uploaded from the central services to the RSU server and can be automatically uploaded during test runs and at the end of test runs. Additionally, log data can be manually uploaded by clicking the upload option. All recorded data is stored on the RSU server.

Log data is processed by the Automatic Data Analysis (ADA) service, and the results are sent back to the RSU server. Currently, the ADA service is manually triggered and verifies if there are any issues during test execution. Once the test runs smoothly, this process can be automated and results returned shortly after the test run on the RSU server.

4.2. Evaluation methods

This paper evaluates the data collected by the cooperative vehicle infrastructure system from two perspectives: statistics and clustering. From a statistical perspective, the evaluation is based on the delay in receiving messages sent by RSUs collected by equipped OBUs vehicles, as well as the vehicle speed obtained through changes in location. It is expressed as follows

$$t_{total} = t_{send} + t_{spread} + t_{queue} + t_{process} \tag{1}$$

Where, t_{total} represents the total time delay of the system; t_{send} represents the transmission delay; t_{spread} represents the propagation delay; t_{queue} represents the queuing delay of the system; $t_{process}$ is the processing delay.

$$t_{send} = \frac{l_{data}}{r_{trans}} \tag{2}$$

$$t_{spread} = \frac{l_{channel}}{v_{spread}} \tag{3}$$

Where, r_{trans} represents the transmission rate; l_{data} is the length of data; $l_{channel}$ is the length of channel; v_{spread} represents the propagation rate of electromagnetic waves on the channel.

$$v_{loc}^{n} = \frac{x_n - x_{n-1}}{\Delta t} \tag{4}$$

Where, v_{loc}^{n} represents the speed of vehicles computed by position difference; x_n is the position of the vehicle at time n; Δt represents the time gap.

In the context of recognizing abnormal data patterns, variations in driving speed, acceleration, and other driver-related metrics are observed across different driving styles [18]. These distinctions give rise to significant disparities in the identification of abnormal values within vehicle driving trajectories, as compared to other types of time series data. Consequently, this study presents a two-stage clustering framework. In the initial stage, statistical metrics pertaining to vehicle trajectories, including average speed, average acceleration, and average deceleration, are employed to categorize drivers into conservative, conventional, and aggressive types [19]. Conservative drivers tend to exhibit lower vehicle speeds, acceleration, and deceleration, resulting in smoother driving trajectories. Conventional drivers typically fall within a moderate range for these indicators. On the other hand, radical drivers tend to have higher speeds and more pronounced acceleration and deceleration patterns. In the subsequent stage, the driver's vehicle category is determined, followed by a detailed trajectory data analysis within the same category. This analysis involves clustering vehicle speed at previous time points, current time, and speed change, enabling the assessment of whether the data falls within the appropriate range.

The primary objective of the initial clustering stage is to delineate distinct driving styles among drivers as comprehensively as possible. This entails grouping vehicle trajectories that exhibit marginal disparities in terms of speed, acceleration, and other pertinent data into a single category. This approach helps circumvent the inadvertent identification of trajectories with elevated speed or acceleration as outliers during the direct clustering phase. Consequently, this study adopts a deep clustering methodology [20] and introduces the Transformer Embedded Clustering (TEC) model to facilitate this process. Given the relatively uniform data volumes across various trajectory types, the model prioritizes data feature extraction followed by classification. Specifically, our research establishes a representation learning model founded on the Transformer architecture and subsequently integrates it with K-means clustering [21] to formulate a comprehensive clustering model.

Since its inception, the Transformer architecture has found extensive applications across various domains, including time series analysis, image recognition, and natural language processing[22]. Notably, it has demonstrated robust feature extraction capabilities [23]. Its calculation formula is as follows:

$$Att\left(Q, K, V\right) = \sigma\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{5}$$

$$h_i = Att\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{6}$$

$$M(Q, K, V) = concat(h_1, h_2, ., h_n)W^o \tag{7}$$

Where, σ represents sigmoid activation function, Q, K and V represent the query, key and value vectors of input features; W^o, W_i^Q, W_i^K and W_i^V are weight matrix.

