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Special Issue Reprint

Advances in Intelligent Transportation Systems

Edited by
Seoungbum Kim and Joyoung Lee

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Advances in Intelligent Transportation Systems

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About the Editors

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Seoungbum Kim is a Professor at Gyeongsang National University, specializing in data driven intelligent transportation systems. His research has advanced traffic flow analysis, connected vehicle data applications, and machine learning based mobility analytics. Trained at The Ohio State University, he has contributed extensively to national C ITS projects, developing analytical frameworks for real time roadway monitoring and driver behavior assessments. His publications in leading international journals and his numerous technical reports for major transportation agencies highlight his commitment to improving the safety, efficiency, and intelligence of modern transportation systems. His work continues to influence emerging mobility technologies and next generation ITS research.

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Special Issue: Advances in Intelligent Transportation Systems

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Over the past decade, Intelligent Transportation Systems (ITSs) have evolved from conceptual frameworks into operationally deployed technologies. This Special Issue, “Advances in Intelligent Transportation Systems”, showcases significant progress in the integration of artificial intelligence, connected and automated vehicles (CAVs), and data-driven decision-support systems. The contributions published here demonstrate how advanced sensing, connectivity, and predictive modeling are reshaping the safety, efficiency, and sustainability of modern transportation networks.

For instance, Kim et al. [1] empirically examined the impact of vehicle-to-vehicle (V2V) warning information on driver behavior, showing that connected vehicle communication can effectively promote safer and more conservative driving patterns in real-world environments. Similarly, Kim H.K. [2] quantified the environmental benefits of automatic idling control in CAVs, finding that smart idling management could reduce CO₂ emissions by 23.6% and idling-related pollutants by over 90%. Beyond vehicle-level systems, Fathurrahman and Gautama [3] introduced spatial performance indicators for traffic flow prediction, illustrating how spatial clustering and node centrality provide new ways to evaluate model robustness beyond conventional accuracy metrics. Complementing these perspectives, Shi et al. [4] proposed a spatio-temporal deep learning model for metro flow prediction that accounts for external factors and periodicity, extending the scope of ITS applications to multimodal public transport systems.

Collectively, these works highlight the accelerating convergence of AI, sensing, and communication technologies in shaping the next generation of mobility systems. Yet, as noted by Zhao et al. [5], challenges remain in mixed-traffic conditions, where the coexistence of human-driven and automated vehicles can produce complex and sometimes counterintuitive safety and efficiency outcomes. Moreover, the institutional and technical infrastructures required for cross-sector data sharing and cooperative governance are still maturing.

Looking ahead, several directions for research and implementation emerge. As the transition toward mixed-traffic environments continues, the integration of legacy vehicles and CAVs must be carefully managed to ensure safety, efficiency, and public acceptance. Interactions among human drivers, automated systems, and infrastructure will shape how effectively new technologies perform under real-world conditions. At the same time, the development of cross-domain data-sharing architectures is becoming increasingly important. Vehicles, roadside infrastructure, and mobile systems generate vast amounts of heterogeneous data that, when integrated, can support real-time decision-making, proactive control, and adaptive traffic management. Furthermore, spatial-temporal performance indicators should play a central role in evaluating the operational reliability of predictive

models. These indicators move beyond simple aggregate metrics by identifying localized vulnerabilities and resilience patterns within transportation networks. Finally, embedding sustainability and environmental objectives directly into ITS design and policy evaluation is essential. The incorporation of emissions reduction, energy efficiency, and ecological metrics—illustrated by [2]—will help ensure that technological innovation aligns with global goals for sustainable mobility.

In conclusion, the studies collected in this Special Issue reveal that ITS research is entering a phase of multidimensional innovation—linking technology, policy, and human behavior toward a more intelligent and sustainable mobility ecosystem. As connected and autonomous systems become increasingly integrated into daily life, fostering collaboration across academia, industry, and government will be essential to ensure that these technologies advance not only efficiency and safety but also equity and environmental stewardship.

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Article

The Modeling and Application of Dynamic Lane Assignment in Urban Areas: A Case Study of Vukovar Street in Zagreb, Croatia

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Featured Application: This research lays the groundwork for implementing dynamic lane assignment (DLA) in urban corridors with variable directional traffic demand. The microsimulation approach enables a validated model for optimizing traffic performance ahead of the planned real-world deployment of lane assignment within Zagreb's urban traffic network.

Abstract: Traffic congestion in urban areas presents significant challenges to mobility, road safety, and the overall quality of the urban traffic network. This study presents a simulation-based modeling framework for dynamic lane assignment (DLA) systems designed to optimize traffic flow on Vukovar Street in Zagreb, Croatia, which is an urban corridor where the existing infrastructure fails to meet capacity demands during peak morning and afternoon hours. Using real-time traffic data and the PTV VISSIM environment, an adaptive DLA model responsive to current traffic conditions was developed and evaluated. The proposed model improves traffic flow efficiency with minimal physical infrastructure changes, focusing on maximizing capacity within existing corridor constraints. The results of this research indicate that the proposed model reduces average vehicle delay by 21.4% and shortens queue lengths by 19%. The effectiveness of the DLA approach is evaluated through comparative analysis with traditional static traffic configurations, demonstrating significant improvements in traffic efficiency, reduced travel times, and enhanced network performance. While this study is limited to a simulation environment, it provides a strong foundation for future real-world applications and offers a practical approach to improving traffic network efficiency.

Keywords: urban mobility; dynamic traffic control; capacity optimization; urban traffic management strategies

1. Introduction

Urban traffic congestion remains a major challenge to maintaining efficient mobility, road safety, and the overall quality of the transport network in the cities. As the population grows, urbanization intensifies, and traffic demand exceeds the capacity of existing infrastructure, especially during peak hours. This imbalance leads to increased travel times, reduced network performance, and the inability to utilize the maximal capacity of the network [1]. Additionally, this issue is not only a constraint on mobility but also affects economic productivity and environmental health, where the decrease in the energy efficiency of the transport network directly affects fuel consumption, the emission of harmful gases,

and noise levels [2,3]. Also, the research in [4] suggests that congestion may reduce urban productivity significantly, with cumulative economic impacts seen globally.

The traditional approach with “static” and non-responsive infrastructure is insufficient to meet the stochastic nature of modern urban traffic flows. Traffic management authorities explore adaptive and intelligent control systems that can respond to real-time traffic [5]. These systems and services are typically implemented in corridors where physical infrastructure expansion is limited and where the real-time control of traffic capacity variations can maximize the quality of the traffic network. Adaptive signal control, variable lane usage, and the integration of other Intelligent Transport Systems (ITS) services are being applied in urban areas, supporting both efficiency and sustainability goals. The following chapter provides a detailed review of these approaches, including international examples of their effectiveness.

Within the framework of the ITS concept, dynamic lane assignment (DLA) was introduced for its potential to reallocate traffic infrastructure in response to demand variations. DLA is defined as the dynamic redefinition of lane directions based on real-time data, enabling flexible responses to directional traffic demands [6–9]. Specific lanes can be re-assigned during peak periods to match the dominant flow, while during off-peak periods, lane usage is returned to balanced (original) configurations. Unlike fixed systems, DLA responds to ongoing changes and can be integrated with other ITS services, contributing to an increase in traffic network quality in high-demand, spatially limited urban areas [10,11]. Recent studies have demonstrated the value of DLA in improving traffic efficiency and reducing congestion, especially at signalized intersections and corridors with time-dependent directional flows [12,13]. Also, adaptive control strategies combined with machine learning models and algorithms show good potential for further refining DLA performance by combining historical and real-time traffic data [14]. The authors in [15] developed a Roadrunner framework that integrates DLA with autonomous intersection control, showing an increase of over 11% in intersection capacity and reduced travel delay (under high traffic volume of over 6376 CAVs/h) by 5%. Also, the PEARL (Predictive Empowered Assignment for Reversible Lanes) system was tested on several congested expressway segments in the U.S., demonstrating that a notable improvement in traffic throughput and a reduction in travel times of over 9% can be achieved [16]. The authors in [17] evaluated a DLA-based Traffic Change system developed to improve traffic flow during roadworks on German highways. This system enables the DLA in the direction with higher demands, which can lead to a 10–15% increase in capacity in the direction of the construction site and a significant reduction in queue length. Another study on the Tsukamoto merge area of the Hanshin Area evaluated a DLA for CAVs, and it demonstrated that the system significantly reduced travel times and improved traffic flow efficiency [18]. Implementing the DLA concept in this context is designed to offer operational benefits with minimal infrastructural changes. This concept has the potential to significantly reduce congestion, improve travel times, and enhance overall network performance. Minimizing changes to existing infrastructure makes DLA a cost-effective and sustainable solution for cities facing similar challenges [19].

Our study is based on the presented research methodologies of applying a real-world microsimulation of DLA in an urban corridor with significant directional traffic variation. Vukovar Street in Zagreb was selected as a known critical corridor due to its spatial limitations and observed peak-hour congestion, making it a relevant setting for DLA development and testing. Using real-time collected traffic data, the PTV VISSIM simulation tool, and a Python environment, we created the first phase of a DLA model tailored to this corridor.

This paper contributes to the field of advanced urban traffic control strategies and provides a practical framework for planners and engineers. After the Introduction, Sec-

tion 2 presents a targeted review of the relevant literature and applications of advanced traffic control and DLA. Section 3 presents the methodology and model development process, while Section 4 presents the results gathered from the simulation models. Section 5 discusses the outcomes and results, and the paper concludes with key insights and future work opportunities.

2. Literature Review

2.1. Urban Traffic Congestion and Control Strategies

Urban traffic congestion remains a critical problem that directly impacts mobility, sustainability, and productivity in rapidly expanding areas. Traditional infrastructure and fixed-time signal control cannot fulfill the needs of increasing traffic demand. This has led to the development and implementation of real-time, traffic-actuated management systems capable of adaptation to stochastic traffic conditions in urban areas. The challenges of traffic control on urban networks have encouraged innovative actuated traffic control and management systems that use real-time data to enhance and improve traffic flow quality [20]. The implementation and usage of Artificial Intelligence (AI), the Internet of Things (IoT) concept, and big and open data analytics have sped up the development of traffic control strategies. The authors in [21] proposed an integrated ITS-AI framework that dynamically adjusts signal plans using real-time sensors and collected traffic data, obtaining a nearly 15% improvement in traffic flow efficiency and an almost 20% reduction in average travel times. Another approach is the use of machine learning systems using video feeds from urban traffic networks that achieve over 93% accuracy in identifying and responding to congestion patterns, optimizing traffic on Indian streets [22]. The inability to adapt existing traffic infrastructure to new traffic situations led to the development of new solutions for traffic-dependent strategies, with the usage of modern technologies, to enable a more harmonized and efficient traffic flow [23,24]. With the focus on the implementation of the urban mobility concept, adaptive traffic control is one stable trend where real-time data collection and processing allow quick responses to variations in traffic situations. In the research presented in [25], proactive and reactive behavior for sharing traffic condition information is considered, where vehicles monitor the road traffic condition and proactively share this information when needed, considering adaptive multi-hop communication. Even though some researchers consider the main problem of traffic congestion to be that of inadequate intersection traffic control, the research in [26] developed an identification method to define the impact of both road infrastructure and traffic signal control. Another approach is the use of big data applications, which enable real-time predictive traffic management. The study in [27] introduces a traffic prediction framework based on multimodal data using machine learning techniques and validated with large datasets, making it a practical solution for real-time traffic management.

2.2. Dynamic Lane Assignment in Urban Traffic Management

In the urban traffic environment where physical infrastructure expansion is not possible, a real-time vehicle-actuated traffic control approach that can be implemented is dynamic lane assignment (DLA). DLA can contribute to optimizing urban traffic flow, particularly in physically limited traffic environments. The authors in the research [28,29] defined the concept of DLA as a novel optimal control of assigning the right-of-way of road space (infrastructure) as needed for the current traffic situation. For example, in peak traffic congestion periods, certain traffic lanes are assigned to directions with higher traffic demand, while non-peak periods allow for previously defined fixed traffic structures. Unlike static, predefined lane configurations, DLA is responsive to a real situation on the traffic network and can be integrated with other Intelligent Transport Systems (ITS

services such as traveler information systems, incident control, etc.), making it suitable for high-demand urban areas that experience occasionally expected bursts of traffic [30,31]. Previous studies have demonstrated that DLA can significantly improve traffic efficiency and reduce congestion in urban areas. For example, in signalized intersections, DLA strategies were found to reduce average intersection delay by up to 14.7% compared to fixed lane assignment configurations [32], and adaptive lane configurations have proven effective in real-time management scenarios, with a reduction in average vehicle delay by up to 21.4% [33]. In the research in [34], a model combining DLA and adaptive signal control reduced total intersection delays by 1.91% and decreased the frequency of lane changing by 13.8%. This research proved that the combination of DLA systems with adaptive traffic control enables better allocation in situations with asymmetric traffic flow demands. The analysis showed that it reduced the capacity losses caused by frequent lane changes by 17.8%. Another approach is the reversible lane network design problem (RL-NDP), where DLA implementation impacted total travel time, which decreased by up to 9%; congested roads were reduced by up to 36%; and traffic delays fell by 22% [35]. A pilot implementation of reversible lanes and adaptive lane reassignment was introduced in France (in the Paris and Grenoble metropolitan areas) to enhance corridor performance [36]. In the Paris region where the research was conducted, the lane capacity increased by 7.5%, and the overall reduction in congestion volume was 15%.

This research focuses on the real-world implementation of DLA in the city of Zagreb, Croatia, at Vukovar Street, which is an excellent representation of an urban corridor with high congestion levels throughout the day. The selected corridor provides a relevant case study due to its heavy traffic flow, directional volume surges during peak times, and physical constraints that limit expansion options. A DLA model tailored to the specific needs of Vukovar Street was developed by utilizing real-time traffic data and simulation tools. The model dynamically assigns lanes based on live traffic data, adjusting lane configurations to maximize capacity within existing spatial limitations [37]. In this paper, the effectiveness of DLA in reducing congestion, improving travel times, and enhancing the overall quality of the urban traffic network will be explored with a description of the real implementation of the concept on a corridor in the city of Zagreb, Croatia. The implementation of DLA is expected to offer several advantages by focusing on real-time lane assignments. This approach can help alleviate congestion without requiring extensive physical infrastructure changes, making it a cost-effective solution for urban traffic optimization [38]. Moreover, DLA's adaptability to fluctuating traffic patterns allows it to efficiently meet peak demands, thereby enhancing the mobility and sustainability of the urban traffic network. This paper presents a methodology and a real-time implementation of DLA on a specific part of the urban traffic network where static lane configurations cannot effectively manage and control traffic demand. Also, it provides practical insights for urban planners and policymakers aiming to optimize existing road infrastructures in similarly congested urban areas.

While DLA produced positive outcomes in the presented international contexts, applications in mid-sized European cities like Zagreb remain unexplored. This study aims to present a microsimulation-based DLA model in an urban corridor with limited expansion capacity.

3. Research Methodology and Model Development

After examining the traffic demand and fluctuations of citizens in the city of Zagreb, a suitable corridor for the testing and real-world implementation of DLA was selected. The corridor is located in the mid-western part of the city, near the Trešnjevka market zone, and is an extension of a major road connecting the eastern and western parts of the city. In this

chapter, the study area (the selected corridor) and the simulation model's development are presented with all the phases needed to implement and test DLA.

3.1. Study Area and Scope

As previously mentioned, based on the traffic analysis in the city of Zagreb, a suitable corridor for DLA implementation was selected. This corridor is located in the mid-western part of the city and forms part of the major traffic flow connecting the east with the west of Zagreb. The macro situation of the selected corridor is presented in Figure 1.

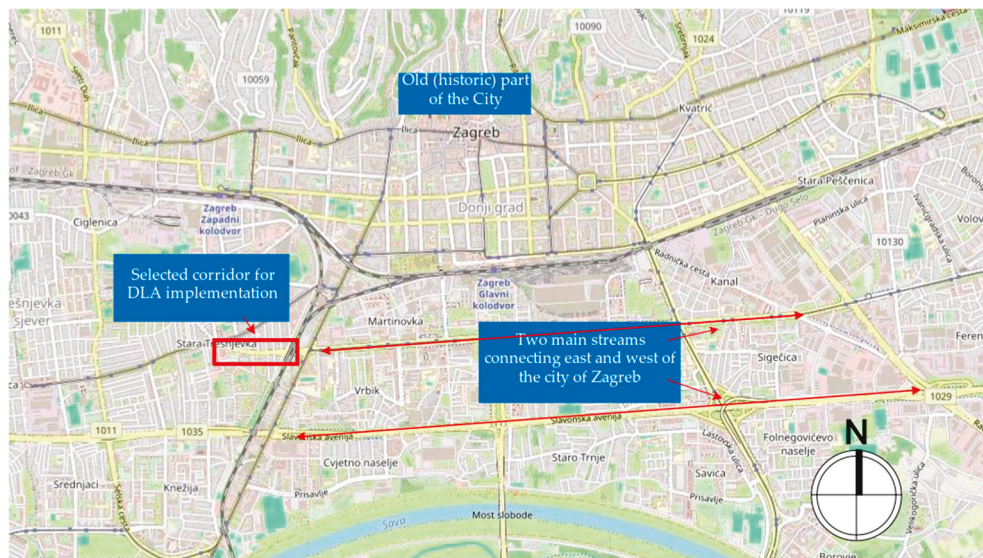


Figure 1. The macro location of the selected corridor.

The corridor is approximately 500 m long and, based on its traffic and structural characteristics, it functions as a roadway with the main direction of movement east–west and vice versa. It consists of three traffic lanes, each between 3 and 3.5 m wide—one lane is designated for eastbound traffic, while the remaining two are designated for westbound traffic.

The corridor experiences high demand with pronounced congestion at peak hours, which the existing infrastructure and traffic control cannot manage efficiently. It includes four critical signalized intersections:

- Vukovar Street–Trakošćanska Street–Ozaljska Street;
- Vukovar Street–Nova Cesta Street;
- Vukovar Street–Florijana Andrašeca Street;
- signalized pedestrian crossing at Cernička Street.

These are presented in Figure 2.

On the selected corridor, the existing traffic cannot cope with the ability to satisfy and provide optimal traffic flow during morning and afternoon peak hours. Even though the corridor itself consists of four signalized intersections, the DLA was observed and tested on the section from intersections (b) to (c) with the inclusion of a signalized pedestrian crossing (d). To develop a reliable and calibrated simulation model, relevant traffic data needed to be collected and analyzed, which is described in the next chapter.

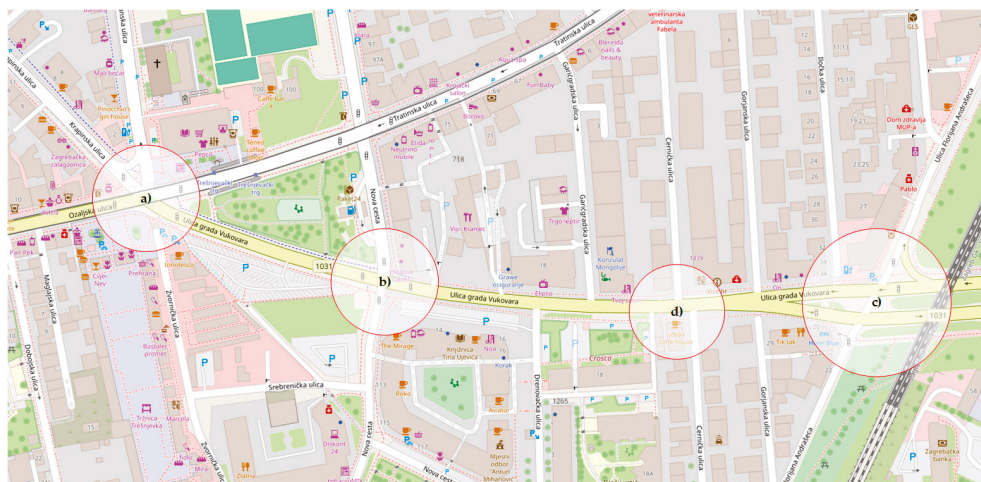


Figure 2. The micro situation of the signalized intersections on the selected corridor.

3.2. Data Collection and Traffic Demand Analysis

Relevant traffic data (vehicle counting) were collected in 15 min intervals over seven days (Saturday to Friday). Figure 3 presents an example of collected vehicle data, both in total (summarized) and by a group of lanes. The collection of pedestrian and bicycle traffic was carried out at signalized intersections and pedestrian crossings. As shown in Figure 3, different movement directions are represented by various colors: traffic coming from the west is marked in green, traffic from the southeast is marked in orange, traffic from the east is marked in yellow, and traffic from the north and northwest is marked in blue. Additionally, the thickness of the arrows visually represents the load in each direction of movement.

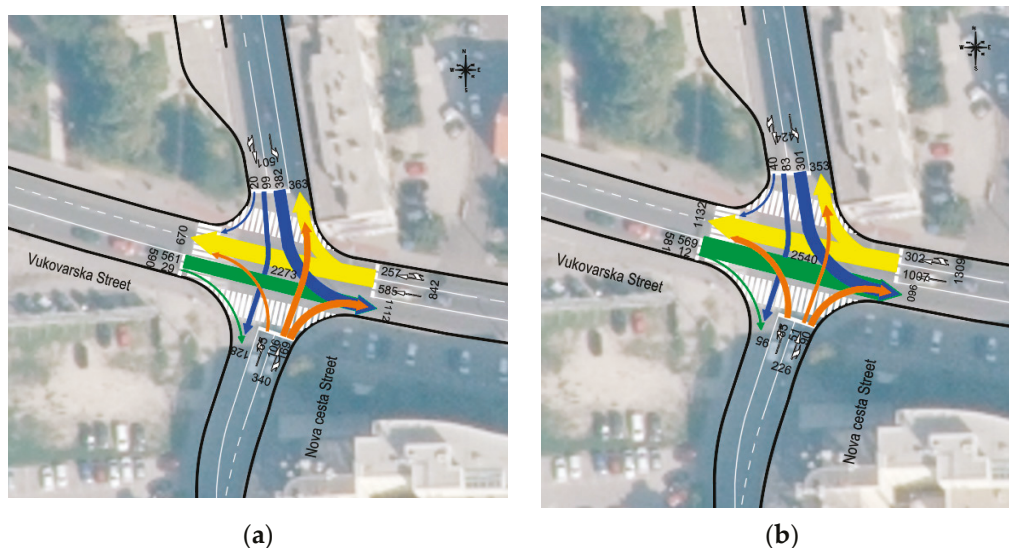


Figure 3. Example of data collection by intersection (a) Vukovar Street–Nova Cesta Street.

Based on the traffic load illustrated in Figure 3, it is evident that the primary directions of movement during both the morning and afternoon peak hours are east–west and west–east. In contrast, the northbound and southbound directions represent secondary flows. This distribution highlights the dominant role of the east–west corridor in accommodating peak-hour traffic demand, while movements toward the north and south remain significantly less pronounced. Differences in the traffic demand in the morning (Figure 3a) and the afternoon peak hours (Figure 3b) are presented, and it can be seen that the exit flow of the west approach during the afternoon peak hour is almost 70% higher than during the

morning peak hour. This information was a trigger for a scheduled DLA implementation according to the traffic demand on the entire corridor. The trend and vehicle demand variations are the same at other intersections along the selected corridor, respectively.

The variation in traffic load ratios between morning and afternoon peak hours is observable across all three Figures 4–6. This trend highlights the dynamic nature of traffic flows and, when considering the geometry of the traffic network, underscores the potential significance of DLA implementation. Such an implementation could substantially enhance the overall functionality and quality of the traffic network.

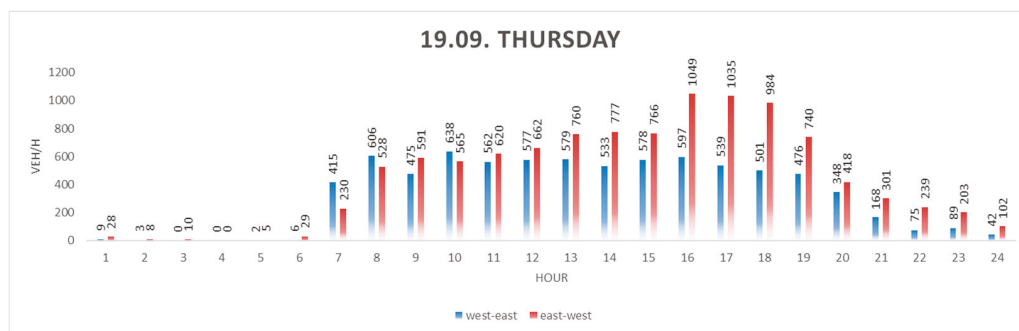


Figure 4. Vehicle count at the intersection (a) Vukovar Street–Trakošćanska Street–Ozaljska Street on the heaviest load day.

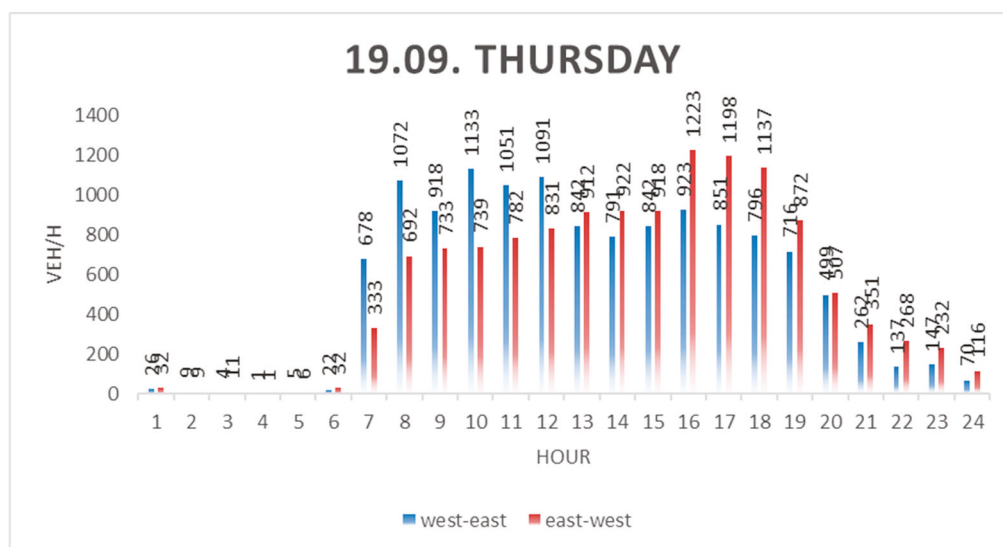


Figure 5. Vehicle count at the intersection (b) Vukovar Street–Nova Cesta Street on the heaviest load day.

Although the analysis included three intersections, a fourth signalized vehicle crossing was not graphically represented, as its traffic load primarily reflects flows from the west and east directions and does not introduce notable variation.

In addition to enhancing network efficiency and operational performance, the implementation of DLA can also play a significant role in improving traffic safety, which is discussed in more detail in the following chapter.

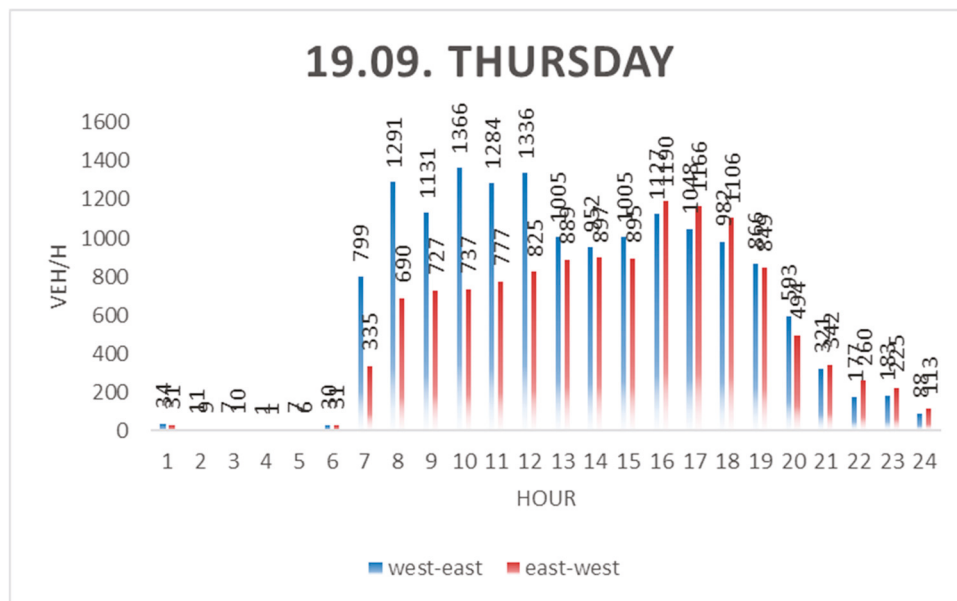


Figure 6. Vehicle count at the intersection (c) Vukovar Street–Florijana Andrašeca Street on the heaviest load day.

3.3. Safety Analysis

The safety analysis of the selected corridor was prepared based on statistical data on the number of accidents in the last three years (from January 2021 to July 2024). The data were obtained by the Zagreb Police Department and contain data on the number and type of traffic accidents. Figure 7 represents the number of accidents for every intersection of the selected corridor for the period of the last three years.

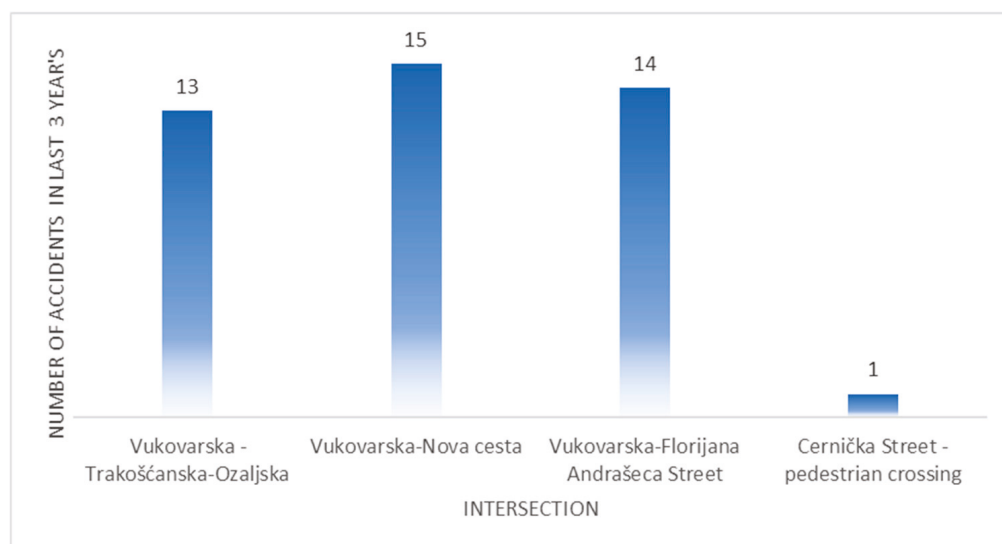


Figure 7. Presentation of accidents at the intersections of the selected corridor.

According to Figure 7, the most unsafe intersection is (b) Vukovar Street–Nova Cesta Street, with 15 recorded accidents, while at the signalized pedestrian crossing, there was only one accident in the past three years. Due to the relatively large number of accidents in the selected corridor, it is notable that there is a possibility of improvement of safety parameters through the implementation of DLA. The following graphs represent the structure (type) of the accidents at every intersection along the corridor.

As shown in previous Figures 8–10, the accidents along the selected corridors are divided into accidents with injured people and accidents with material damage (with no fatalities), which points to the need for better horizontal markings of pedestrian crossings and closer considerations of traffic safety aspects, especially for pedestrians. According to papers [39–41], DLA implementation can significantly impact the traffic safety of a part of the network. Firstly, the traffic flow can be harmonized, reducing congestion and vehicle interactions (with the minimization of stop-and-go actions). Secondly, DLA reduces the number of lane-switching needs and actions that directly reduce the possibility of sideswipes and merging accidents. Even though drivers can be confused during the first period after DLA implementation, on a longer scale with proper signalization, it improves driver awareness and minimizes hesitation and erratic driver behavior [42].

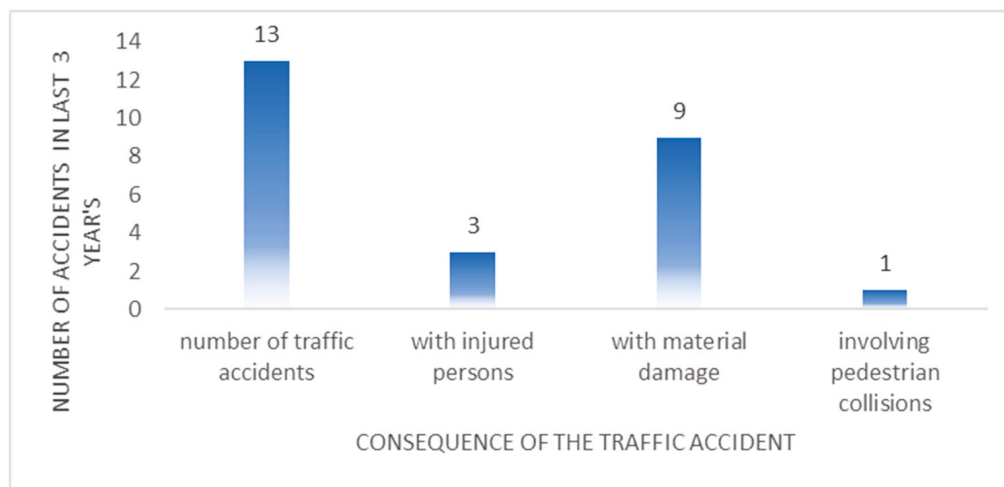


Figure 8. Types of accidents at the intersection (a) Vukovar Street–Trakošćanska Street–Ozaljska Street.

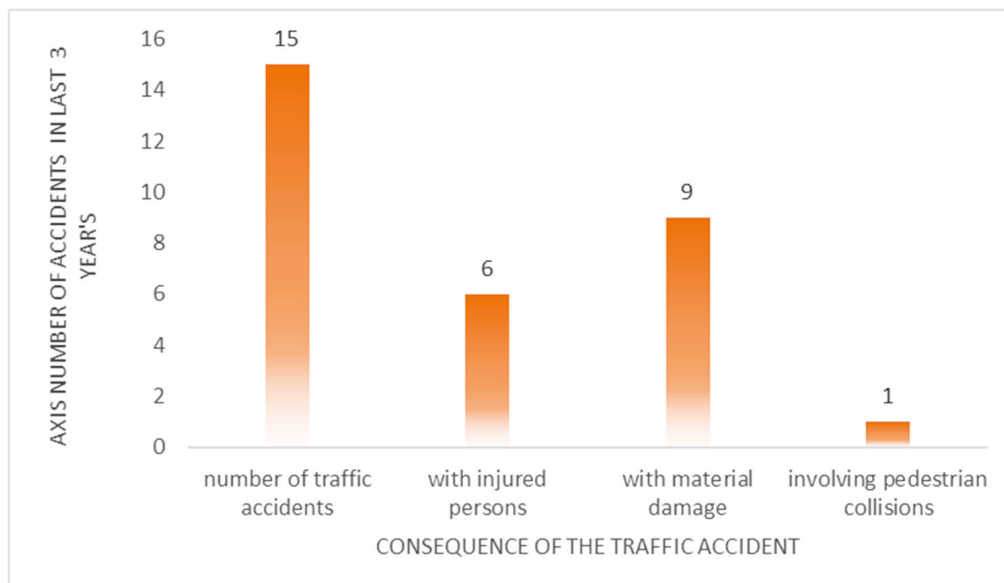


Figure 9. Types of accidents at the intersection (b) Vukovar Street–Nova Cesta Street.

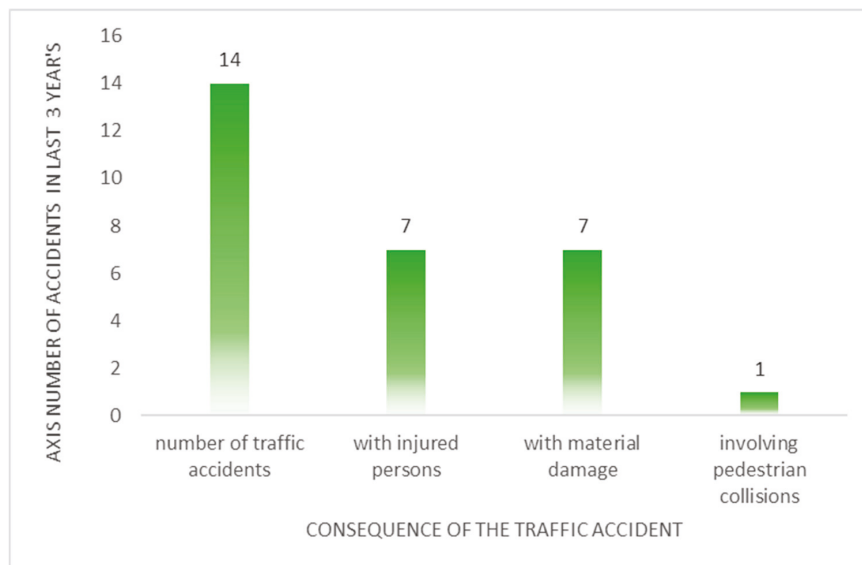


Figure 10. Types of accidents at the intersection (c) Vukovar Street–Florijana Andrašeca Street.

3.4. Design Framework and DLA Development

After a thorough analysis of the collected traffic data (the number of vehicles, vehicle categorization, etc.) and complete traffic demand analysis, it was determined that the selected corridor has great potential for implementing the DLA concept. Existing traffic control cannot meet peak traffic demand during morning and afternoon hours, and the full capacity of traffic network elements is not used. The new traffic regulation on the selected corridor consists of a DLA implementation designed to optimize lane utilization during peak hours and reallocate lane designation based on historically collected and analyzed traffic data. It is necessary to emphasize that this is the first implementation of dynamic traffic control in Croatia's traffic network.

According to the presented simulation model, the existing situation consists of one eastbound lane and two westbound lanes. In the DLA scenario, two phases are defined:

- The detection of increased traffic volume in westbound lanes;
- The dynamic reallocation of the center (middle) lane to operate bidirectionally, increasing capacity in the peak direction.

A transitional phase between the normal operation and DLA change ensures safe lane reconfiguration. This phase includes the following:

- Temporary closing of the center lane to empty it of vehicles already in the lane;
- Detecting the eventual presence of any remaining vehicles;
- The controlled reopening of the lane in the new direction once the transition is complete.

This DLA concept depends on real-time traffic demands, particularly during peak periods, through controlled transitions of the central lane direction.

3.4.1. Interface Configuration and Technical Setup

For the development of the simulation model, the PTV VISSIM microsimulation model (version 2024) was used and connected to the Python programming language (version 3.11.9) via the COM (Component Object Model) interface. This connection enables bidirectional communication between the simulation software and the programming environment, allowing for automated simulation control and the advanced analysis of results. In this setup, PTV VISSIM executes the actual traffic simulation, including vehicle generation, movement control, and interaction modeling within the network. Python, on the other hand, manages the simulation process—it loads the model, sets parameters, starts and

stops the simulation, and retrieves and analyzes the output data. Communication between the two systems is established using the win32com.client library, which provides access to all COM objects within PTV VISSIM. This integration enables the flexible execution of multiple simulation scenarios, the optimization of input conditions, and more efficient processing of traffic data.

3.4.2. Model Structure

The traffic model is based on the integration of the PTV VISSIM microsimulation environment with an external Python-based control logic using the COM API interface. This setup enables the implementation of DLA on the middle lane, triggered by predetermined traffic conditions. The model structure is presented in Figure 11.

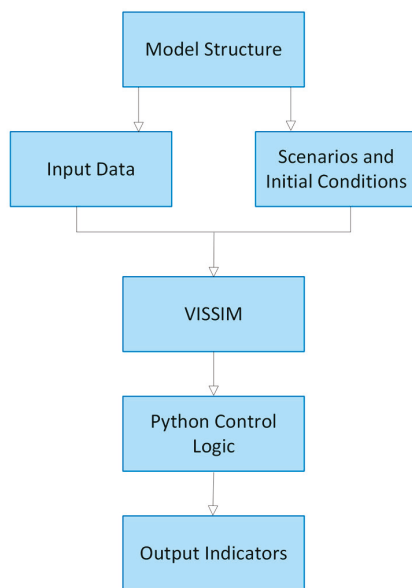


Figure 11. The structure of the developed DLA model.

The model relies on three core components: input data, scenario design, and control logic integration within the PTV VISSIM simulation environment. Input data included geometric parameters (segment length, lane width, and signalized intersections), traffic characteristics (hourly volumes, peak/off-peak loads, and vehicle composition), and driver behavior settings (desired speed, headway, reaction time, acceleration, and deceleration profiles, with predefined values within the model for desired speed ranging from 40 to 60 km/h). The Python-based control logic, integrated via the COM API, monitors traffic flow in real time, manages the activation of DLA conditions, and orchestrates the transition between DLA scenarios to reflect realistic adaptation dynamics. To assess the model's operational impact, node-based indicators were extracted from all signalized intersections along the corridor for each movement direction. These included total vehicle throughput (Vehs(All) [vehicles/hour]), cumulative delay (VehDelay(All) [seconds]), the average queue length per lane (Qlen [meters]), numerical level of service (LOSVal(All)), and carbon monoxide emissions (EmissionsCO [grams]). Together, these indicators provide a multidimensional evaluation of system performance, combining traffic efficiency, service quality, and environmental impact across all tested configurations.

3.4.3. DLA Modeling

The DLA concept was developed through the Python–VISSIM interface to enable dynamic lane direction changes in response to varying traffic conditions. This process

incorporated parameter tuning, stochastic variability, and iterative scenario testing to refine model behavior and validate simulation outputs.