The projection is a parameter matrix, and the dimension satisfies the following equation:

$$W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_Q} \tag{8}$$

$$W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k} \tag{9}$$

$$W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_V} \tag{10}$$

$$W_i^O \in \mathbb{R}^{d_{\text{model}} \times hd_v} \tag{11}$$

After using Transformer for feature extraction, the extracted deep features are clustered using Kmeans, and the principle is as follows:

$$J\left(c^{(1)}, ., c^{(m)}, \mu_1, ., \mu_K\right) = \frac{1}{m}\sum_{i=1}^{m}\left\|x^{(i)} - \mu_{c^{(i)}}\right\| \tag{12}$$

Where, $c^{(i)}$indicates the cluster center which the $i-th$ sample belongs to. μ_i represents the $i-th$ cluster center. $x^{(i)}$ is the $i-th$ sample.

It can be concluded that the loss function of the algorithm is:

$$\min e_{c^{(1)},.,c^{(m)},\mu_1,.,\mu_K} J\left(c^{(1)}, ., c^{(m)}, \mu_1, ., \mu_K\right) \tag{13}$$

Due to the significant difference in the amount of abnormal data and normal data in the vehicle trajectories, conventional clustering algorithms cannot meet the requirements for identifying abnormal data. Therefore, this article uses the HDBSCAN algorithm to identify the abnormal values of the trajectories. Unlike the conventional DBSCAN[24] algorithm, HDBSCAN[25] defines the distance between two points as follows:

$$d_{mreach-k}(a, b) = \max\left\{core_k(a), core_k(b), \text{distance}(1, b)\right\} \tag{14}$$

$$core_k(x) = d\left(x, N^k(x)\right) \tag{15}$$

Where, $d(x, N^k(x))$ represents Euclidean distance , $core_k(x)$ represents the distance between the current point and the $k-th$ neighboring point, k represents the minimum number of sample points. This measurement method can effectively satisfy the Hartigan consistency condition.

4.3. Evaluation results

By collecting information received from RSUs along the route using equipped OBU vehicles and comparing the signal delays upon reception, as shown in Fig. 3.

It can be observed that the delay in receiving Cooperative Awareness Messages (CAM) sent by RSUs is less than 50 ms.

Additionally, the TEC model proposed in this paper is compared with the Kmeans algorithm, DBSCAN algorithm, and SOM al-

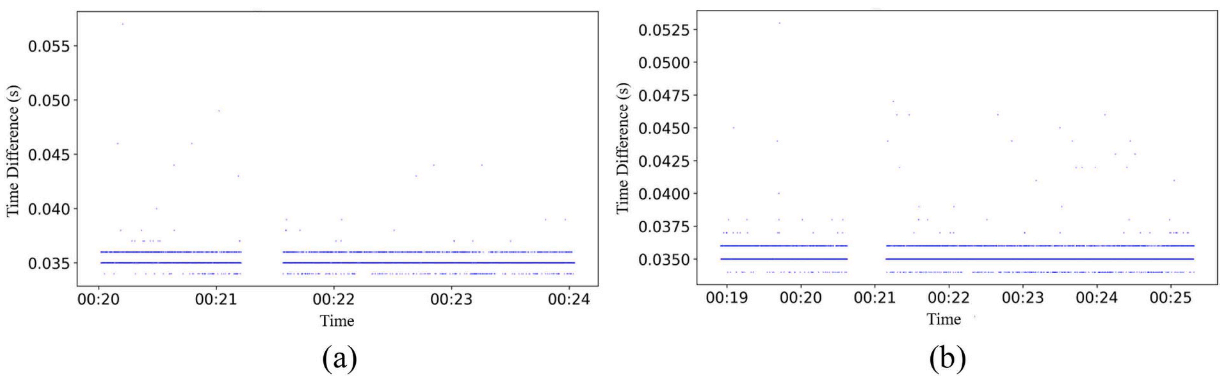

Fig. 3. Delay in Receiving Information of Vehicles: (a) vehicle 1; (b) vehicle2.

gorithm. The contour coefficient, SSE, and CH index are selected for effectiveness evaluation, The calculation formulas for several indicators are as follows :

$$SC = \frac{b_i - a_i}{\max(a_i, b_i)} \tag{16}$$

$$SSE = \sum_{i-1}^{n} (\hat{y}_i - y_i)^2 \tag{17}$$

$$CH = \frac{tr(B_k)m - k}{tr(W_k)k - 1} \tag{18}$$

Where, m is the number of training samples , k is the number of categories , $B_k$is covariance matrix between categories , W_k is the ontra class covariance matrix , tr is the trace of matrix; a_i is the average distance from sample i to other points in the same cluster , b_i is the average distance from sample i to other clusters。 .

The results are shown in the Table 1.

The abnormal value recognition results of the TEC-HDBSCAN model are shown in Fig. 4.

From the figure above, it can be seen that the proposed model can accurately detect outliers. When the speed and acceleration are too high, the data is considered outliers. To address the identified irregular data, this paper employs an approach involving the calculation of the average speed both before and after a particular point of data. This allows for the correction of these anomalies. Furthermore, in an effort to mitigate the influence of equipment irregularities, collection environment factors, and other potential issues, we implement the NDVI Time-Series (HANTS) algorithm to smooth the sequence of speed data, as shown in Fig. 5:

From the figures above, it can be seen that the smoothed curve can accurately reflect the trend of vehicle speed changes. It is worth noting that due to system equipment issues, some of the vehicle trajectories in the figure are lost, and these trajectories are connected with green lines.

5. Experiments of cooperative vehicle infrastructure system

5.1. Analysis of typical scenarios

This paper evaluates the effectiveness of cooperative vehicle infrastructure system in two major event categories: DENM and IVI. DENM events are designed to warn road users about potential hazards ahead. Warnings regarding road safety are conveyed through DENM messages or decentralized environmental notification messages. Broadcast DENMs serve as alerts to nearby or upstream road users to avoid dangers and reduce safety risks. When a vehicle encounters a DENM event, two distinct areas are delineated: The trajectory defines the path that vehicles should follow when approaching the event location, indicated by the green area. The event location marks the starting point of a hazard situation in the driving direction, and the relevant area associated with the hazard situation is represented by the black area with cones.

IVI events, on the other hand, notify road users of traffic measures, particularly dynamic traffic signs and variable information signs. These traffic measures are communicated through IVI or in-vehicle information messages. IVI messages are generated by road operators or road management authorities and are used to inform road users about these traffic measures.

5.2. Typical scenario experiment

If the driver receives a warning of a DENM event on the HMI, the warning is considered positive. If the positive warning is accurate, then it is a valid and genuine warning. For example, if the event is relevant to the driver and the driver receives the warning[26].

IVI events are evaluated similarly to DENM events: When traveling in the opposite direction unrelated to IVI events, no warnings should be issued to the driver. In the direction of IVI events, drivers within the detection area should receive advance warnings as part of C-ITS research and applications. Drivers should be warned at least before reaching the event location. When driving in the relevant area, drivers should already be aware of traffic measures.

In order to fully evaluate the effectiveness of the vehicle road collaborative system, this article uses the BWM-IGR method to evaluate the system from four aspects: efficiency, safety, impact on the environment, and economic and social impact. In terms of efficiency, consider three indicators: average road speed, road capacity, and information transmission delay; In terms of safety, consider three indicators: vehicle acceleration and deceleration times, average headway, and average collision time; In terms of

Table 1
Clustering results of different methods.

	Silhouette Coefficient	SSE	CH
Kmeans	0.996	6290.00	3124.09
HDBSCAN	0.994	4202.51	3300.76
SOM	0.995	11316.73	2975.21
TEC	0.997	3234.36	4616.72

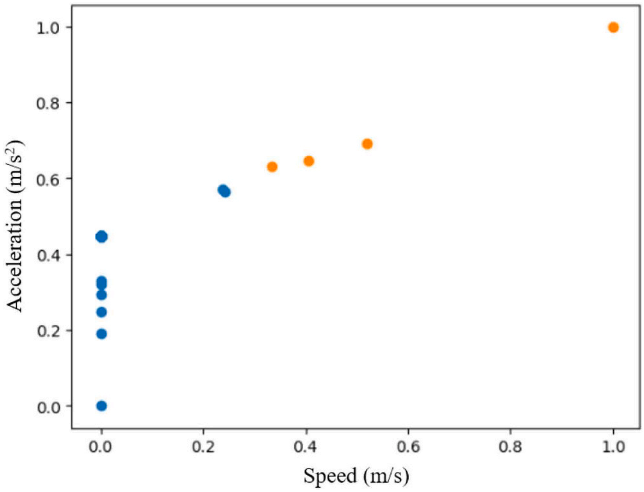

Fig. 4. TEC-HDBSCAN clustering effect.