To assess DLA performance under high-demand conditions, the morning peak hour was selected as the primary use case. Emphasis was placed on addressing the imbalance in lane allocation: the corridor currently provides one lane for west-to-east traffic and two lanes for the opposite direction despite significantly increased eastbound volumes during the morning rush period. This asymmetry results in operational inefficiencies under the static lane arrangement.

Accordingly, three simulation scenarios were introduced: a calibrated baseline without DLA (Scenario 1), an active DLA configuration during the morning peak (Scenario 2), and a transitional setup (Scenario 3) capturing the effects of real-time directional switching between morning and afternoon flow patterns.

In the DLA-enabled scenarios, the central lane dynamically accommodates eastbound traffic when predefined congestion thresholds are exceeded. This logic (Figure 12) also incorporates a temporary closure period during lane reversal to ensure vehicle clearance and maintain operational safety. This dynamic configuration highlights the adaptability of the DLA system in managing directional traffic imbalances and improving overall corridor performance.

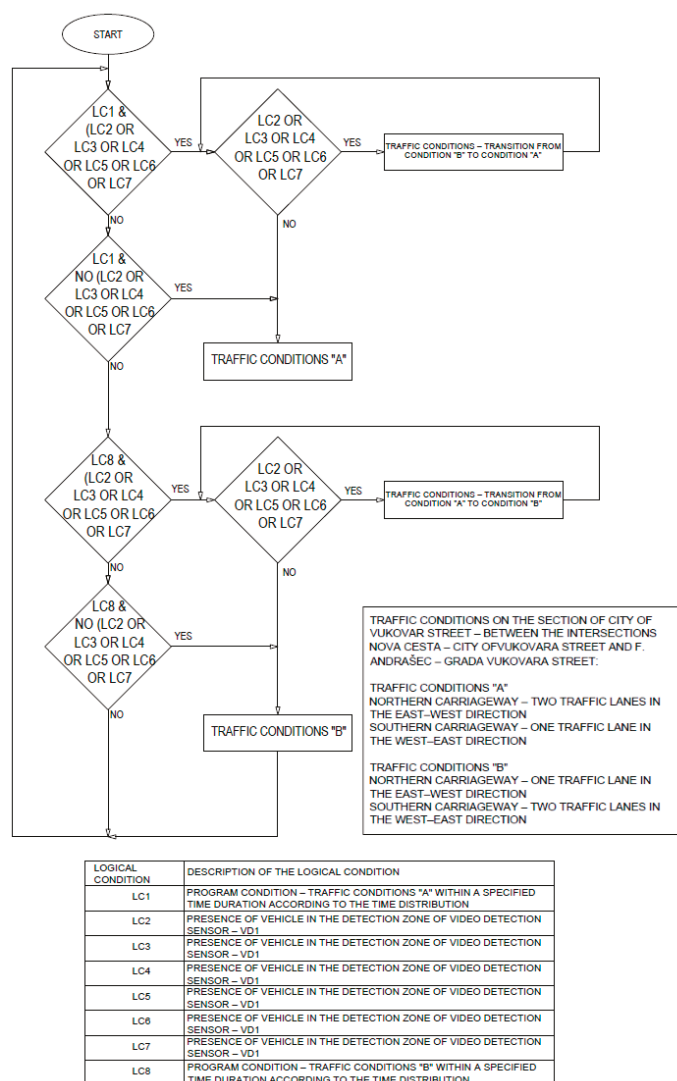


Figure 12. The logic of DLA modeling according to traffic conditions.

4. Results

After relevant traffic data were collected, the existing traffic model was developed and calibrated in the PTV VISSIM simulation tool. The existing traffic model enables precise calibration, verification, and validation of selected evaluation parameters. Also, the main purpose of the calibrated existing traffic model (with defined evaluation parameters) is to ensure a basis for the evaluation of newly proposed scenarios and their benefits. After the traffic model of the existing traffic situation was developed and calibrated in the PTV VISSIM tool, the DLA concept was developed and then implemented as an upgrade of the existing model.

4.1. Calibration and Validation of Microsimulation Model

The calibration of the model was performed with GEH statistics [43], which is defined by the following equation:

$$GEH = \sqrt{\frac{2(M - C)^2}{M + C}} \quad (1)$$

where

M —hourly traffic from the simulation model;

C —real-world hourly traffic collected from the field.

GEH statistics facilitate a comparison between two traffic volume sets: real-world volumes and simulation-derived volumes. A GEH value below five indicates a suitable calibration of the simulation model, ensuring that traffic parameters closely reflect real-world conditions. With that, at least 85% of the total traffic volume should have a GEH value lower than five to confirm the model's reliability. On the other hand, if the GEH value exceeds 10, the model is classified as inaccurate, indicating that it does not accurately represent the actual traffic conditions. In this research, GEH values for all approaches of the simulation model were below five, indicating that the model is adequately defined and calibrated. As mentioned earlier, the simulation models were developed using the PTV VISSIM 2024 software, with a duration of 4500 [s]. The first 900 [s] were excluded from the evaluation due to the model's "warm-up" period. Additionally, based on the collected and analyzed traffic data, the period from 7:00 to 12:00 a.m. was selected for DLA implementation.

To ensure the reliability of the simulation results, the model was validated using the empirical data on average travel times collected during a representative weekday that matched the conditions used for demand input. Validation focused on the total time spent on the network by vehicles traveling in both east-to-west and west-to-east directions. For each direction, three controlled field runs were conducted, and the recorded average travel times were compared with the average total time spent (TTS) obtained from ten simulation runs under the baseline (non-DLA) scenario. The TTS indicator served as the key metric for verifying the model's temporal accuracy. In cases where notable deviations were observed, driver behavior parameters such as desired speed, headway, and acceleration profiles were iteratively adjusted to improve alignment with real-world conditions. Additionally, traffic signal plans from the field were analyzed and verified against the modeled settings to ensure consistency in phase sequences, cycle lengths, and coordination. This comprehensive validation process confirmed that the model accurately replicates observed traffic dynamics and provides a reliable foundation for evaluating the impact of dynamic lane assignment strategies.

4.2. Evaluation Parameters and Results

The defined evaluation parameters were extracted from the node evaluation option in PTV VISSIM, which are relevant for the representation of the DLA impact. The evaluation parameters are the following:

- Vehs(All)—the number of vehicles [n/h];
- VehDelay(All)—the delay of all vehicles on the observed intersection [s];
- Qlen—the queue length per lane on the observed intersection [m];
- LOSVal(All)—the level of service as a numerical value;
- EmissionsCO—emissions of carbon monoxide [g].

Each of the evaluation parameters was recorded for all movement directions at three signalized intersections of the observed corridor (excluding the pedestrian crossing/intersection). Below are the results of the existing situation simulation and the proposed DLA implementation scenario for the morning peak hour (7:00–8:00 a.m.). The analysis of the results is presented in the Discussion section. The results are presented separately for each intersection within the traffic model (three signalized intersections). For each location, the previously defined evaluation parameters are presented for the existing situation and the proposed DLA implementation scenario during the morning peak hour.

Table 1 presents the simulation results for the intersection of Vukovar Street–Trakošćanska Street–Ozaljska Street. The same evaluation parameters are presented for the remaining signalized intersections in Tables 2 and 3.

Table 1. The results of the simulation for the existing situation and DLA situation of Vukovar Street–Trakošćanska Street–Ozaljska Street.

Evaluation Parameter	Existing Situation	DLA Scenario
Vehs(All)	2050	2092
VehDelay(All) [s]	15.5	18.13
Qlen [m]	11.61	14.92
LOSVal(All)	2.45	2.82
EmissionsCO [g]	1418.62	1634.82

Table 2. The results of the simulation for the existing situation and DLA situation of Vukovar Street–Nova Cesta Street.

Evaluation Parameter	Existing Situation	DLA Scenario
Vehs(All)	2236	2351
VehDelay(All) [s]	83.76	35.14
Qlen [m]	59.77	48.21
LOSVal(All)	4.36	3.45
EmissionsCO [g]	4028.97	2183.96

Table 3. The results of the simulation for the existing situation and DLA situation of Vukovar Street–Florijana Andrašeca Street.

Evaluation Parameter	Existing Situation	DLA Scenario
Vehs(All)	2674	2756
VehDelay(All) [s]	25.15	23.71
Qlen [m]	14.19	10.19
LOSVal(All)	2.83	2.50
EmissionsCO [g]	1574.63	1608.83

These simulation results provide the basis for evaluating the effectiveness of DLA implementation. A detailed comparison and analysis of the observed differences is presented

in the Discussion chapter. All the results (approach detailed) are available from the authors but are not presented due to paper length limitations.

5. Discussion

After the development of the existing traffic model and the implementation of the DLA concept in the upgraded model, the results were collected and presented in the previous chapter. The main objective is to evaluate the effectiveness of DLA in improving traffic flow and to secondarily observe its environmental performance. As mentioned before, the defined evaluation parameters are the number of vehicles, vehicle delay, the average queue length, level of service, and the emission of CO, which will all be separately considered.

5.1. Number of Vehicles, Vehicle Delay, and Level of Service

The total number of vehicles passing through the simulation model was slightly higher in the DLA scenario (0.02%, 0.05%, and 0.03%), which indicates that DLA implementation increased the intersection flow by reallocating lanes to match directional demand during peak hours. Overall, more vehicles were processed per hour, followed by a significant reduction in the average vehicle delay. The results of the DLA implementation were most notable at the middle-signalized intersection (Vukovar Street–Nova Cesta Street), where vehicle delay was reduced by 58.05%. At the edge intersections of the simulation model, the situation was slightly different because DLA did not have a direct impact on the traffic situation. On the Vukovar Street–Trakošćanska Street–Ozaljska Street intersection, the vehicle delay increased by 16.97%, and on the Vukovar Street–Florijana Andrašeca Street intersection, the vehicle delay was reduced by 5.73%.

As for the level of service values, it must be noted that the values in the tables represent the internal PTV VISSIM performance score, which is not based solely on the average delay but also on the volume-to-capacity ratio, signal plan complexity, and other parameters. Nevertheless, the values follow the number of vehicles and vehicle delay trend, so at the middle intersection, the LoS is increased from D to C, suggesting that DLA has a positive effect on operational performance. At the first intersection (eastbound direction), the LoS was slightly decreased from B to C following the same explanation as the vehicle delay, and at the last intersection, the LoS was increased from the value C to B. It can be noted that with the implementation of DLA, the capacity in the eastbound direction is increased, following smoother traffic flow and better lane utilization.

5.2. Queue Length Analysis

Queue length serves as an indicator of congestion at signalized intersections, and the ability of the control and optimization techniques to process the arriving vehicles is determined. Again, as with the previous indicators, the greatest queue length decrease is at the middle intersection under the DLA scenario by approximately 19.3%. The first intersection of the model experiences some increase in the queue length by 28.49% (from 11.61 m to 14.92 m). Also, as expected, at the last intersection of the model (Vukovar Street–Florijana Andrašeca Street), the queue length decreased by 28.22%, or from 14.19 m to 10.19 m. It can be noted that with the dominant eastbound direction with active DLA, traffic can clear more effectively during each signal cycle. This is particularly important in dense urban corridors where physical limitations and intersection spacing exist.

5.3. Environmental Impact—CO Emissions

The carbon monoxide (CO) emissions were analyzed as part of the evaluation to assess the environmental implications of DLA implementation. According to the results, the difference in CO emissions before and after the DLA implementation is not noticeable, with the only reduction being at the Vukovar Street–Nova Cesta Street intersection. The major

decrease was from 4028.97 g to 2183.96 g, which represents 45.77%. Again, the main reason for such a large decrease in CO emissions is the implementation of the DLA concept, which impacts the harmonization of the traffic flow. As expected, on the edge intersections, there is an increase in CO emissions (15.22% at the Vukovar Street–Trakošćanska Street–Ozaljska Street intersection and 2.17% at the Vukovar Street–Florijana Andrašeca Street intersection).

Even though this research focuses on the isolated implementation of DLA on Vukovar Street, the selected corridor is an integral part of an urban traffic network. The presence of pedestrians and public transport services influences the effectiveness of signal control strategies, and this was considered during the development of the simulation model. Also, the intergreen matrices for pedestrians were calculated and included in the signal timings. The implementation of DLA will be taken into account when analyzing the impact and interactions with adjacent corridors, coordinated signal control, and overall network performance. Also, this study did not incorporate surrogate safety measures (such as Time-to-Collision (TTC)), but their importance in evaluating traffic safety is notable. Indicators like TTC show the real nature of vehicle conflicts and the safety implications of lane assignment strategies. However, due to the defined scope of this research, the current study focused on performance metrics and traffic network parameter improvements. In the next phases of this research, we will integrate surrogate safety analysis using tools like the surrogate safety assessment model (SSAM) or similar to assess the impact of DLA on traffic safety.

5.4. Limitations

While the findings of this study offer promising insights into the potential benefits of dynamic lane assignment (DLA) in urban traffic corridors, several limitations should be acknowledged. First, the analysis was conducted using a single case study—Vukovar Street in Zagreb—which, although representative of directional congestion in urban settings, may limit the generalizability of the results to cities with different geometric, regulatory, or traffic flow characteristics.

Second, the model assumes the reliable and timely availability of traffic data to trigger lane direction changes. In practice, the effectiveness of a DLA system would depend heavily on the accuracy and responsiveness of real-time data collection infrastructure, such as traffic detectors, sensors, and communication systems. Third, driver behavior in the model does not fully account for behavioral adaptation to dynamic lane changes, especially in the early phases of implementation when unfamiliarity with the system may affect compliance and performance.

Finally, the implementation of DLA systems requires significant technological, institutional, and operational readiness, including dynamic signage, signal control integration, and traffic management protocols. These factors were not explicitly modeled but would play a crucial role in real-world deployment. Despite these limitations, the study provides a robust framework for evaluating core operational benefits under controlled conditions and can serve as a foundation for future, more complex investigations.

6. Conclusions

In this research, the modeling and possible real-world implementation of a dynamic lane assignment (DLA) system on one of the most congested corridors in the city of Zagreb—Vukovar Street was explored. The first phase of a DLA concept was developed through the integration of collected real-time traffic data, detailed demand analysis, and microsimulation using the PTV VISSIM tool with Python to address uneven peak-hour traffic demand. The main goal is to optimize traffic flow without physical infrastructure expansion.

The simulation model was calibrated, and the model with the proposed DLA concept was developed. In the first phase, the middle lane acts as a dynamic lane, adjusting the direction according to traffic demand. The simulation results confirmed that DLA can significantly improve the performance of the traffic network when applied at targeted corridors. The most notable improvements in evaluation parameters were achieved at the middle intersection of the corridor where the DLA concept was implemented (Vukovar Street–Nova Cesta Street). Vehicle delay was reduced by over 58%, queue length was decreased by 19%, and CO emissions dropped by 46%, respectively. These results demonstrate that DLA can reallocate the capacity in traffic networks to match variable traffic demand.

On the other hand, the DLA implementation had a direct impact on the edge intersections and delay, and emissions slightly increased due to downstream prioritization. Network-wide coordination and careful scenario planning to avoid displacing the congestion are essential.

Future research will focus on expanding the scope of DLA implementation but also on implementing the DLA variable in smaller time frames and with greater frequency. Also, this first phase of DLA implementation is planned for real-world implementation at the observed corridor, and the impacts on real traffic will be observed and analyzed. Additionally, simulations will be extended to cover full-day traffic variations and multi-peak scenarios.

Overall, this research offers valuable insights for urban traffic planners and policymakers who focus on improving traffic efficiency and sustainability in dense urban environments using Intelligent Transport System services.

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Article

A Method of Selecting Automated Driving Service Sections Considering Spatial Influence Factors

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Abstract: Currently, the level of automated driving technology is level 3 service in Korea, and the level 4 service has been launched overseas and is reaching the stage of commercialization. For commercialization, it is necessary not only to stabilize automated driving technology but also to prepare for service applications. To apply and expand automated driving services, it is most urgent to secure the safety of automated driving technology, and it is necessary to prepare for efficient procedures and methods suitable for automated driving services. In this study, considering the two aspects of AV manufacturer and service provider, the spatial factors affecting the safety of ADS are estimated using disengagement information in the level 3 service field data in Korea, and the method is proposed to select the automated driving service sections using spatial information analysis. To validate the method, the matching rate is compared and analyzed by applying it to the other testbed, which is currently being prepared for the level 4 car sharing service. According to validation results, it judged that the proposed method could be used to select the automated driving service section efficiently in the planning stage before deploying AVs and providing services.

Keywords: automated driving service; spatial ODD; spatial information analysis; factors influencing safety; automated driving service selecting method

1. Introduction

Automated driving technology is a key field in the era of the 4th industrial revolution and is included in the national future strategic industry. It is currently in the commercialization stage. Level 3 automated driving paid services are being provided in Korea at the level of the Society of Automotive Engineers (SAE) technology [1], and level 4 paid services have been launched abroad, such as the San Francisco Robotaxi service in the United States [2]. Advanced technology is important for level 5 fully automated driving, but service aspect preparation is also necessary to expand services by fully commercializing automated driving technology. It is important to apply autonomous driving technologies to the transport service industry, as shown in a previous study [3]. In this regard, the Ministry of Land, Infrastructure and Transport has been promoting a total of 22 Research and Development (R&D) projects since 2021, including six services, to advance automated driving technology and demonstrate living lab by promoting the Korea Autonomous driving Development Innovation Foundation (KADIF) led by the government. Here, the importance is that it will provide services to the public in a living lab city selected from a sub-project, one of the 22 R&D projects in the KADIF. Therefore, it is important to select a spatial range and operation section in which safe and stable services are possible according to the purpose and characteristics of each service.

However, although some regions in Korea provide pilot operation and paid services at the level of automated driving level 3, automated driving technology at level 4 is under development or is in the testing stage for demonstration. Therefore, it is still difficult to identify the Operational Design Domain (ODD) for sections and areas where level 4 automated driving service is possible. Moreover, according to a study conducted in Korea, users consider safety as the most important factor in the transportation sector, and they mentioned that securing the safety of automated driving technology is most urgent for the expansion and dissemination of automated driving services [4].

In addition, to provide automated driving services to the public at a living lab, it is necessary to analyze the spatial conditions of the living lab area and select sections that can provide services in advance before testing automated driving technology directly at the site. Since the central government and local governments to introduce automated driving services need to ensure inclusiveness and welfare, especially in public transportation, it is not reasonable to select a specific Car Original Equipment Manufacturer (OEM) and its ODD in advance, but necessary to apply the proposed analysis method to the expected service sections.

According to the definition of the SAE automated driving level, the greatest difference between levels 3 and 4 can be seen as to whether a human performs disengagement, which leads to the minimum risk condition in the event of a dangerous situation, or whether the system performs disengagement, so the safety of automated driving can be identified through the occurrence of disengagement [5].

With respect to automated driving technology, [6–11], etc., have conducted research to validate the technology of automated vehicles, but few studies have been conducted in terms of services. In addition, regarding the safety of automated driving [12–21], many studies have been conducted using field data and simulations; however, few studies have evaluated the effects of crashes or services, and few studies have been conducted on the factors affecting the safety of automated driving.

Therefore, this study estimates the spatial factors that affect the safety of automated driving by using actual field collection data based on spatial ODD, which reflects the characteristics of each service under development in the KADIF. Then, on the basis of the estimated spatial influence factor, a method for selecting the automated driving service section is proposed. A framework for selecting an automated driving service section is then presented by synthesizing the procedure of the proposed method in this study. Finally, the analysis method is validated by applying the automated driving car-sharing service under development within the KADIF to the test bed.

This paper is composed as follows. Section 2 explains the status of the collected data and the pre-processing process. Section 3 explains the method using spatial information analysis to estimate the influencing factors based on spatial ODD elements that can affect the safety of automated driving and explains a method for selecting an automated driving service section. Section 4 presents the analysis results that performed the analysis method proposed in Section 3 and presents a framework that synthesizes the entire analysis method and procedure. Section 5 explains the validation process and results through the application of the analysis method and framework proposed to the test bed in other regions. Section 6 describes the interpretation of the validation results, and Section 7 describes the conclusions, contributions of this study, and future research tasks.

2. Data Analysis

2.1. ODD Elements

This study uses the spatial ODD reclassified by [22]. On the basis of previously published literature, relevant standards, and legal data, the spatial ODD has been reclassified

based on the characteristics of the services being developed within the KADIF. The space ODD classification and the elements used are given in Appendix A.

2.2. Field Data Collection

The data used are the actual field data collected from the level 3 paid service in the automated driving pilot zone in Sangam, Seoul, provided by the Seoul Metropolitan Government. The data collection period is 10 months, from May 2022 to February 2023. The collected field data includes four routes, but only two routes that provided services over the entire collection period of 10 months were used for analysis. The other two routes are excluded because they were added in the middle of the period.

The service operation status for the two routes to be analyzed is shown in Figure 1 and Table 1. Each vehicle is modified and operated by different small- and medium sized start up companies in Korea, respectively.