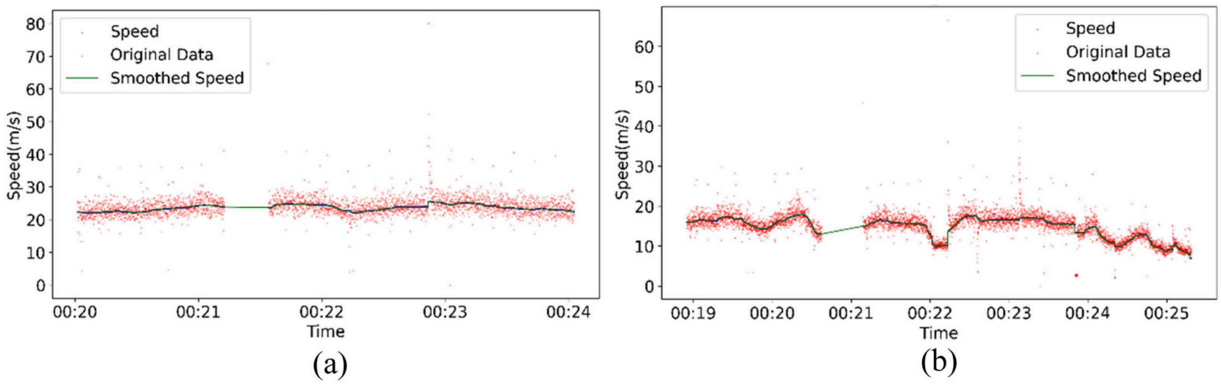

Fig. 5. Display of Vehicle Speed Smoothing Effect: (a) vehicle1; (b) vehicle2.

environmental impact, two indicators are considered: construction cost, carbon dioxide emissions, and noise; In terms of economic and social impact, consider the impact on economic growth and government reputation.

There are generally three methods for determining indicator weights: subjective weight[27], objective weight[28], and combination weight[29]. Subjective weights can reflect people's preferences, but are easily influenced by the environment; Objective weights rely on actual data, but cannot utilize expert experience. Therefore, in the evaluation process of actual vehicle road collaborative systems, subjective and objective weights should be considered. Therefore, this article combines the BWM model[30] and IGR model[31] to assign appropriate weights to each indicator.

The BWM model can use less comparison to obtain consistent results. After determining a set of standards$\{c_1, c_2, ., c_n\}$, experts determine the best and worst standards C_B and C_W, and then use 1–9 to determine the preferences of the best and worst standards relative to other standards $A_B = \{a_{B1}, a_{B2}, ., a_{Bn}\}$, $A_W = \{a_{W1}, a_{W2}, ., a_{Wn}\}$. Among them, $a_{BB} = a_{WW} = 1$, the optimal standard weights $W = \{W_1, W_2, ., W_q\}$are then obtained using the following equation:

$$\min \max \left\{ \left| \frac{W_B}{W_j} - a_{Bj} \right|, \left| \frac{W_j}{W_W} - a_{jW} \right| \right\} \tag{16}$$

$$s.t. \sum_{j=1}^{n} W_j = 1, W_j \geq 0, j = 1, 2, ., n \tag{17}$$

For ease of calculation, it can be transformed into the following linear model:

$$\min \xi \tag{18}$$

$$\left| W_B - a_{Bj} * W_j \right| \leq \xi \tag{19}$$

$$\left|W_j - a_{jW} * W_W\right| \leq \xi \tag{20}$$

$$\sum_{j=1}^{n} W_j = 1 \tag{21}$$

$$W_j \geq 0, j = 1, 2, ., n \tag{22}$$

The IGR model combines the gray correlation method and TOPSIS method, and its calculation process is as follows:

Normalize the initial evaluation matrix $X = (x_{ij})_{n*m}$ to obtain the norm matrix $R = (r_{ij})_{n*m}$, and then calculate the positive and negative ideal alternatives for the alternative solutions:

$$\begin{cases} V_j^+ = \max(r_{ij}) \\ V_j^- = \min(r_{ij}) \end{cases} \tag{23}$$

Next, calculate the gray relationship coefficient between the $i-th$alternative solution and the positive ideal solution regarding the $j-th$ indicator.

$$\zeta_{ij}^+ = \frac{N + \rho M}{d_{ij}^+ + \rho M}, \rho \in \left(0, 1\right) \tag{24}$$

Where, $N = \min_i \min_j d_{ij}^+, M = \max_i \max_j d_{ij}^+, d_{ij}^+ = d(x_{ij}, V_j^+) = \left|x_{ij} - V_j^+\right|$.

Calculate the gray relationship coefficient between the $i-th$ alternative solution and the negative ideal solution regarding the $j-th$ indicator

$$\zeta_{ij}^- = \frac{N + \rho M}{d_{ij}^- + \rho M}, \rho \in \left(0, 1\right) \tag{25}$$

Where, $N = \min_i \min_j d_{ij}^-, M = \max_i \max_j d_{ij}^-, d_{ij}^- = d(x_{ij}, V_j^-) = \left|x_{ij} - V_j^-\right|$.

The comprehensive approximation between the alternative solution and the ideal solution is:

$$G_i(W_j) = \sum_{j=1}^{n} \frac{\zeta_{ij}^+}{\zeta_{ij}^+ + \zeta_{ij}^-} W_j \left(i = 1, 2, ., m\right) \tag{26}$$

Introducing the Lagrange operator, the normalized weight is obtained as:

$$W_j^{IGL} = \frac{\sum_{i=1}^{m} \frac{\zeta_{ij}^+}{\zeta_{ij}^+ + \zeta_{ij}^-}}{\sum_{i=1}^{m} \sum_{j=1}^{n} \frac{\zeta_{ij}^+}{\zeta_{ij}^+ + \zeta_{ij}^-}} \tag{27}$$

Afterwards, combining the two weights, the final weight is obtained as follows:

$$W_j^* = \alpha * W_j + \beta * W_j^{IGL} \tag{28}$$

Where, α and β are weight coefficients.

Then, according to the origin score of different choices get by expert grading method, the final scores are:

$$Score_f = W_j^* * Score_o \tag{29}$$

Where, $Score_f$ represents the final score; $Score_o$ represents the origin score.

5.3. Experiment study

The tests conducted in December 2019 provided a wealth of vehicle traffic conditions for DENM warning events, including road construction, hazardous queues, traffic conditions, and adverse weather conditions.

Fig. 7 depicts the log data signals most relevant to the event assessment in the X-Y chart. The X-axis represents the time span of the event, starting when the OBU approaches the tracked event and ending when the OBU departs from the event location. The Y-axis depicts multiple proportions of the recorded parameters defined in the right legend.

The blue line in the graph represents the vehicle's speed, the orange line indicates the absolute distance from the vehicle to the trajectory, and the purple line signifies the absolute distance from the vehicle to the event location. Below the X-axis, various types and colors of markers depict the recorded event actions of the control center and HMI warnings. When the control center detects the vehicle in tracking mode, light blue markers are displayed.

Fig. 6(a) shows the data in the log record, with more than one row of points indicating that the control center executed as expected, constituting a truly effective event. In other words, the control center issues warnings to drivers near the driving direction, event trajectory, and event location. Drivers are not warned beyond the tracking range. Fig. 6(b) presents data from log records, indicating that the performance of the center meets expectations. This qualifies as a genuine and effective affirmative event, meaning that the control center notifies the driver of the event within the detection and relevant areas along the driving direction.

On December 12th to 13th, 2019, four OBUs and the control center recorded and analyzed over 100 DENM events. From April 23rd to 24th, 2020, approximately 100 IVI events were recorded and analyzed from two OBUs and the control center. All events can be classified into genuine validity and erroneous invalidity. This indicates that the control center operates reliably, correctly notifying DENM events to drivers in a timely manner while driving in the right location on the recorded road, and does not generate false warnings.

In the realm of intelligent transportation systems, when a driver either doesn't receive or receives an incorrect event warning, it's deemed a negative outcome. The two images above correspond to negative events depicted in Figs. 6 and 7, indicating a sole row of data points for signal reception, signifying the vehicle's failure to receive messages from the intelligent transportation system. Various tests have also demonstrated that issues related to the availability of RSUs and testing infrastructure can notably result in the loss of events and warnings, including false positives. However, it's essential to clarify that these errors can't be attributed to the performance of C-ITS technology.

Next, using the BWM-IGR model proposed in this article, evaluate whether intelligent connected transportation systems are adopted or not, the BWM algorithm is a commonly used evaluation model, which relies on a certain degree of subjectivity. It primarily depends on expert ratings to compare different criteria and generate a rating matrix. This matrix is then used to solve an optimization problem, ultimately deriving the final weights for each criterion. In contrast, the IGR model is based on real data, including traffic flow and vehicle trajectory data before and after the installation of the Intelligent Connected Transportation System. These real data are normalized to ensure they are on the same scale. The IGR model utilizes a combination of the TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) and gray relation analysis to determine objective evaluation weights. These objective weights are then combined with subjective weights using an average value method to obtain the final weights. The results are as follows: Tables 2 and 3.

From two tab.

s above, the combination weight is:

$$W_j^* = \left(0.14, 0.097, 0.085, 0.122, 0.062, 0.056, 0.111, 0.085, 0.102, 0.120\right) \tag{30}$$

$$Score_f = \left(6.709, 6.125\right) \tag{31}$$

As can be seen from the formula above, it can be seen that the vehicle road collaboration system built in this article has better results in terms of traffic efficiency, safety, and economic and social impact compared to before it was not built.

6. Conclusion

This paper introduced the development of a new intelligent connected cooperative vehicle infrastructure system, validating its performance through both data analysis and experiments. The key conclusions drawn from the study are as follows:

(1) Expanding on the existing framework of vehicle-road collaboration, we established a new intelligent network for vehicle-road cooperation with minimal latency. This is achieved through the integration of advanced technologies such as intelligent RSU, intelligent OBU, data fusion techniques, and edge computing.

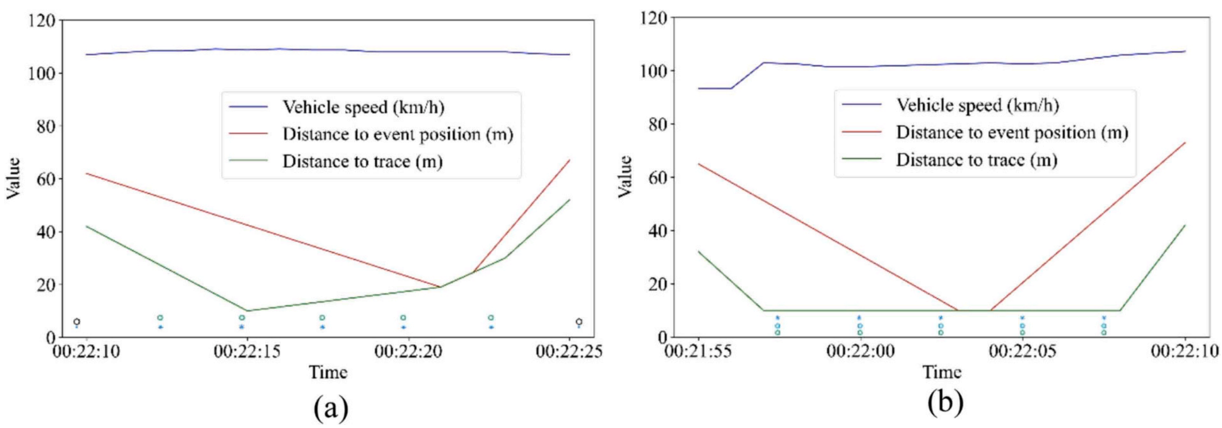

Fig. 6. Genuine and Effective Events: (a) DENM; (b) IVI.