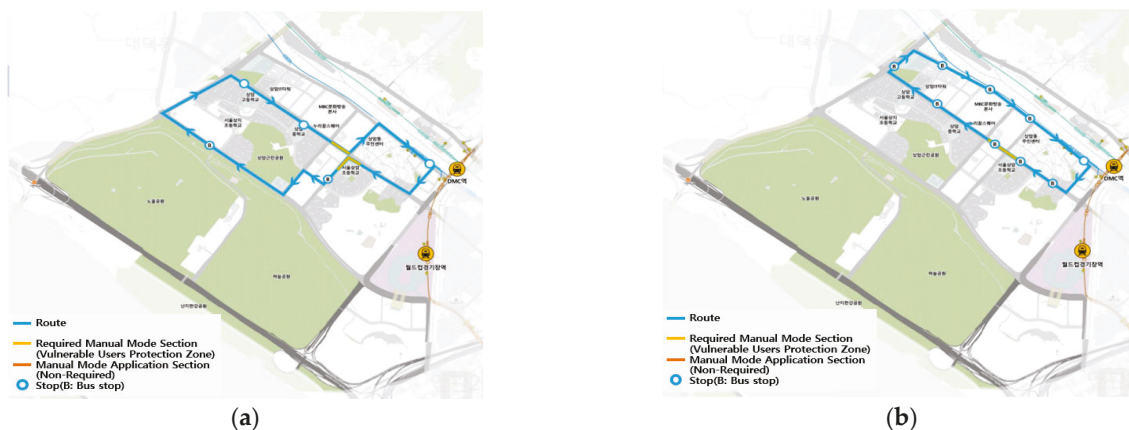


Figure 1. The route status of automated driving paid services in Sangam. (a) Route A. (b) Route B.

Table 1. Operation status of automated driving paid services in Sangam, Seoul.

Route No.	Route Length	Operation Time	Frequency/Day
Route A	5.3 km	09:30~12:00, 13:30~16:00	10 Times
Route B	4.0 km	08:00~17:00	16 Times

2.3. Status of Field Data

The field data used in this study are collected by an automated driving vehicle sensor and transmitted to the roadside unit (RSU) through the communication terminal in vehicles. The data are then transmitted and stored to the Cooperative-Intelligent Transport Systems (C-ITS) center server in Seoul every second through commercial networks such as long-term evolution (LTE). The provided data are monthly and consist of 27 columns, including vehicle and location information and vehicle condition information. This study uses a driving mode change (ctrl control mode) related to the safety of automated driving, a vehicle ID (terminal ID) that can identify individual vehicles, and latitudinal and longitudinal coordinates (latitude, longitude) to identify where the driving mode change occurred, time (system time) to identify when the driving mode change occurred, and speed (spd) information that can be used to select the range for extracting multiple driving mode change points. Examples of the automated driving data columns used in the analysis are presented in Table 2.

Table 2. Sample of the data columns used in this study.

No.	Terminal ID	System Time (s)	Latitude (°/'/'')	Longitude (°/'/'')	Spd (km/h)	Ctrl Control Mode
1	A_1	1651628242255	37.57749977	126.8975646	0	1
2	A_2	1651628249477	37.58131030	126.8784991	8	0
3	B_1	1651628267152	37.57845468	126.8961456	40	1
4	B_2	1653975832127	37.57653044	126.898886	38	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮

2.3.1. Field Data Pre-Processing

This section describes the data pre processing procedure for generating a dataset for analysis to extract automated driving mode change multiple points. First, the definition of data for changing the automated driving mode is defined as the latitude and longitude coordinates at the time when the automated driving code '1' is continuously entered and then changed to the manual driving code '0', as shown in Figure 2. To analyze the point of change in the automated driving mode, it is necessary to pre process the raw data, which is the process of extracting the valid sample. This study performed two steps of pre processing to generate data samples for analysis.

	day_time	latitude	longitu	spd	ctrl_control_mode_cd
301315	2022-06-25 6:18	37.57567	126.895	39	1
301318	2022-06-25 6:18	37.57568	126.895	39	1
301321	2022-06-25 6:18	37.57568	126.895	39	1
301324	2022-06-25 6:18	37.57568	126.895	39	1
301327	2022-06-25 6:18	37.57593	126.8945	45	1
301330	2022-06-25 6:18	37.576	126.8944	45	1
301333	2022-06-25 6:18	37.57607	126.8943	45	1
301335	2022-06-25 6:18	37.57614	126.8942	45	1
301339	2022-06-25 6:18	37.5762	126.8941	44	1
301342	2022-06-25 6:18	37.5762	126.8941	44	1
301345	2022-06-25 6:18	37.5762	126.8941	44	0
301348	2022-06-25 6:18	37.5762	126.8941	44	0
301351	2022-06-25 6:18	37.57643	126.8937	32	0
301354	2022-06-25 6:18	37.57647	126.8936	29	0
301357	2022-06-25 6:18	37.57651	126.8935	25	0

Figure 2. Definition of driving mode change (disengagement) on data (example).

2.3.2. 1st Pre-Processing

The 1st pre-processing step is the process of extracting data samples included in the analysis target area range and service operating hours from the raw data. The 1st pre-processing process is performed through eight steps, as shown in Figure 3, using the R 4.2.3 program.

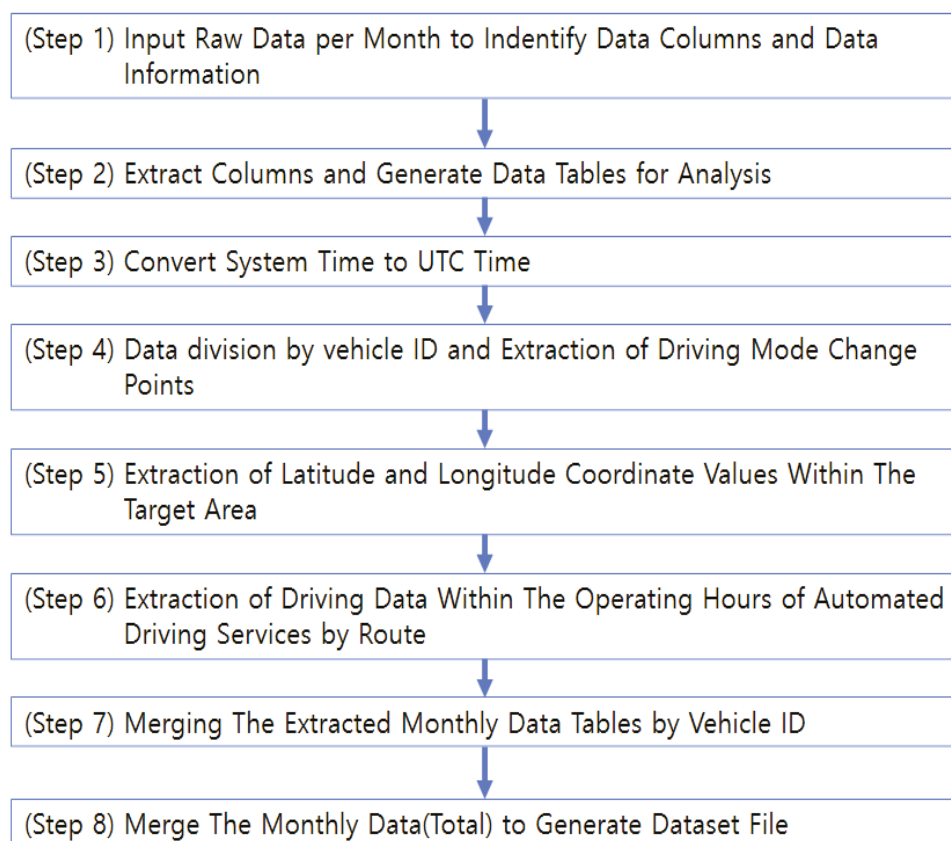


Figure 3. The 1st pre-processing process.

The number of the automated driving mode change point data by vehicle ID is 83 to 3080, and the total number is 14,390, as shown in Table 3.

Table 3. Number of driving mode changes by vehicle ID after 1st pre-processing.

No.	Vehicle ID	Number of Driving Mode Changes (Number)
1	A_1	3080
2	A_2	527
3	A_3	125
4	A_4	2778
5	A_5	2681
6	A_6	83
7	B_1	995
8	B_2	2466
9	B_3	1655
Total		14,390

The entire dataset after the 1st pre processing generated using the driving mode change information of the field data is shown in Figure 4. This dataset includes data from routes other than the automated driving service operation route (green dotted line). That is the added routes and test data. It also includes outlier data located outside the route due to the characteristics of the Global Positioning System (GPS). For the accuracy of the analysis, it is necessary to remove these data through the 2nd pre processing.

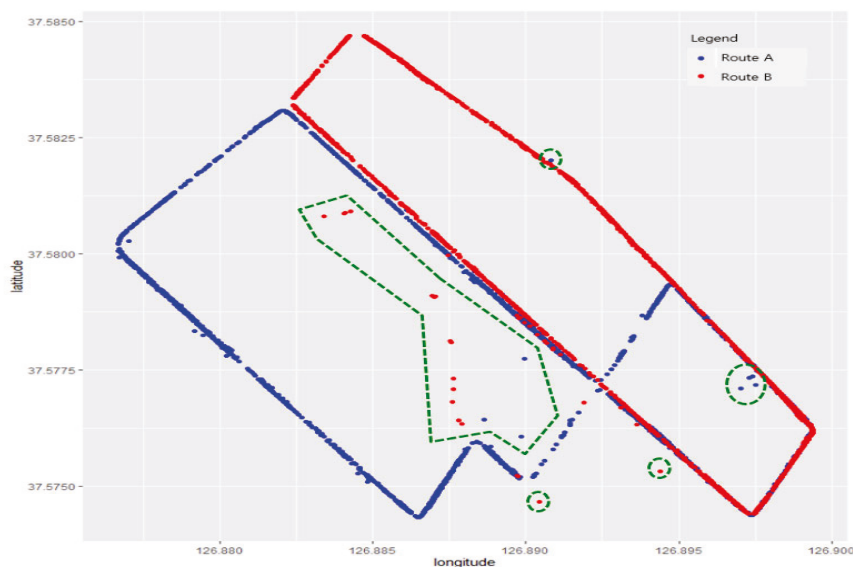


Figure 4. Dataset after 1st pre-processing using R 4.2.3 (Source: [22]).

2.3.3. 2nd Pre-Processing

The process of performing the 2nd pre-processing of the dataset generated through the 1st pre-processing is as follows. QGIS 3.30.1 ver. was used to convert the data into a shapefile format, which was then overlapped with standard node links and High Definition (HD) maps to remove data located outside the automated driving service route. The HD map is built up to the lane unit of the link, so the data outside the lane range of the HD map are defined as outliers on the basis of the driving direction, selected and deleted from the edit mode. The final dataset for spatial information analysis generated after performing the 2nd pre-processing process is shown in Figure 5.



Figure 5. Dataset after 2nd pre-processing using QGIS 3.30.1 (Source: [22]).

2.4. Analysis of Driving Characteristics of Automated Driving Data

The driving characteristics of the automated driving data are used to calculate the reference value that sets the size of grids when selecting the automated driving mode change multiple points. First, when the coordinates of the automated driving mode change points created through pre processing were checked, no points were found that matched both latitude and longitude. Therefore, after generating grids of the same size, find grids within these grids that contain many coordinates of the driving mode change. And then convert

those grids into the coordinate format to extract automated driving mode change multiple points.

The size of the grid may vary depending on the criteria value. In this study, since data are collected every second, the driving behavior of the automated vehicle between 1 s and the next 1 s data are the same, so the size of grids is based on the driving distance per vehicle per second. Since the performance of automated vehicles developed by two service providers may be different, calculate the driving distance per second based on the average monthly speed per vehicle for each route and then calculate the average driving distance per second per month for each route. The average driving distance per second per month for each route can be calculated as follows.

First, the time average speed of the vehicle may be calculated through Equation (1).

$$v = \frac{1}{N} \sum_{i=1}^N u_i \quad (1)$$

where v is the time-average speed of vehicles (km/h), N is the number of vehicles (vehicle), u_i is the speed of the i th vehicle (km/h).

The average speed per second of individual vehicles per month can be calculated through Equation (2).

$$v_a = \frac{\sum_{i=1}^n d_i}{3.6 \times \sum_{i=1}^n t_i} \quad (2)$$

where, v_a is the average speed per second of individual vehicles per month (m/s), d_i is the driving distance of an individual vehicle per month (km), t_i is the driving time of individual vehicles per month (h), n is the number of vehicles (vehicle), and 3.6 is the conversion factor in units of speed.

The average driving distance per second per month for each route can be calculated through Equation (3).

$$d_{avg} = \frac{\sum_{i=1}^n (t_i \times v_i)}{n} \quad (3)$$

where d_{avg} is the average driving distance per second per month (m), t_i is the driving distance of an individual vehicle per month (s), v_i is the speed of the individual vehicle per month (m/s), and n is the number of vehicles (vehicle).

2.5. Construction of Spatial Information

To analyze spatial factors at driving mode changes at multiple points, it is necessary to analyze spatial factors at locations matching the automated driving mode change points, so the corresponding area, including the field data collection target section, is selected as the area to be analyzed. To this end, this study constructed spatial information on the Sangam automated driving pilot zone, which is the area to be analyzed.

The spatial information was constructed via the National Standard Node Link (2023-03-29 ver.) provided by the ITS National Transportation Information Center. After the link of the target section is filtered through the QGIS program, the object is matched with the link ID on the basis of the spatial ODD element through the road view and field survey by the portal site. This study organized the entities in units of links, considering that it is a basic study to select the section where the automated driving service is possible. The method and procedure for constructing spatial information are shown in Figure 6. The finally established spatial information and object table are shown in Figure 7.

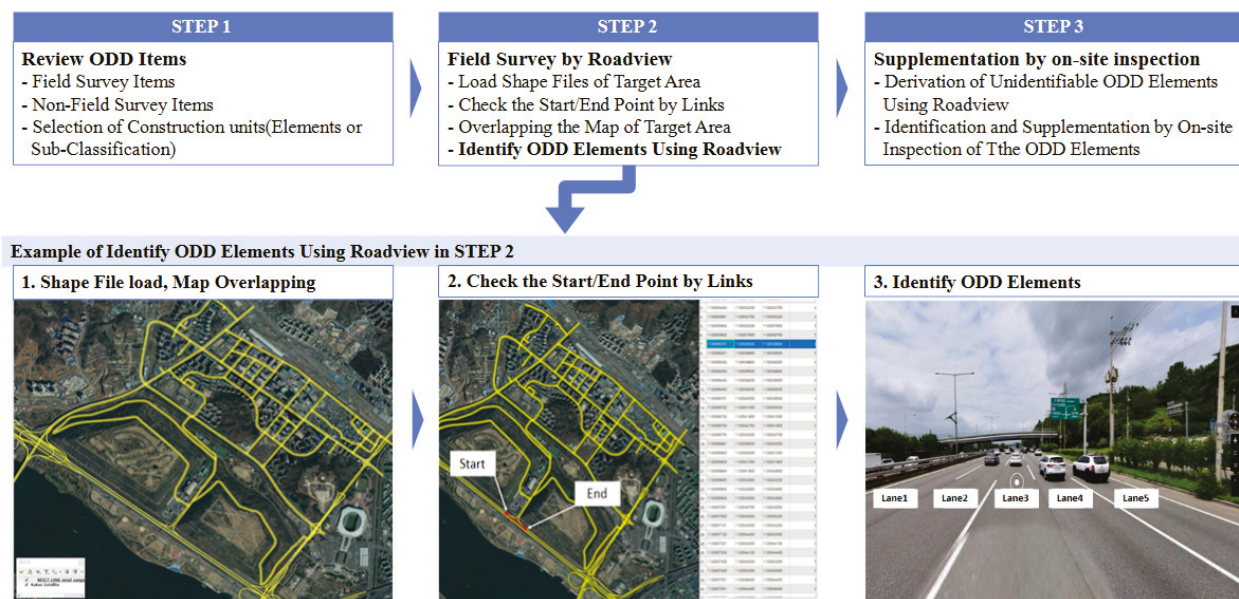


Figure 6. The method and procedure for constructing spatial information.

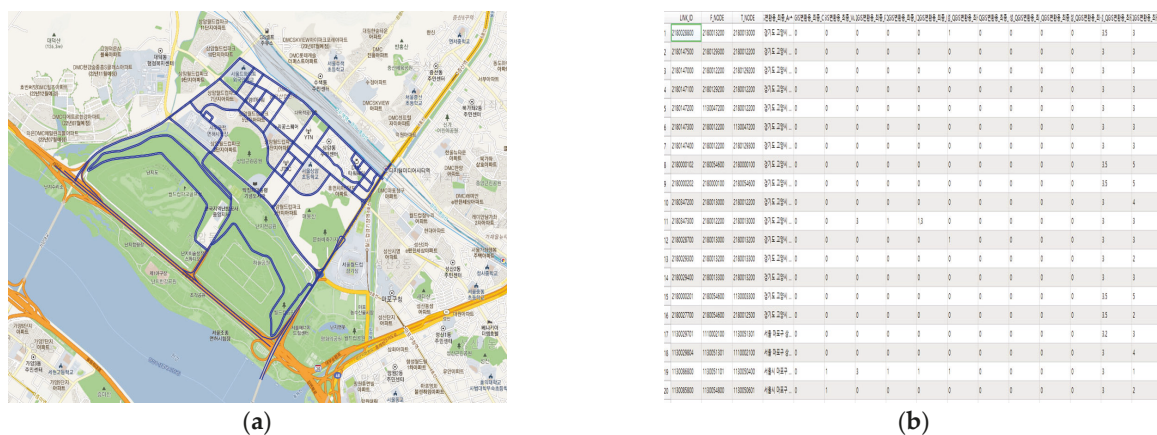


Figure 7. Constructed spatial information (a) and entities table (b) (Source: [22]).

3. Methods

3.1. Automated Driving Mode Change Multiple Spot

The method of selecting the automated driving service section proposed performs a total of 3 steps. First, automated driving mode change multiple-point analysis was performed via the pre-processed dataset and the constructed spatial information. First, grids are generated to identify driving mode changes at multiple points. Then, a frequency analysis is performed using this grid and the latitude and longitude coordinate datasets of the driving mode change points. Then, the center coordinates of the identified multiple spots are generated to extract the driving mode change at multiple points.

Second, spatial factors that affect the safety of automated driving can be estimated by identifying common factors on the basis of spatial ODD elements at the extracted points. Third, to select the automated driving service section, a condition analysis that applies estimated spatial influencing factors and current legal provisions that must be observed is performed. The detailed analysis method is described in this subsection.

3.1.1. Generation of Grid

This section describes how to generate grids at equal intervals to extract automated driving mode changes at multiple points. Grids of the same size can be created via the

vector layer generation function supported by QGIS. To set the size of the grids as described above, the average driving distance per second per month (excluding values that are 0) for each vehicle ID is determined as a criterion value. The criterion value may vary depending on the data collection cycle. In this study, as shown in Table 4, the average driving distance per second ranged from a minimum of 7.05 m to a maximum of 7.33 m; therefore, the size of the grids was set to $7.5 \text{ m} \times 7.5 \text{ m}$ to include the maximum value. The results of grid generation by route are shown in Figure 8.

Table 4. Calculation results of the monthly average speed and distance per second.

No.	'22.05.	'22.06.	'22.07.	'22.08.	'22.09.	'22.10.	'22.11.	'22.12.	'23.01.	'23.02.
Average Speed (km/h)	25.4	26.38	26.35	25.54	25.9	25.37	25.41	25.59	25.37	26.33
Distance per Second(m)	7.06	7.33	7.32	7.09	7.19	7.05	7.06	7.11	7.05	7.31

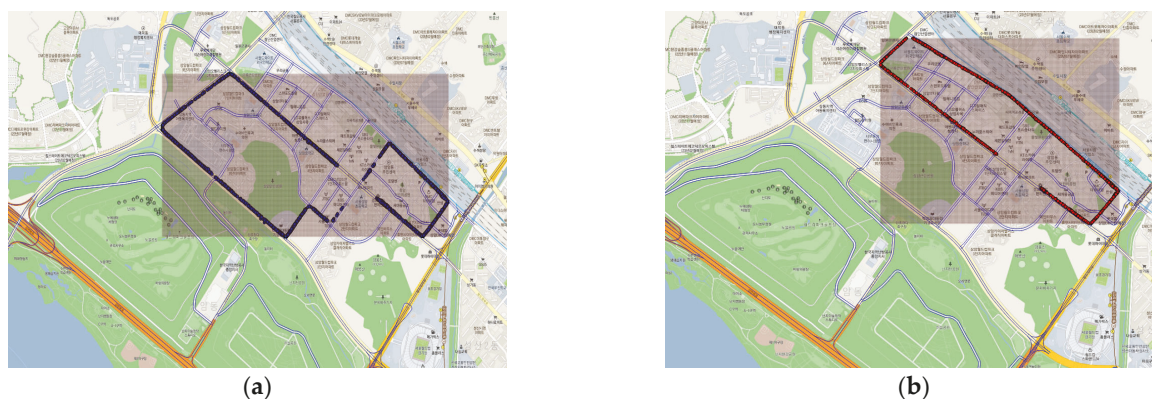


Figure 8. Output screen grid of route A (a) and route B (b).

3.1.2. Frequency Analysis

Perform frequency analysis using the function to calculate the number of points included in the polygon supported by QGIS. The polygon calculation algorithm calculates the number of points of the point layer included in the polygon layer from the input point layer and the polygon layer. The new polygon layer is generated by adding a field with the number of points contained in each polygon to the same field as the input polygon layer. This study did not apply weights because only the driving mode change was considered in the collected field data.

In the case of route A, the input parameters for frequency analysis are the shape file of the automated driving mode change point of route A in the point name, the grid of route A generated in the polygon name, and “Frequency” in the field name. The input parameters of route B are the shape file of the automated driving mode change point of route B in the point name, the grid of route B generated in the polygon name, and “Frequency” in the field name. The screens of input parameters for frequency analysis by route are shown in Figure 9.

Driving mode change multiple spots are extracted by selecting the grids in which the value of the ‘frequency’ data field generated by frequency analysis is greater than the criterion value. By frequency analysis, the newly generated grid layer is selected to open the entity table, the generated ‘frequency’ fields are sorted in ascending order, and all data fields with values higher than the criterion value are selected. Here, the criterion value is set on the basis of the number of operations in 10 months for each automated driving service route. When calculating the number of daily operations and the number of weekday operations for 10 months, route A is calculated to have operated approximately 1780 times, and route B is

approximately 2848 times. In this study, 178 times, 10% of the total number of operations of route A was set as the criterion value. The criterion value for the grid size for selecting the driving mode change for multiple points can be calculated via Equation (4).

$$a_i = (b_i \times c_i \times \alpha_i) \times (\beta/100) \quad (4)$$

where a_i is the criterion value for the grid size for selecting the driving mode change multiple spots, b_i is the daily operation time of automated driving, c_i is the number of weekday operations of automated driving, α_i is the number of additional operations of automated driving, and β is the ratio.



Figure 9. Screen of inputting parameters for frequency analysis of routes A (a) and B (b).

Since the grids extracted through this process are in the form of polygons, they must transform into the form of points to know the exact location. Since the grids are a square of $7.5 \text{ m} \times 7.5 \text{ m}$, the center of the square is the center of the diagonal connecting each corner; it can be calculated simply by the following equation. If the coordinates of the 2 points are $A(x_1, y_1)$ and $B(x_2, y_2)$, the center $C(x, y)$ of A and B can be calculated through Equation (5).

$$C(x, y) = \left(\frac{x_1 + x_2}{2}, \frac{y_1 + y_2}{2} \right) \quad (5)$$

The center points can be generated easily by using the centroid algorithm supported by the QGIS. In this study, the input layer for obtaining the centroid is the selected driving mode change multiple grid layers.

3.2. Method of Estimating Spatial Influence Factors of Automated Driving Mode Change

Factors that can affect the safety of automated driving can exist in various factors, such as spatial or dynamic factors. However, this study estimates the factors affecting the safety of automated driving only for spatial ODD factors related to environmental factors, which account for approximately 25% of the results of the analysis of the cause of automated driving disengagement submitted to the Department of Motor Vehicles (DMV), California (2015–2016) [23].

First, using road view (Naver Map, July 2022 ver.), identifies the common spatial ODD elements in front of the driving direction at the driving mode change multiple points extracted by the method described above. Using the frequency table, a qualitative data analysis method, only overlapping spatial ODD elements at each point are aggregated to estimate factors that can affect the safety of automated driving. Here, elements like street trees, lamps, and curbs, which are common elements of the road, are excluded because they are not significantly related to the safety of automated driving. As shown in Figure 10, com-

mon elements in red marks were identified through the road view to estimate spatial ODD elements affecting the safety of automated driving.

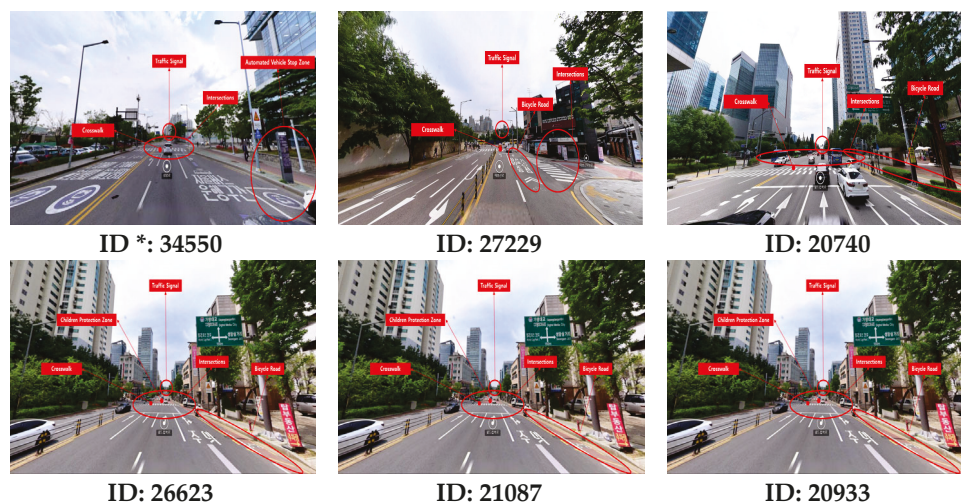


Figure 10. Results of ODD elements identification in road view (Source: [22]). * IDs: multiple points of the automated driving mode change.

3.3. Method of Selecting Automated Driving Service Section

The method of selecting the automated driving service section is performed through condition analysis using the expression of QGIS in consideration of spatial factors affecting the safety of automated driving estimated by the method described in Section 3.2 and current legal regulations. The selection of the automated driving service section is conducted in a total of 2 steps.

First, the considerations when selecting scenarios are the level of automated driving technology and service characteristics. The level of technology is selected for level 3, which currently provides paid services, and level 4, which is preparing to commercialize the service. Here, according to the SAE automated driving vehicle level definition, the biggest difference between level 3 and level 4 is whether humans perform disengagement, leading to Minimum Risk Conditions, or whether the system performs disengagement in the event of a dangerous situation. So, in the case of level 4, it is assumed that services can be provided in all sections that meet the spatial ODD elements presented and essential requirements for automated driving. Next, considering the characteristics of the service, car-sharing and demand–response public transportation services were selected with clear characteristics. The selected scenarios are presented in Table 5.

Table 5. Scenario for selection of automated driving service section.

No.	Scenario
1	Level 3 vs. Level 4 of Automated Driving Service Sections
2	Level 3 vs. Level 4 Automated Driving Car-Sharing Service Sections
3	Level 3 vs. Level 4 Automated Driving Demand–Response Public Transportation Sections

Second, the condition analysis was conducted via the expression function of the QGIS for each scenario. In scenario 1, the conditions for the level 3 automated driving service section are input into the conditional expression to find links, including all spatial ODD elements, that affect the safety of automated driving. For level 4, only the construction of the HD map is input, as previously assumed. Here, pedestrian-only roads were identified through a field survey. The conditional inputted screen for scenario 1 is shown in Figure 11.

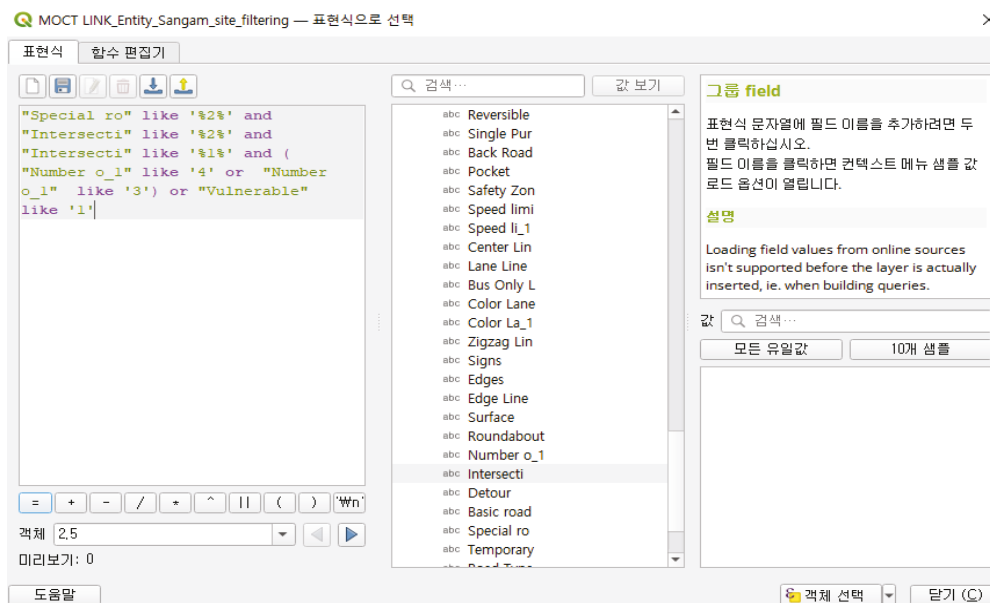


Figure 11. Screen of input conditions for selecting level 3 automated driving services sections.

In scenario 2, for the level 3 automated driving car-sharing service section, the conditions of scenario 1 are input equally, and the conditional expression is input to find additional links that include parking lots and AV stops to enable the picking and turning of the car-sharing service. Level 4 is the same as in scenario 1. In scenario 3, for the level 3 automated driving demand response public transportation service section, the conditions of scenario 1 are input equally, and the conditional expression is input to find additional links that include bus stops and AV stops that can enter and exit public transportation services. Level 4 is the same as in scenario 1. The conditional input screen for scenario 2 is shown in Figure 12, and that for scenario 3 is shown in Figure 13.

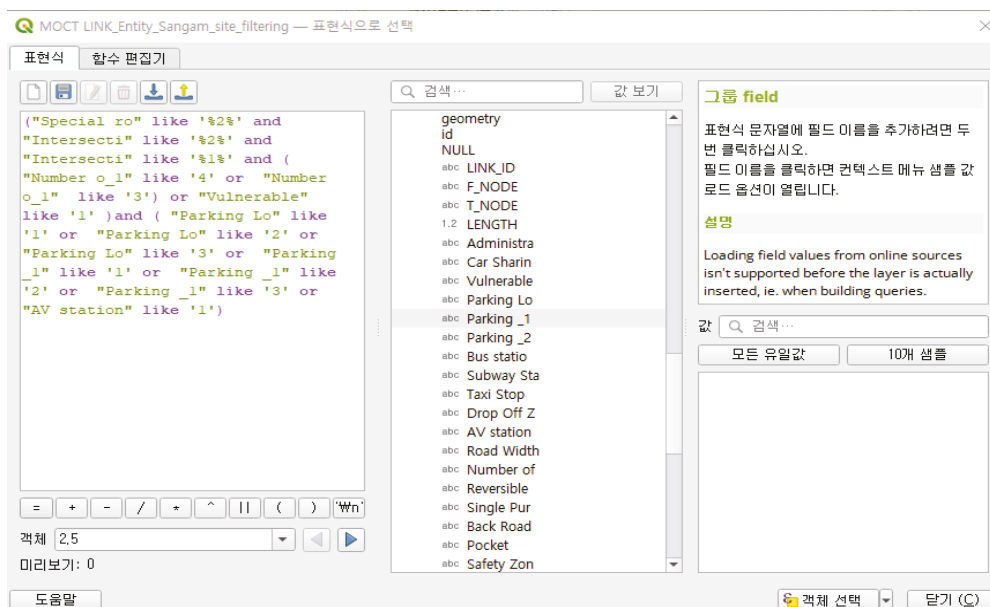


Figure 12. Screen of input conditions for selecting level 3 automated driving car sharing service sections.

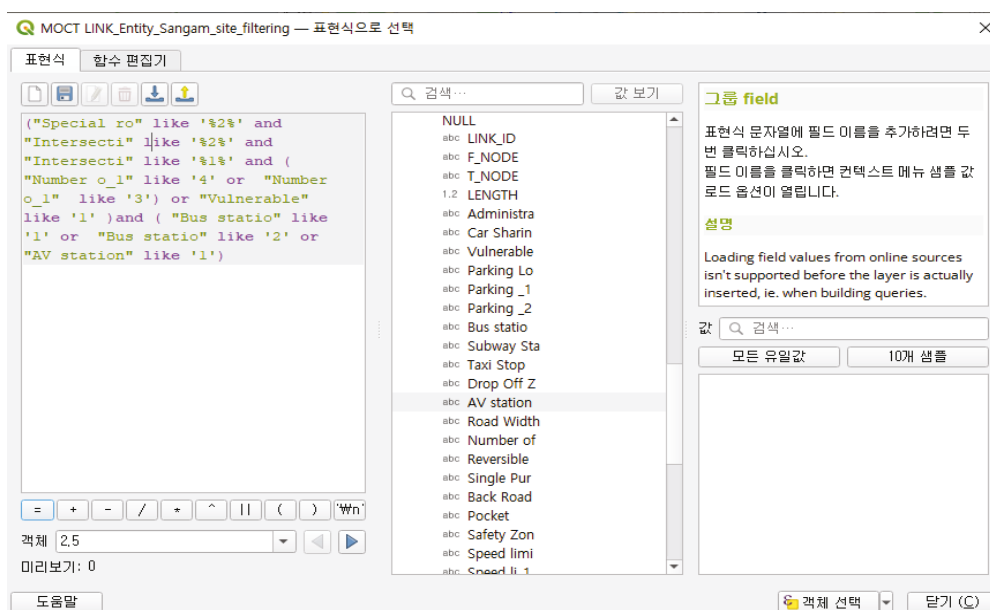


Figure 13. Screen of input conditions for selecting level 3 automated driving demand response public transportation service sections.

4. Results

4.1. Automated Driving Mode Change Multiple Points

As shown in Figure 14, the results of the automated driving mode change multiple spots derived by the frequency analysis and Equation (4) described above presented that route A had four grids and route B had two grids, a total of six grids.

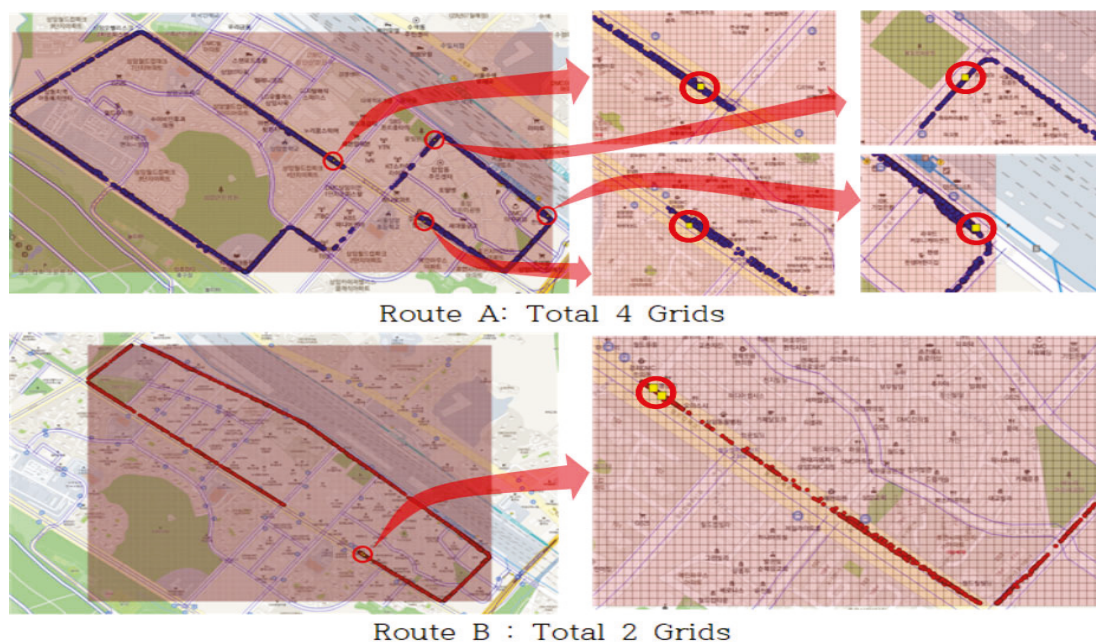


Figure 14. Results of extracting driving mode change multiple grids (Source: [22]).

The table of the centriod layer generated by the centriod algorithm contains the position coordinates of each centriod. Because these are decimal coordinates, a transformation to latitude/longitude coordinates is required to confirm their position on the map. The decimal coordinates are converted into latitude/longitude coordinates via Equation (6) and

can be converted by adding an X/Y field to the layer supported by QGIS. The six converted centroids are shown in Figure 15.

$$\text{Decimal degrees} = \text{degrees} + (\text{minites}/60) + (\text{seconds}/3600) \quad (6)$$



Figure 15. Results of driving mode change multiple points centroid conversion (Source: [22]).

Table 6 shows the results of latitude/longitude coordinate conversion of six driving mode change multiple points extracted from QGIS.

Table 6. Results of centroid conversion at automated driving mode change multiple points (Source: [22]).

ID	X (Longitude)	Y (Latitude)
34550	126.8992	37.57638
27229	126.8945	37.57915
20740	126.8902	37.5784
26623	126.894	37.57618
21087	126.8941	37.57623
20933	126.894	37.5763

4.2. Results of Estimating Spatial Influence Factors of Automated Driving Mode Change

A qualitative data analysis method was used to estimate the spatial ODD factors affecting the safety of autonomous driving via the method described above. Statistical analysis of the quantitative data was impossible because only six samples of the derived automated driving mode were used to change multiple points. Therefore, in this study, although the relationships between mutual elements cannot be statistically analyzed, the statistical analysis method of qualitative data, which can confirm the information held by the data, is used, as presented in Table 7. The frequency table and relative frequency are used.

After listing the relative frequency of spatial ODD elements that exist in the same order at each point in ascending order, we estimated and presented elements with a relative frequency of 10% or more as spatial factors that could affect the safety of automated driving. As a result, it appears as crosswalks, intersections, traffic lights, and bicycle roads.

Table 7. Spatial ODD elements affecting automated driving mode change (Source: [22]).

ID ODD		34550	27229	20740	26623	21087	20933	Total	RF *
Crosswalk		O	O	O	O	O	O	6	0.13
Traffic Signal		O	O	O	O	O	O	6	0.13
Intersections		O	O	O	O	O	O	6	0.13
Bicycle Road		X	O	O	O	O	O	5	0.11
Turn-Only Lane		X	X	O	O	O	O	4	0.09
Median Strip		X	O	X	O	O	O	4	0.09
Signs	Warning	O	X	X	O	O	O	4	0.09
	Regulatory	O	O	O	X	X	X	3	0.07
	Instruction	X	O	X	X	X	X	1	0.02
Vulnerable Users Protection Zone		X	X	X	O	O	O	3	0.07
Fire-Fighting Facilities		X	X	X	O	O	O	3	0.07
Automated Vehicle Stop Zone		O	X	X	X	X	X	1	0.02

* RF: Relative Frequency.

4.3. Selecting Automated Driving Service Section

This section describes the results of the analysis of selecting the automated driving service section. The results for scenario 1 comparing levels 3 and 4 shown through the condition analysis are shown in Figure 16a,b; the level 3 service is the red section, and the level 4 is the sky blue section.

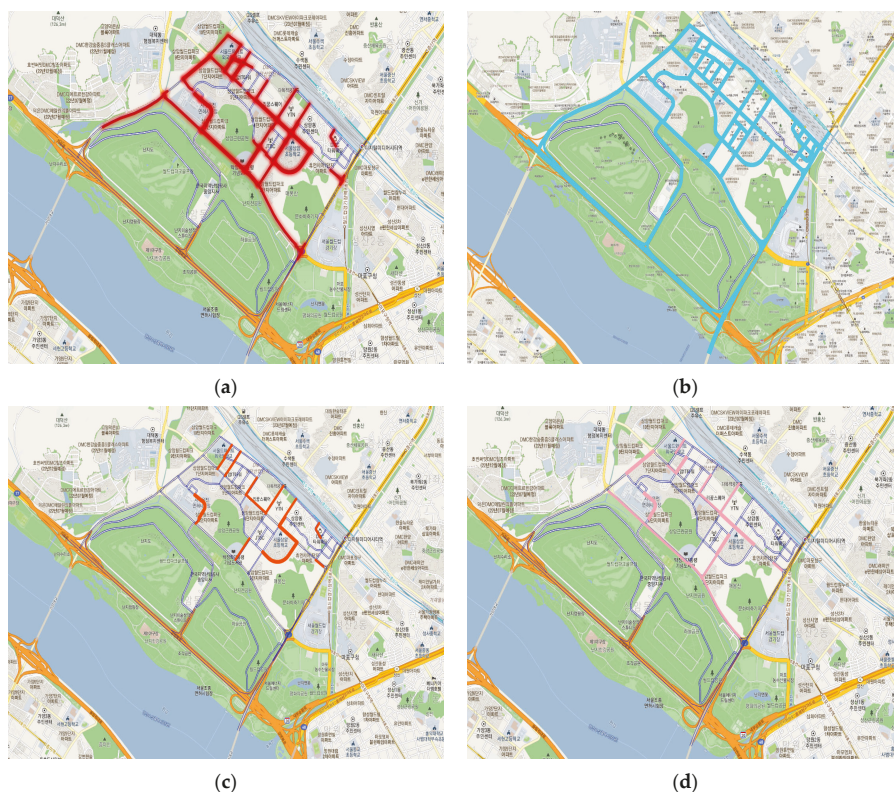


Figure 16. Results of selecting automated driving service section by scenarios. (a) Lv. 3 automated driving service section. (b) Lv. 4 automated driving service section. (c) Lv. 3 automated driving car-sharing service section. (d) Lv. 3 automated driving demand-response public transportation service section.