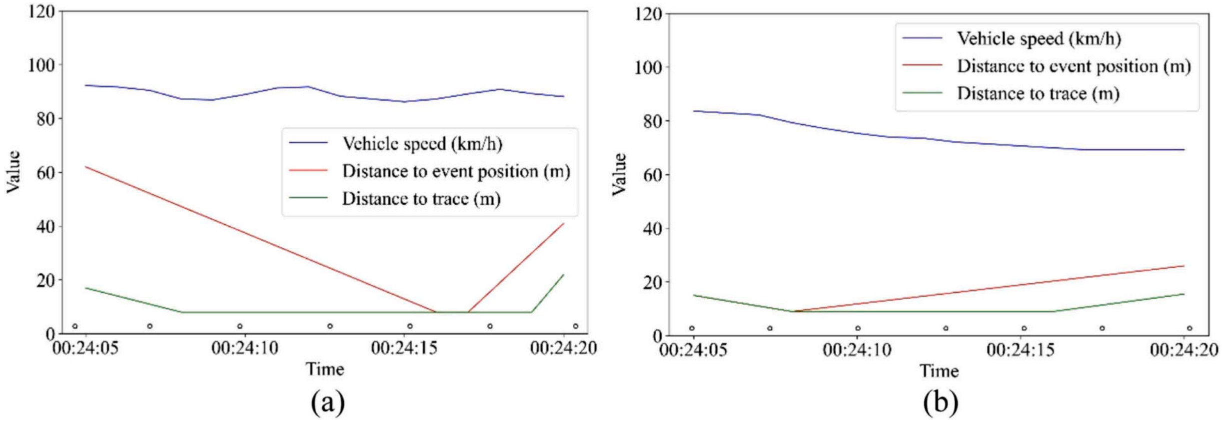

Fig. 7. Passive and Invalid Events: (a) DENM; (b) IVI.

Table 2
The subjective weights based BWM.

Primary indexes	Weight	Secondary indexes	Final Weight
A	0.217	A1	0.063
		A2	0.107
		A3	0.047
B	0.262	B1	0.128
		B2	0.064
		B3	0.025
C	0.217	C1	0.148
		C2	0.069
D	0.304	D1	0.087
		D2	0.130

Table 3
The objective weights based on IGR.

Primary indexes	Weight	Secondary indexes	Final Weight
A	0.347	A1	0.217
		A2	0.087
		A3	0.123
B	0.262	B1	0.116
		B2	0.059
		B3	0.087
C	0.174	C1	0.073
		C2	0.101
D	0.217	D1	0.117
		D2	0.110

(2) The TEC algorithm proved to be highly effective in accurately categorizing drivers' behavior. Comparative analysis revealed significant improvements in the Silhouette coefficient, Sum of Squared Errors (SSE), and Calinski-Harabasz (CH) indices—registering enhancements of 0.1%, 23.04%, and 28.50%, respectively. When combined with the HDBCSAN algorithm, it exhibits enhanced capability in detecting abnormal data.

(3) Employing the BWM-IGR model enabled the evaluation of the system's effectiveness. The proposed vehicle-road collaborative system demonstrated superior performance in terms of traffic efficiency, safety, and socio-economic impact compared to the pre-existing system.窗体顶端.

However, this study has some limitations. In the system development, the primary focus was on guiding traditional human driving vehicles and did not fully consider scenarios where autonomous and human driving vehicles coexist. Future research in intelligent connected systems could explore the convergence of three networks, namely intelligent communication networks, smart road networks, and green energy networks, to facilitate technological and business advancements.

CRediT authorship contribution statement

Chunjie Li: Conceptualization, Methodology, Writing - original draft. **Chengcheng Xu:** Conceptualization, Writing - review &

editing. **Yusen CHEN:** Visualization, Software. **Zhibin Li:** Visualization, Software.

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that inappropriately influence our work, there is no professional or other interest of any nature or kind in any product, service and/or company that could be constructed as influencing the position presented in, or the review of, the manuscript entitled.

Data availability

The data that has been used is confidential.

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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