The results for scenario 2 comparing the levels 3 and 4 automated driving car-sharing service are shown in orange for level 3, as shown in Figure 16c, and the same sky blue for level 4, as in scenario 1.

The analysis results of scenario 3 comparing the levels 3 and 4 automated driving demand response public transportation service are shown in pink for level 3, as shown in Figure 16d, and the same sky blue for level 4 as scenarios 1 and 2.

4.4. Framework for Selecting of Automated Driving Service Sections

In this subsection, a framework for selecting an automated driving service section is presented, as shown in Figure 17, by synthesizing the analysis method and procedure described in Section 3. Methods. The framework is composed of a total of five steps, and for versatility, various analysis methods could be applied in addition to the analysis methods performed in this study.

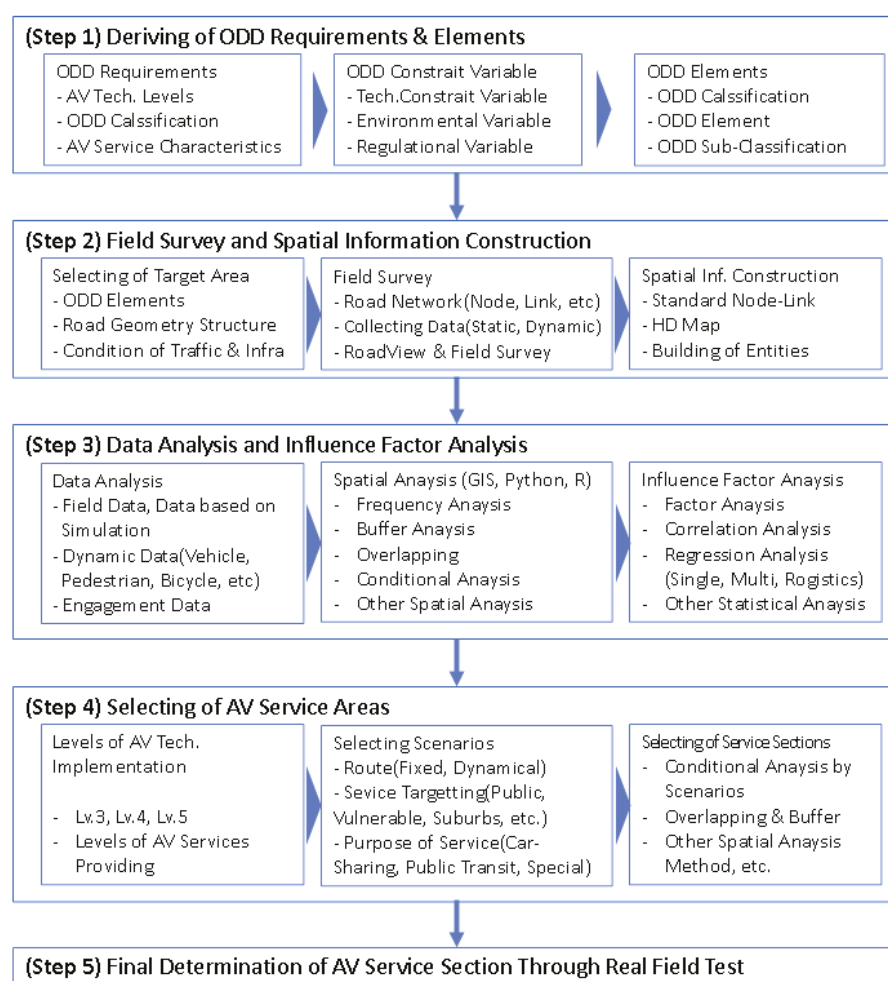


Figure 17. Framework for selecting automated driving service sections.

5. Validation

To prove the validity of the method proposed in this study, it is validated by applying it to test beds in other regions. The test bed for validation was the Jeju Advanced Science and Technology Complex (ASTC), which is currently conducting tests for the development of level 4 automated driving car-sharing service technology. The results are validated by comparing and analyzing the matching rates between the level 3 and level 4 automated driving car-sharing service sections selected through the method proposed in this study and the actual demonstration section in the test bed.

ber of links, and approximately 94% in the distance, and the matching rate between the demonstration section and the planned section is more than 81% in the number of links and more than 70% in the distance.

The matching rate between the planned section and the target section of level 4 is 100% consistent in both the number of links and the distance, and the matching rate between the demonstration section compared to the planned section is about 74% in the number of links and more than 84% in the distance.

Here, the target section is the entire demonstration section, including vulnerable user protection zones that must be legally driven in manual mode within the test bed. The planned section is the selected section by the method proposed in this study, and the demonstration section is the section finally confirmed through actual field tests. The results of the comparative analysis of the matching rate are presented in Table 8.

Table 8. Results of comparative analysis of the matching rates for selecting of automated driving car-sharing service section.

Division		AV Levels	
		Level 3	Level 4
Planned Section(A)	Links (Num)	11	70
	Distance (m)	2571.72	17,613.15
Demonstration Section(B)	Links (Num)	9	52
	Distance (m)	1810.04	14,930.68
Target Section(C)	Links (Num)	12	70
	Distance (m)	2711.28	17,613.15
Matching Rate of Planned Section Compare to Target Section ($A/C \times 100$), (%)	Links	91.67	100.00
	Distance	94.85	100.00
Matching Rate of Demonstration Section Compare to Planned Section ($B/A \times 100$), (%)	Links	81.82	74.29
	Distance	70.38	84.77

The automated driving car-sharing service section selected through the proposed method is shown in yellow for level 3 and red for level 4, as shown in Figure 20a. The demonstration section in Jeju ASTC, which was confirmed after the actual driving test, is shown in Figure 20b. Here, the yellow is the section where level 3 should be driven, and the red is the section where the service is available for level 4. The green is the section where the automated driving service is not possible because the HD map cannot be constructed.

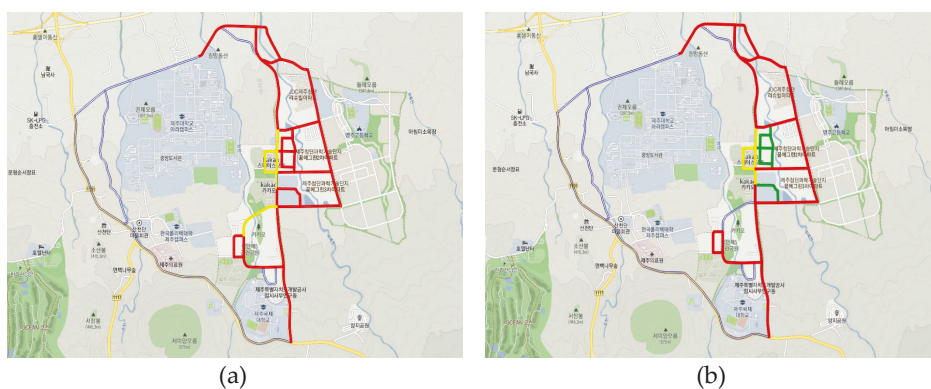


Figure 20. Results of selecting automated car-sharing service section by proposed method (a) and real testbed section (b).

6. Discussion

The results of the analysis indicate that the matching rate of the demonstration section compared with the planned section is relatively lower than that of the planned section compared with the target section. The reason is that it was impossible to construct an HD map, a key requirement for automated driving, in this section, as scanning was impossible because of habitual illegal parking, such as the green section in Figure 19b. However, in the planning section, compared with the target section, the matching rate is greater than 91% in all the cases, and in the demonstration section, compared with the planning section, the matching rate is greater than 70% in all the cases. Therefore, the method proposed in this study can be applied to efficiently select sections that can provide services in advance in the planning step for the deployment of automated driving services in the future. Thus, the proposed method can be expected to save time and costs required for field surveys and actual tests.

7. Conclusions

One needs to consider two aspects when planning the operational design (ODD). First, car OEMs have their own ODDs mechanically when producing ADS-equipped vehicles; however, they cannot guarantee that they are in real road traffic environments because of unexpected spatial influence factors. Second, service providers who do not carry out OEMs should also have their own ODDs in their service sections to provide passengers with automated vehicle service safely. The proposed method considers these two aspects by reflecting the disengagement of ADS-equipped vehicles and the spatial influence factors in the target service section.

The purpose of this study is to develop a method for selecting an automated driving service section that can be used when central and local governments plan to introduce services in the future. Since the central government and local governments to introduce automated driving services need to ensure inclusiveness and welfare, especially in public transportation, it is not reasonable to select a specific car OEM and its ODD in advance, but it is necessary to apply the proposed analysis method to the expected service sections.

In this study, on the basis of the expected ODD, the spatial factors affecting the safety of automated driving were estimated with automated driving mode change (i.e., disengagement) data obtained from level 3 automated vehicles, which were actually operated with payment services in domestic urban areas. On the basis of those factors, the method of selecting the automated driving service section was proposed based on spatial information analysis. This study consists of three subparts as follows.

First, the spatial factors that affect the safety of automated driving were estimated by using the field data obtained from the level 3 automated driving services in Korea. As a result, those factors were derived with a high probability of collision between dynamic factors, such as crosswalks, traffic lights, intersections, and bicycle roads.

Second, the method of selecting automated driving service sections with spatial information analysis was proposed on the basis of those estimated factors, and then, the framework for selecting the automated driving service section was presented by synthesizing the procedures of the proposed method in this study.

Third, the proposed analysis method was validated by applying it to a testbed of the automated driving car-sharing service project sponsored by the Korea Autonomous Driving Development Innovation Foundation (KADIF). As a measure of effectiveness (MOE), the matching rate between the service section derived through the proposed method and the demonstration section and target section in the target testbed (i.e., Jeju Advanced Science and Technology Complex) was compared and analyzed. As a result, in the level 3 automated driving car-sharing service, the matching rate of the planned section compared

to the target section was about 91% for the number of links and 94% for the section distance, and the matching rate of the demonstration section compared to the planned section was about 81% for the number of links and about 70% for the section distance. In level 4, the matching rate of the planned section compared to the target section was 100% consistent with both the number of links and the distance, and the matching rate of the demonstration section compared to the planned section was about 74% in the number of links and more than 84% in the section distance. Therefore, the analysis method proposed in this study proved that it is possible to select sections that can provide the service in advance in the planning stage before the deployment of the automated driving service.

Notably, this study has two main features that contribute to automated vehicle deployments and their service applications, especially compared with previous studies. First, for the first time in Korea, the main ODD factors affecting the safety of automated driving were estimated via spatial information analysis with disengagement data obtained from actual automated vehicle services operations. Second, the spatial ODD-based methodology was developed to select the automated driving service section in advance using spatial information analysis.

As a result of applying the analysis method proposed in this study to the demonstration testbed of the Jeju ASTC, it is believed that this methodology can contribute to the promotion of the commercialization of efficient and safe automated driving services as the basic methodology that can be used when deploying automated driving, such as selecting the automated driving pilot driving zone in the future. In addition, it is expected that the methodology proposed in this study will be used not only for the living lab city of the KADIF but also for the selection of service operation areas in the automated driving pilot zone currently being expanded and operated.

This study has several limitations, as follows. First of all, since the collected field data of automated driving vehicles were limited, the precise location-based analysis was not performed, and the spatial information analysis that was link-based was performed only on static factors.

The other limitation is that when estimating spatial ODD elements that affect the safety of automated driving, the quantitative analysis such as statistical models was not performed due to insufficient number of samples, and the influencing factors for spatial information analysis were estimated only by qualitative analysis. To improve this limitation, it is necessary to analyze quantitative influencing factors for the entire driving mode change point in units of segments in the further studies, after subdividing the link or building spatial information entities on units of points.

In addition, it is also necessary to analyze the influencing factors of dynamic factors related to road traffic environment around automated vehicles, when collecting additional automated driving data and dynamic information based on the influencing factors derived from this study. It should be considered when conducting detailed research, such as sensitivity analysis among those factors after precisely building spatial information entities, including point information.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. ODD elements and classifications for level 4 automated driving services (scenery)
(Source: [22]).

Attribution	Sub-Attribution	ODD Elements		Sub-Classifications	
Scenery (Non-Moveable Elements)	Zones	Place of Rental/Return of Shared Car		Car-Sharing Zone	
				Car-Sharing Only Platform (On the Road)	
		Vulnerable Users Protection Zone		School Zone	
				Children Protection Zone	
				Senior Zone	
		Parking Lots	Legislation	On-Road Parking Lot	
				Off-Street Parking Lot	
				Attached Parking Lot	Apartment
					Residence
					Commercial
			Type	Drive in Parking	
				Mechanical Parking	
				Mixed Parking	
			Form	Right Angle Parking	
				Parallel Parking	
				30° Forward Parking	
				45° Forward Parking	
				45° Cross Parking	
				60° Forward Parking	
				60° Reverse Parking	
				Stopper Present or Not	
		Bus Station		Station in Bus Only Lane	
				Station in Regular Lane	
				Subway Station Entrance	
		Taxi Station		Taxi Stand (First-In-First-Out Type)	
				General Taxi Stand	
		Vehicle Stop Zone		Lobby of Building	
				Valet Zone	
				Transit Stop Zone	
				Automated Vehicle Stop Zone	

Table A1. Cont.

Attribution	Sub-Attribution	ODD Elements	Sub-Classifications	
Scenery (Non-Moveable Elements)	Drivable Area	Road Type	National Highway	Expressway
				National Highway
			Metropolitan City Road	
			Local Road	
			City Road	
			County Road	
			District Road	
		Geometry	Crossing gradient	
			Longitudinal Slope	
			Curvature	
		Lane Specification	Lane Width	
			Number of Lane	
			Variable Lane Status	
			Bus Only Lane Status	
			Back Road	One-Way
				Two-Way
			Turn-Only Lane	Right-Turn
				Left-Turn
			Safety Zone	
			Speed Limit	
		Line Specification	Solid Line	White
				Yellow
				Blue
			Dotted Line	White
				Yellow
				Blue
			Mixed Line	White
				Yellow
				Blue
			Double Solid Line	White
				Yellow
				Blue
		Line Specification	Driving Guidance Line	Blue
				Green
				Pink
			Zigzag Line	
		Signs	Warning Sign	Road Work Zone
				Wildlife Sanctuary
				Etc
			Regulatory Sign	U-Turn
				No Parking
				Etc
			Instruction Sign	Traffic Direction
				Only Way
				Etc

Table A1. Cont.

Attribution	Sub-Attribution	ODD Elements	Sub-Classifications	
Scenery (Non-Moveable Elements)	Drivable Area	Signs	Assistance Sign	
		Edge	Fire-Fighting Facilities	
			Guardrail	
			Median Strip	
			Curb	
			Bicycle Road	
			Gutter	
			Shoulder	
			Solid Line	White
				Yellow
				Red
			Dotted Line	White
				Yellow
			Double Solid Line (Yellow)	
		Surface	Asphalt	
			Concrete	
			Earth and Sand (Non-Paved)	
			Crushed Stone (Non-Paved)	
			Gravel	
			Block	
			Ice	
	Junction	Roundabouts	Roundabouts (N-Way)	
		Intersections	Intersections (N-Way)	
			Bicycle Road (Y/N)	
			Traffic Signal Status	Traffic Signal
				Non-Traffic Signal
				Flash Traffic Signal
				Unprotected Traffic Signal
				C-ITS
			Detour Possibility	Dead-end Road
				Cul-De-Sac
	Basic Road Structures	Building Structure	Building (All Buildings)	
		Road Structures	Streetlight	
			Traffic light	
			Street Tree	
			Sidewalk	
			Traffic Island	
			Bollards	
	Special Structure	Special Structure	Bridge	
			Crosswalk	
			Railway Crossing	
			Weaving section	
			Speed Bump	
			Tunnel	

Table A1. Cont.

Attribution	Sub-Attribution	ODD Elements	Sub-Classifications	
Scenery (Non-Moveable Elements)	Special Structure	Special Structure	Square	
			Entry and Exit Block	
			Tollgate	
	Temporary Road Structure	Work Zone	Large-Scale Construction	Public Work Subway Construction

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Spatial Performance Indicators for Traffic Flow Prediction

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Abstract: Traffic flow prediction, crucial for traffic management, relies on spatial and temporal data to achieve high accuracy. However, standard performance metrics only measure the average prediction errors and overlook the spatiotemporal aspects. To address this gap, this study introduces three simple spatial key performance indicators (KPIs): Global Moran's I, Getis-Ord General G, and Adapted PageRank Algorithm Modified (APAM). We evaluated the traffic prediction results for synthetic clustering scenarios and four different prediction methods applied to the PeMSD8 dataset using spatial KPIs. Spatial KPIs are calculated based on traffic prediction errors and the adjacency matrix of the traffic network. Our results demonstrate that spatial KPIs can effectively differentiate between synthetic clustering scenarios. Global Moran's I measures the spatial autocorrelation, Getis-Ord General G measures the spatial clustering of high/low values, and the univariate analysis of APAM deduces the distribution of node importance by considering node centrality and node values. Getis-Ord General G showed the highest sensitivity, being capable of distinguishing between methods with similar average RMSE, whereas Global Moran's I and APAM univariate analysis revealed subtle differences between methods. Spatial KPIs serve as important complementary metrics for performance evaluation in the design of robust traffic management systems.

Keywords: traffic prediction; spatiotemporal prediction; spatial autocorrelation; clustering; centrality; Global Moran's I; Getis-Ord General G; PageRank

1. Introduction

Traffic flow prediction is crucial for improving traffic management systems, with applications such as traffic signal control and route guidance. However, predicting traffic flow in traffic networks is challenging because of their nonlinear dynamic nature, limited resources, spatiotemporal dependency, and seasonality [1]. In recent years, the abundance of traffic data has led to increased interest in traffic predictions, especially in the machine learning community.

Traffic flow prediction poses a challenging problem due to the following factors: (1) spatiotemporal dependencies and (2) external factors such as weather conditions and events [2]. Temporal aspects of traffic flow usually arise from the seasonality of data due to human behavior. For example, during weekdays, the traffic flow usually has an M-shaped pattern consisting of two peaks: morning and evening rush hour peaks, whereas, during weekends or holidays, the traffic flow pattern is different. Traditional prediction methods, such as Seasonal Autoregressive Integrated Moving Average (SARIMA) [3], use only the temporal aspects of the data and ignore the spatial dependencies present in traffic networks. To improve prediction accuracy, these methods separate training data with different temporal patterns, such as weekdays, weekends, and holidays. The spatial aspects of traffic prediction are summarized in Tobler's first law of geography, which states that everything is related to everything else, but the things near are more related than those distant [4]. This behavior originates from the topology of traffic networks, which is represented as a graph with an adjacency matrix.

In the last decade, spatiotemporal prediction methods that take advantage of both temporal and spatial data have become popular because the addition of spatial contexts can improve the prediction accuracy [5]. Examples are Attention Based Spatial-Temporal Graph Convolutional Networks (ASTGCN) [6] that utilize recent, daily periodic, and weekly periodic data as temporal contexts and an undirected graph of the traffic network as spatial contexts using the attention mechanism, and Spatial-Temporal Synchronous Graph Convolutional Networks (STSGCN) [7] that synchronously capture both spatial and temporal correlations directly.

Different prediction methods have different spatiotemporal characteristics based on the spatial and temporal information. For example, the addition of hourly, daily, and weekly periodic data to complement recent data introduces temporal periodicity and improves the prediction performance during peak hours [8]. However, introducing a graph network that represents the spatial structure of the traffic network allows the traffic prediction method to utilize spatial information, resulting in better performance [9]. These characteristics affect the traffic prediction results, such as the performance of the traffic prediction and spatial distribution of the prediction at each location.

Unfortunately, the literature usually relies only on standard performance KPIs, such as RMSE, MAE, and MAPE, to compare prediction techniques [10]. These KPIs only provide an average point-wise error of the prediction accuracy from the entire traffic network, without information on the underlying distribution related to the spatiotemporal characteristics of the method. Although this approach simplifies the evaluation process, the requirements of real-world traffic management systems are more complex than the average prediction errors, leading to a discrepancy between the research findings and their practical applicability. For example, a traffic flow prediction method with bad prediction node clusters will have a more negative impact than other methods with uniformly distributed prediction errors in traffic signal control applications. This is because bad prediction node clusters degrade the control performance of the area, and this degradation can propagate further to neighboring areas.

The lack of a variety of prediction models' KPIs has been acknowledged, and researchers are attempting to solve this problem in various domains, such as databases [11], classification problems [12], sparse spatiotemporal point processes [13], and uncertainty in spatial forecasting [14]. However, such KPIs are usually limited to particular applications or require modifications to the prediction method, and most of them cannot be applied to traffic flow prediction problems. While some studies on traffic prediction have considered prediction accuracy across different forecast horizons, they have been primarily limited to multi-step prediction problems. Evaluating the short- and long-term predictions of a spatiotemporal prediction model is important to understand its robustness and adaptability in real-world applications [15]. However, current standard KPIs do not provide a comprehensive evaluation of these temporal aspects. Similarly, the evaluation of the spatial aspects of spatiotemporal methods in traffic prediction is currently lacking.

In this study, we aimed to investigate various spatial metrics commonly utilized in the domain of Geospatial Information Systems (GIS) and network graph analysis, including Global Moran's I [16], Getis-Ord General G [17], and Adapted PageRank Algorithm Modified (APAM) [18]. These metrics were chosen because of their simplistic nature, which makes them easy to interpret. Traffic prediction methods use various input data and algorithms, resulting in different levels of spatial characteristics. We consider these metrics to be the spatial KPIs utilized to measure the spatial context present in the traffic flow prediction method. We recognize that evaluating both spatial and temporal aspects is important. However, we will focus only on spatial aspects, deferring the evaluation of temporal aspects to future research.

Our experiments primarily focused on spatiotemporal prediction methods that utilize spatial information, such as the structure of the traffic network based on a graph adjacency matrix. We compared the results of spatial KPIs that evaluate different traffic flow prediction methods on the PeMSD8 dataset [19], measured on freeway traffic networks

in California. We considered four traffic flow prediction methods: (1) STSGCN [7], (2) ASTGCN [6], (3) DDGCRN [20], and (4) STAEformer [21]. These methods were chosen for their diverse approaches to incorporating spatial information in traffic prediction while having similar average RMSE. We specifically chose spatiotemporal traffic prediction that can effectively capture the intricate localized spatiotemporal correlations present in the traffic network, which aligns with the recent research in the field. To provide insight into the capabilities of spatial KPIs under different scenarios, we created synthetic scenarios by modifying the traffic flow prediction results to exhibit various clusters in the form of hotspots and coldspots. This allows us to demonstrate the capabilities of spatial KPIs to distinguish different scenarios when the standard accuracy KPIs fail to do so.

The remainder of this paper is organized as follows. In Section 2, we briefly describe the traffic network graph and the traffic prediction problem. In Section 3, we explain the materials and methods, including (1) different spatial KPIs such as Global Moran's I, Getis-Ord General G, and Adapted PageRank Algorithm Modified (APAM) value for evaluating the spatial aspects of spatiotemporal prediction models and (2) experimental setups such as datasets, clustering scenarios for the case study, and different traffic prediction methods to generate traffic flow prediction results. In Section 4, the results of the evaluations for all clustering scenarios and traffic prediction methods utilizing spatial KPIs are presented. In Section 5, we summarize the main findings and discuss the implications of spatial KPIs for traffic management systems. The conclusion and future work are summarized in Section 6.

2. Preliminaries

2.1. Traffic Networks Graph

In this study, we consider a traffic network as an undirected graph $G = (V, E)$, where V denotes the vertices or nodes of the graph with the number of nodes defined as $|V| = N$ and E represents the set of edges that indicate the connection between nodes. The graph is represented by an adjacency matrix $A \in \mathbb{R}^{N \times N}$. In this study, each node in a traffic network G represents a traffic sensor that measures traffic data.

2.2. Traffic Flow Prediction Problems

Suppose that the traffic sensor at each node n measures the t -th traffic flow. The traffic prediction problem is used to predict the traffic flow data in the future. Given a traffic flow series $X_{t-T+1:t}$ in the previous T time intervals, the traffic prediction method predicts T' intervals in the future, which can be summarized as $[X_{t-T+1:t}, \dots, X_t] \rightarrow [X_{t+1}, \dots, X_{t+T}]$, where each vector $X_i \in \mathbb{R}^N$ represents the traffic flow data of all nodes for each time interval in the traffic network. Traffic flow prediction problems are illustrated in Figure 1.

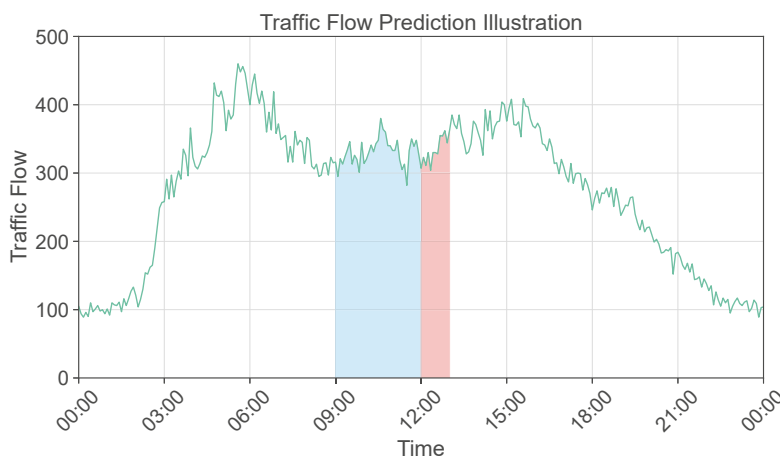


Figure 1. Illustration of traffic flow prediction problems. The area highlighted in blue represents past states $[X_{t-T+1:t}, \dots, X_t]$, which are utilized to predict future states $[X_{t+1}, \dots, X_{t+T}]$, represented by the area highlighted in red.

3. Materials and Methods

3.1. Spatial KPIs

This study aims to enhance the evaluation of traffic prediction by incorporating spatial KPIs alongside standard accuracy KPIs. This study focuses on three specific measures from the domain of GIS and network graph analysis: spatial autocorrelation measured by Global Moran's I, the spatial clustering of high/low values measured by Getis-Ord General G, and node centrality measured by the Adapted PageRank Algorithm Modified (APAM).

3.1.1. Spatial Autocorrelation (Global Moran's I)

Global Moran's I [16] is a measure of spatial autocorrelation that evaluates the relationship between feature values at different locations, considering their spatial proximity and covariance. Global Moran's I provides a single summary measure of spatial autocorrelation for an entire network, allowing researchers to quantify the overall degree of spatial dependence [22]. Despite its simplicity, Global Moran's I has several applications in traffic management systems such as describing the urban traffic state spatial pattern [23], investigating the impacts of the built environment on traffic states [24], and analyzing road traffic crashes by severity [25]. The metric determines whether the feature values exhibit a positive or negative correlation across spatial distances. Global Moran's I is calculated using Equation (1).

$$I = \left[\frac{n}{\sum_i^n (x_i - \bar{x})^2} \right] \left[\frac{\sum_i^n \sum_j^n w_{i,j} (x_i - \bar{x}) (x_j - \bar{x})}{\sum_i^n \sum_j^n w_{i,j}} \right] \quad (1)$$

Equation (1) for calculating Global Moran's I involves several variables: n represents the total number of features, x_i corresponds to the feature values at a specific location i , $\bar{x}$ represents the average value of all features in the network, and $w_{i,j}$ denotes the element i, j in the adjacency matrix of a graph network. The resulting values of Global Moran's I range from +1 to −1, where a value of +1 indicates maximum positive spatial autocorrelation, 0 indicates a random spatial pattern with no significant spatial autocorrelation, and −1 indicates maximum negative spatial autocorrelation. Spatial autocorrelation refers to the degree to which neighboring locations have similar tendencies. Positive spatial autocorrelation means that neighboring nodes have tendencies to spatially cluster, whereas negative spatial autocorrelation means that neighboring nodes tend to be dispersed.

Global Moran's I can also be calculated as a statistical measure to examine the spatial distribution of values in a network. This involves testing the null hypothesis, which states that the spatial arrangement of these values is a result of random spatial processes.

$$E[I] = -1/(n - 1) \quad (2)$$

$$V[I] = E[I^2] - E[I]^2 \quad (3)$$

$$z_I = \frac{I - E[I]}{\sqrt{V[I]}} \quad (4)$$

$$p_I = 1 - \text{CDF}(z_I) \quad (5)$$

In the above equation, $E[I]$ represents the expectation of I , $V[I]$ represents the variance of I , and $\text{CDF}(z_I)$ represents the cumulative distribution function of z_I -score. The resulting p_I -value and z_I -score were used to evaluate spatial autocorrelation. If the p_I -value of Global Moran's I is deemed statistically significant, this allows us to reject the null hypothesis. Consequently, a positive z_I -score suggests positive spatial autocorrelations in networks, with higher values representing higher correlations (and the opposite holds true).

In this study, we considered Global Moran's I to evaluate the spatial autocorrelation of the traffic flow prediction error of a spatiotemporal traffic prediction method. We argue that

different traffic prediction methods have different levels of spatial information utilization, resulting in different levels of spatial autocorrelation.

In traffic flow prediction, the spatial autocorrelation of the prediction errors provides important information that can enhance traffic management systems. The spatial distribution of prediction errors in traffic networks is nonrandom because of the complex interdependencies between nodes and the inherent spatial structure of the traffic prediction method. The variety of input data and algorithm in traffic prediction methods results in different levels of spatial autocorrelation. The Global Moran's I provides valuable insights into this spatial autocorrelation, allowing us to quantify whether prediction errors are clustered, dispersed, or randomly distributed across the network.

3.1.2. Spatial Clustering of High/Low Values (Getis-Ord General G)

The Getis-Ord General G statistic [17] is a statistical measure that can be used to infer the presence of spatial clustering of high/low node value in the network graph. The null hypothesis associated with this statistic assumes no spatial clustering. The Getis-Ord General G statistic provides an overall assessment of the spatial clustering.

Getis-Ord General G provides a simple and straightforward way to assess the degree of spatial clustering in an entire network [26]. Getis-Ord General G has seen some applications in traffic management systems such as hotspot analysis in traffic safety management [27] and high-risk area identification for traffic crashes [28]. These applications highlight the statistic's effectiveness in identifying spatial clusters. Getis-Ord General G is calculated using Equation (6).

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j} x_i x_j}{\sum_{i=1}^n \sum_{j=1}^n x_i x_j}, \forall j \neq i \quad (6)$$

The Getis-Ord General G statistic is a measure used to assess the spatial clustering of feature values. It calculates the z_G -score by considering the number of features, the feature values in each location, and the elements of the spatial weights matrix. The adjacency matrix cell values are typically between 0 and 1, which ensures that the resulting range of the Getis-Ord General G statistic is also between 0 and 1.

$$z_G = \frac{G - E[G]}{\sqrt{V[G]}} \quad (7)$$

$$E[G] = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j}}{n(n-1)}, \forall j \neq i \quad (8)$$

$$V[G] = E[G^2] - E[G]^2 \quad (9)$$

$$p_G = 1 - \text{CDF}(z_G) \quad (10)$$

In the equation above, $E[G]$ represents the expectation of G , $V[G]$ represents the variance of G , and $\text{CDF}(z_G)$ represents the cumulative distribution function of z_G -score. When the obtained p_G -value (derived from the z_G -score) of the Getis-Ord General G statistic is deemed statistically significant, we can reject the null hypothesis. A positive z_G -score indicates that high-value nodes in the network are clustered together in proximity (hotspots). Conversely, a negative z_G -score signifies that low-value nodes in the network are spatially clustered (coldspots).

Understanding the spatial clustering tendency of a traffic prediction method is an important task. A sporadic high-value node can be caused by an event or sensor fault. However, a spatial clustering of high-value nodes suggests a systematic problem. With Getis-Ord General G, we can infer the tendency of hotspots or coldspots in the traffic prediction error distribution.

3.1.3. Node Centrality Measure (Adapted PageRank Algorithm Modified)

PageRank [29] is a method to compute a ranking of the importance of every web page based on the graph of the web. PageRank utilizes the graph network structure of web networks to measure the global ranking of each web page, which reflects the relative importance of each web page within the network. PageRank is a well-known algorithm for measuring node centrality and is one of the algorithms behind the Google search engines.

The main idea of PageRank can be described by the “random surfing model”. In this model, a user randomly navigates the web by following hyperlinks on the current webpage. The probability that the user clicks on a particular web page indicates its importance. Using this concept, web pages that are more linked to other web pages will be considered more important because they are more likely to be visited by users.

The PageRank PR of node P in graph $G = (V, E)$, with adjacency matrix A and element i, j of the adjacency matrix defined as a_{ij} , can be defined by the following equation:

$$A^* = (a_{ij}^*)_{i,j} \quad (11)$$

$$a_{ij}^* = \begin{cases} \frac{a_{ij}}{c_j} & \text{if } c_j \neq 0 \text{ and } i \neq j \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

$$PR_P(k+1) = \alpha A^* PR_P(k) + \frac{(1-\alpha)}{n} I_n \quad (13)$$

where $PR_P(k)$ is the PageRank of node P in iteration k ; A^* is the adjacency matrix normalized by the number of outbond links from each node; n is the number of nodes; and α is the damping factor, typically set to 0.85, which represents the probability that the user will click on a hyperlink. The algorithm is usually initialized with an equal PageRank value for every page, and the value is updated iteratively until convergence. By calculating the PR of each node, we can rank the importance of all webpages based on centrality measures.

PageRank is typically applied to webpage networks. Unfortunately, traffic networks differ from webpage networks. Centrality measures based on PageRank focus only on the topology of the network and do not consider the data in the network. However, traffic networks are complex systems with a large amount of data measured by sensors, and these data, along with the network graph, are important pieces of information. Traffic networks are also significantly smaller than webpage graphs with fewer edges per node. The concept of “random surfing model” is also debatable in traffic networks as a vehicle needs to take connected routes and is not able to exhibit “teleporting” from one node to the others. Despite its limitation in traffic network, PageRank and its variants have been used to rank nodes in traffic network graphs, and the ranking can be utilized for urban traffic optimization [30] and as a signal to predict congestion [31]. The ability to know the importance of nodes on a graph is important, and, in traffic management systems, knowing the highly important nodes can help to minimize the risks of network-wide disruptions.

We consider a variant of PageRank, the Adapted PageRank Algorithm Modified (APAM) [18], established for ranking nodes in an urban network by utilizing traffic data. The main idea behind APAM is the addition of a data matrix D , which allows the algorithm to incorporate important traffic data. The Algorithm 1 is summarized as follows.

In the APAM algorithm, the damping ratio α is an important parameter representing the weighting between the importance of the network topology and data features. The APAM results are the rankings of each node in the traffic network based on the element of the eigenvector.

The APAM helps to determine the importance of each node in the traffic flow prediction method based on two factors: the prediction error of a node and its node centrality. To simplify the metric, we performed a univariate analysis of the resulting APAM values and drew conclusions based on the moments of the distribution. The univariate analysis of APAM will help to analyze the distribution of the APAM values of all nodes and provide

insights, such as the spread of APAM values, asymmetry of the distribution, and prevalence of outliers. For example, if the univariate analysis reveals that there are some nodes with significantly higher APAM values than the rest of the nodes (which we consider as outliers), we could perform targeted improvement targeted towards those nodes.

Algorithm 1: APAM algorithm.

Assuming a traffic network graph $G = (V, E)$ with N nodes.

1. Obtain adjacency matrix A and the transition matrix A^* by normalizing the adjacency matrix based on Equation (11).
 2. Construct the data matrix $D \in \mathbb{R}^{N \times L}$ with L represents the number of data features.
 3. Construct a vector $\mathbf{v}_0 \in \mathbb{R}^L$ that represents the importance of each data features.
 4. Obtain a vector $\mathbf{v} = D \cdot \mathbf{v}_0$.
 5. Construct the matrix $V = [\mathbf{v} \ \mathbf{v} \ \dots \ \mathbf{v}]$.
 6. Construct the matrix $K = A \odot V + \epsilon \cdot F$ with ϵ is a small value represents the inverse of the total amount of data in the network and F represents is a $N \times N$ -dimensional matrix with all value of the elements equal to 1.
 7. Transform the matrix K into stochastic matrix K^* by normalizing it.
 8. Calculate the matrix $M_{APAM} = \alpha A^* + (1 - \alpha) K^*$
 9. Find the eigenvector $\mathbf{x}_1$ based on the dominant eigenvalue $\lambda_1 = 1$ of the matrix M_{APAM} . The element of this eigenvector is the PageRank value for each associated node, $\mathbf{x}_1 = [PR_1 \ PR_2 \ \dots \ PR_N]$.
-

In this study, we only showed the results of variance, skewness, and kurtosis as part of the univariate analysis. The mean of the APAM value distribution is not informative because the APAM value is derived from the eigenvector of the dominant eigenvalue $\lambda_1 = 1$; hence, the value is dependent on the number of nodes.

3.2. Case Study

In this case study, we evaluate the proposed spatial KPIs using two approaches. First, clustering scenarios were created based on the traffic prediction results of STSGCN [7] for the PeMSD8 dataset. The result is a graph with RMSE as its node value, with the graph adjacency matrix defining its structure. The PeMSD8 dataset is a subset of the PeMS dataset containing traffic flow data from 170 sensors in San Bernardino, CA, USA. We created various clustering scenarios by swapping the node values of the graph to form hotspots and coldspots. This allowed us to test the sensitivity of the spatial KPIs to various clustering scenarios. Second, we compared the evaluation of the spatial KPIs tested on four traffic flow prediction methods applied to the PeMSD8 dataset. These methods were chosen because of their diverse approaches for incorporating spatial information into traffic prediction. The aim of this approach is to validate the spatial KPIs against real traffic prediction results. By evaluating both synthetic scenarios and real prediction methods, we aimed to demonstrate the capabilities of spatial KPIs in distinguishing spatial patterns that are indistinguishable using standard accuracy metrics.

3.2.1. PeMSD8 Dataset

In this case study, we evaluated the traffic flow prediction results of the PeMSD8 dataset, a subset of the well-known PeMS dataset that contains highway traffic data from California [19]. The PeMSD8 dataset includes both traffic flow data and graph adjacency matrix of the California freeway networks. This dataset was chosen specifically because it is widely used as a reference benchmark to evaluate the traffic flow prediction performance.

The PeMSD8 dataset used in this study was derived from real-time traffic measurements obtained by the Caltrans Performance Measurement System (PeMS). These measurements were collected every 30 s and aggregated into 5-min intervals. In this study, we chose the PeMSD8 dataset, a subset of the PeMS dataset that specifically focuses on traffic data from San Bernardino between July and August 2016. To remove redundancy, each

detector in this dataset was chosen to be located at least 3.5 miles from the neighboring detectors, resulting in a total of 170 detectors [6].

The dataset comprised three types of traffic states: traffic flow, traffic speed, and occupancy. However, in this study, we focused only on the traffic flow predictions. The dataset also includes an adjacency matrix that represents the network graph, explaining the spatial relationship between traffic sensors as shown in Figure 2. This adjacency matrix enables the use of graph-based traffic flow prediction methods that rely on predefined graph structures. Further details of the PeMSD8 dataset are presented in Table 1.

Table 1. Summary of the PeMSD8 dataset.

Number of Nodes	170
Dataset Length	17,856
Dataset Interval	5 min
Time Range	July 2016–August 2016
Data Types	Traffic flow, traffic speed, occupancy, and adjacency matrix

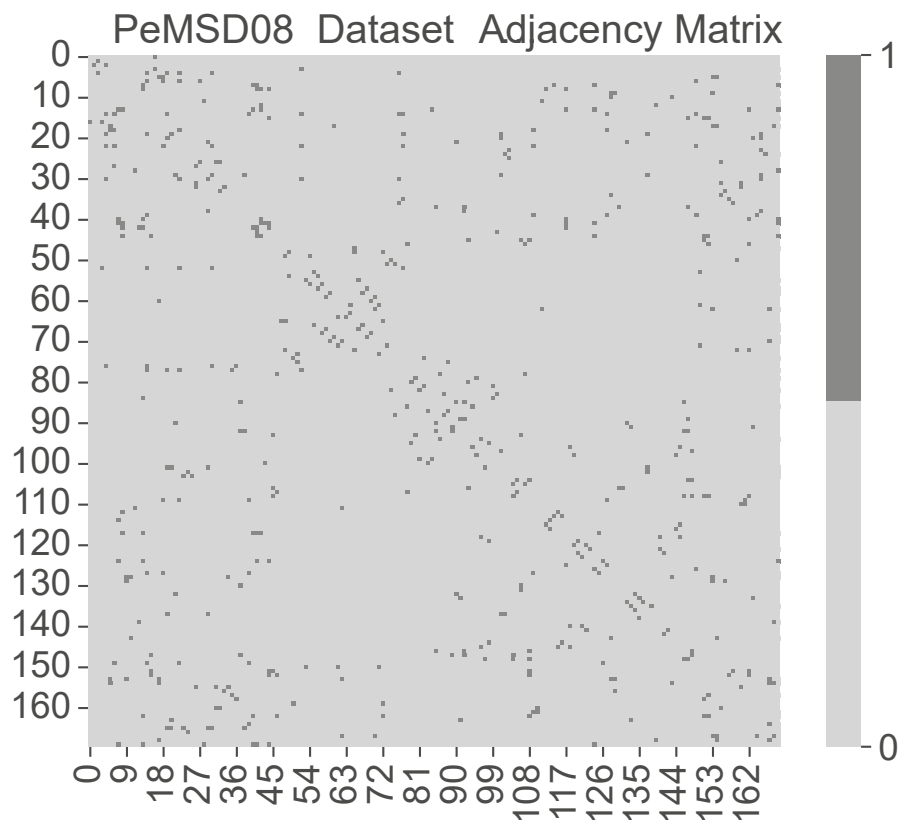


Figure 2. Adjacency matrix of PeMSD8 datasets.

3.2.2. Clustering Scenario

In this study, we considered different clustering scenarios to evaluate and validate whether spatial KPIs can provide information related to the synthetic spatial clusters. We assume that the clusters formed in the traffic flow prediction results are influenced by the spatial characteristics present both in the traffic flow prediction methods and the traffic flow itself. For example, if traffic flow prediction utilizes traffic flow data from neighboring nodes (similar to convolution), we expect a higher positive spatial correlation between nodes with close proximity, resulting in spatially clustered nodes.

A cluster of nodes with poor prediction accuracies is undesirable and should be avoided because it signals a systematic prediction accuracy problem. However, the average

prediction accuracy did not provide any information regarding this. The analogy can be derived from image denoising problems, where speckle noises are harder to denoise compared to salt-and-pepper noises, owing to their multiplicative nature [32].

A flowchart of the experiments based on traffic flow prediction for calculating the spatial KPIs is shown in Figure 3. We considered the RMSE of each node as the traffic prediction result. The traffic prediction results to be evaluated are a graph with RMSE as its node value, with the graph adjacency matrix defining its structure. Clustering scenarios were created based on the traffic prediction results of STSGCN [7] for the PeMSD8 dataset. Based on the prediction results, we created clusters of nodes with similar node values by swapping the node value of a group of nodes located close to each other with the value of the nodes with the largest or lowest prediction error. The location of the cluster is predetermined by selecting a group of nodes that naturally form a cluster.

There are two types of clusters based on the node value considered: (1) high node values or hotspot denoted as “H” and (2) low node values or coldspot denoted as “L”. We also considered two different types of cluster’ topologies: (1) line clusters and (2) star clusters, as illustrated in Figure 4. The different cluster scenarios and the number of nodes in each cluster are summarized in Table 2. The line HH scenario refers to a scenario in which there are two high-value node clusters or hotspots in the form of a line cluster, and each cluster consists of five nodes. Because we only swap the node values, the topology of the network for both the original scenario and the clustering scenario remained identical. The locations of the clusters were similar for scenarios with similar numbers of clusters and cluster topologies. The locations of the clusters on each clustering scenario are shown in Figure 5. Each scenario had an identical average RMSE and was indistinguishable when evaluated using the standard prediction error measure.

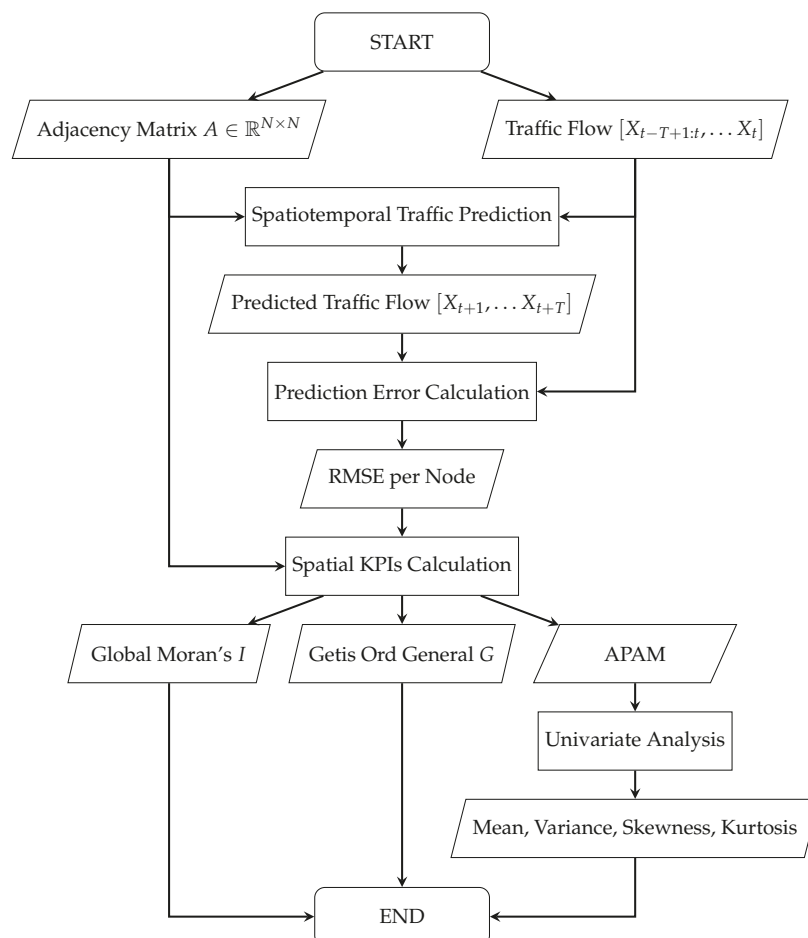


Figure 3. Flowchart of the experiment.

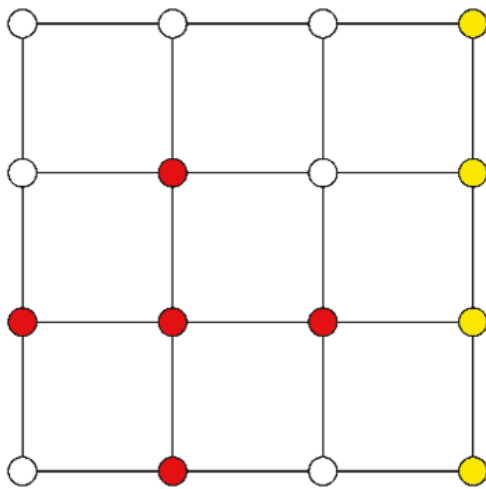


Figure 4. Illustration of two types of cluster based on topology: (1) line cluster represented by yellow nodes and (2) star cluster represented by red nodes.

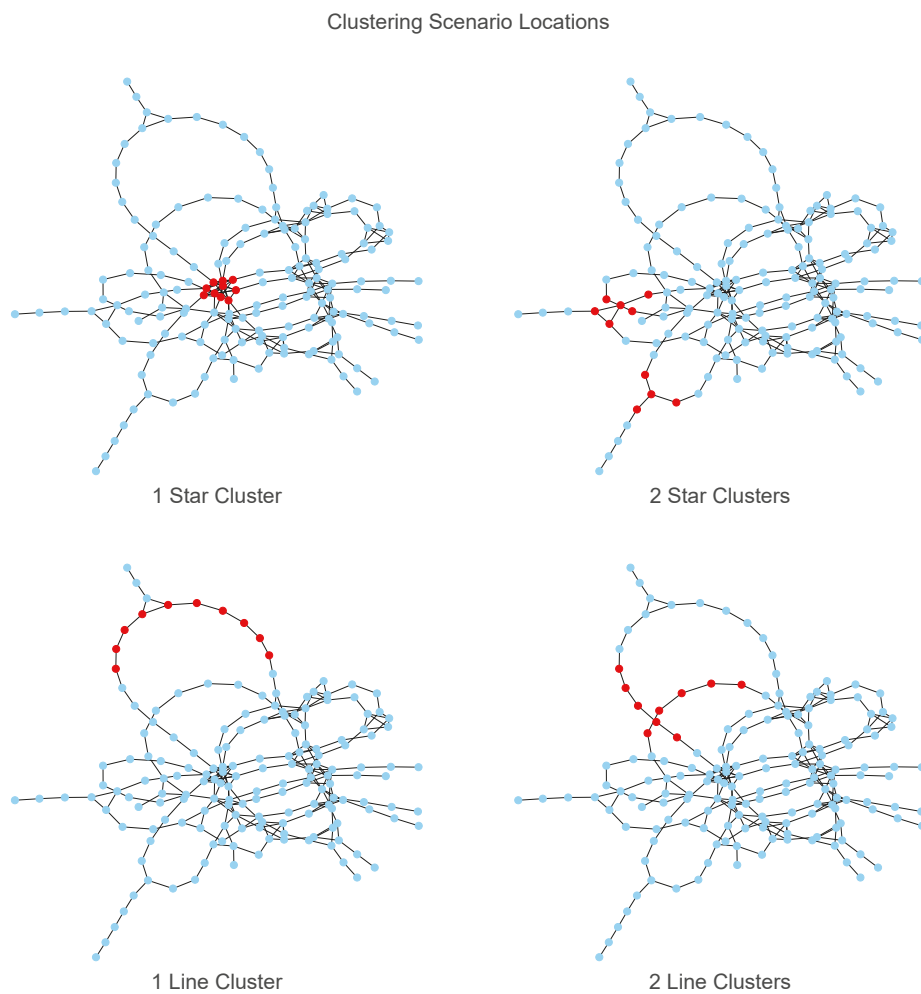


Figure 5. Location of cluster for each clustering scenario represented by red nodes: (1) “1 Star Cluster” denotes locations for Star H and Star L, (2) “2 Star Clusters” denotes locations for Star HH, Star LL, and Star HL, (3) “1 Line Cluster” denotes locations for Line H and Line L, and (4) “2 Line Clusters” denotes locations for Line HH, Line LL, and Line HL. The graph network is automatically generated based on the adjacency matrix and does not represent real location.

Table 2. Clustering scenarios.

Scenario	Number of Nodes Per Cluster	
	Cluster 1	Cluster 2
Star H	10	0
Star L	10	0
Star HH	6	4
Star LL	6	4
Star HL	6	4
Line H	10	0
Line L	10	0
Line HH	5	5
Line LL	5	5
Line HL	5	5

3.2.3. Traffic Flow Prediction Methods Comparison

The clustering scenarios show ideally formed clusters that may not appear in real traffic flow prediction results. In reality, the spatial pattern is not as simple as obvious clusters. Traffic networks are heterogeneous in nature because of factors such as congestion points (e.g., intersections, on-ramps, off-ramps, and toll booths) and varied land-use patterns (e.g., residential areas and central business districts). This complex and nonlinear nature affects the measured traffic flow and is reflected in the traffic flow prediction results.

To demonstrate the capability of spatial KPIs to differentiate traffic flow prediction methods, we compared four different traffic flow prediction methods to predict traffic flow from the PeMSD8 dataset:

1. Spatial–Temporal Synchronous Graph Convolutional Network (STSGCN) [7] builds a spatial–temporal graph by connecting all nodes with themselves at adjacent time steps to synchronously capture the spatial–temporal correlation. The input data of STSGCN are spatial–temporal network series consisting of several interval recent data in the form of a spatiotemporal graph. The spatiotemporal graph connects each node at time t with its neighboring nodes (based on the adjacency matrix) and itself, but at times $t - 1$ and $t + 1$. In general, STSGCN consists of graph convolution layers and aggregation layers;
2. Attention Based Spatial–Temporal Graph Convolutional Networks (ASTGCN) [6] consist of (1) a spatiotemporal attention mechanism, utilized to capture the dynamic spatiotemporal correlations from the traffic flow data, and (2) the spatiotemporal convolution that captures the spatial patterns by simultaneously employing graph convolutions and standard convolutions to describe the temporal features. ASTGCN utilizes hourly, daily, and weekly data as inputs. In general, ASTGCN is built on spatiotemporal blocks consisting of spatial attention layers, temporal attention layers, and Graph Convolutional network (GCN) layers. The GCN layer requires prior knowledge of the network structure, in the form of the adjacency matrix;
3. Decomposition Dynamic Graph Convolutional Recurrent Network (DDGCRN) [20] integrates a dynamic graph convolution recurrent network with a recurrent neural network-based model that generates dynamic graphs that adapt to time-varying traffic signals, enabling the extraction of both spatial and temporal features from the data. The input data of DDGCRN are recent traffic flow data but the method includes daily embedding, weekly embedding, and spatial embedding, resulting in spatiotemporal embedding. DDGCRN does not require a predefined adjacency matrix because it uses a dynamic graph generation method for spatial embedding that captures the dynamic spatial dependencies from the input data;
4. Spatio–Temporal Adaptive Embedding Transformer (STAEformer) [21] proposes a new input embedding, spatiotemporal adaptive embedding, in addition to the usual feature embedding and periodicity embedding and applies it to the vanilla transformer. The input data utilized by STAEformer are recent traffic flow data.

STAEformer is composed of an embedding layer, vanilla transformers that act as both the temporal transformer layer as well as the spatial transformer layer, and a regression layer, without any graph modeling such as any other spatiotemporal prediction method.

For each method, we evaluated the traffic flow prediction using a standard prediction accuracy measure, RMSE, for each individual node. Figure 6 shows the traffic flow prediction results evaluated using RMSE. The average RMSE for all traffic flow prediction methods are summarized in Table 3. In Figure 6, we can see some differences between methods such as STAEformer, which has more nodes with deep blue color, showing more nodes with low prediction error, but evaluating the graph with visual inspection is difficult and requires expertise. For example, we could not evaluate which had a higher spatial autocorrelation or which showed more hotspots. The spatial clusters in the graph plot are not clearly visible, and visual inspection becomes difficult if the traffic networks are larger.

Table 3. Average RMSE comparison for all traffic flow prediction methods.

Method	Average RMSE
STSGCN	25.0563
ASTGCN	27.0996
DDGCRN	20.6516
STAEformer	19.5069

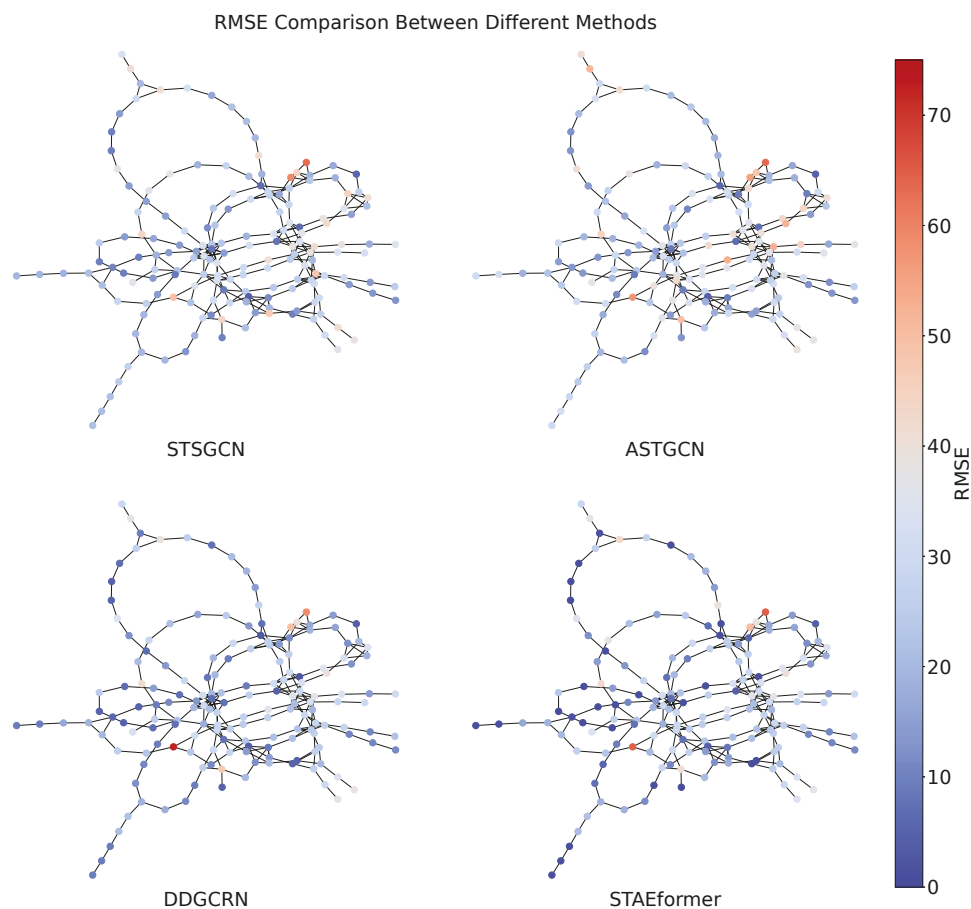


Figure 6. Traffic flow prediction results of the PeMSD8 datasets predicted by STSGCN [7], ASTGCN [6], DDGCRN [20], and STAEformer [21]. The graph network is automatically generated based on the adjacency matrix and does not represent real location. The colour on each node represents the RMSE of each node.

4. Results

In these experiments, we evaluated different traffic flow prediction methods using Global Moran's I , Getis-Ord General G , and a univariate analysis of APAM (mean, variance, skewness, and kurtosis) as the spatial KPIs. For Global Moran's I and Getis-Ord General G , the confidence level chosen is 90%, and the null hypothesis can be rejected if the p_I -value or the p_G -value is lower than 0.05.

4.1. Comparison Between Different Clustering Scenarios

To analyze the capabilities of spatial KPIs, we created 10 different clustering scenarios by swapping node values to create artificial hotspots or coldspots. The Global Moran's I values for all the scenarios are summarized in Table 4. All scenarios had significant p_I -values and positive z_I -scores, indicating a positive spatial autocorrelation. Compared to the original STSGCN results, all scenarios have higher z_I -scores, indicating that the existence of clusters increases the spatial autocorrelation of the network. This finding indicates that a larger value of I can signal clustering in the network.

Table 4. Global Moran's I for each scenario.

Scenario	I	p_I -Value	z_I -Score
Original	0.1690	0.0086	2.6286
Star H	0.3316	0.0000	5.0705
Star L	0.2557	0.0001	3.9302
Star HH	0.2115	0.0011	3.2661
Star LL	0.2799	0.0000	4.2942
Star HL	0.2659	0.0000	4.0838
Line H	0.3671	0.0000	5.6044
Line L	0.2125	0.0010	3.2811
Line HH	0.3364	0.0000	5.1421
Line LL	0.2056	0.0015	3.1770
Line HL	0.4337	0.0000	6.6051

Hotspot scenarios, except for Star HH, have a higher spatial autocorrelation than their coldspot counterparts. Figure 6 shows that high-value nodes are less common than low-value nodes and are more sporadic. The hotspot clustering scenario transforms the sporadic pattern into a cluster, thereby significantly increasing the spatial autocorrelation. The results also show that line clusters exhibit a clearer difference between hotspots and coldspots compared to star clusters. Line HL shows the largest G , further indicating that the Global Moran's I is more sensitive to line clusters. Based on these findings, Global Moran's I can detect an increase in spatial autocorrelation caused by clustering scenarios.

In addition to spatial autocorrelation, it is important to determine the type of cluster that appears in traffic prediction results. If hotspots are more dominant, then a large spatial autocorrelation is detrimental to the network, as this suggests locations with a large systematic error. However, the dominant coldspots suggest that spatial relationships are well-captured by traffic prediction methods. This leads us to the second proposed spatial KPIs, Getis-Ord General G , which measures the spatial clustering of high- or low-value nodes.

The Getis-Ord General G values for all the scenarios are summarized in Table 5. All scenarios, except star L, star HH, line H, and line HH, showed significant p_G -values with positive z_G -scores, indicating the spatial clustering of high node values. The four mentioned scenarios have p_G -values larger than 0.05, so the null hypothesis cannot be rejected, and there is no tendency between hotspots or coldspots.

An interesting aspect of these results is that hotspot scenarios do not generally increase the G value, and vice versa, as Getis-Ord General G stated. Of all hotspot scenarios, only the G value of Star H increased, but the value increased significantly. On the other hand, all coldspot scenarios, except Star L, have increasing G values. However, in all cases, hotspots and coldspots always had opposite effects on the G value. For example, line H had a

decreasing G value, whereas line L had an increasing G value. This finding suggests that hotspots and coldspots have opposite effects, and the existence of both might cancel each other out.

Table 5. Getis-Ord General G for each scenario.

Scenario	G	p_G -Value	z_G -Score
Original	0.0205	0.0273	1.9220
Star H	0.0245	0.0000	7.2793
Star L	0.0199	0.1276	1.1380
Star HH	0.0196	0.2373	0.7150
Star LL	0.0215	0.0006	3.2192
Star HL	0.0205	0.0313	1.8619
Line H	0.0199	0.1224	1.1631
Line L	0.0212	0.0021	2.8650
Line HH	0.0199	0.1371	1.0935
Line LL	0.0213	0.0013	3.0039
Line HL	0.0213	0.0016	2.9469

The clustering scenarios, such as star HH, show two obvious hotspots on the left and bottom left of the network if we inspect it visually in Figure 7. However, the p_G -value is not significant so it does not have a tendency for hotspots or coldspots. If we inspect the original scenario (Figure 6), we can see that most of the high-value nodes are scattered. The star H scenario swaps these nodes into predetermined locations on the left and bottom left of the network, as shown in Figure 5. The results of these swaps not only create hotspots, but also possibly create coldspots or random spatial patterns that could reduce the G value. The question is which will have a greater impact on the network, as not all clusters are identical.

If we compare Global Moran's I and Getis-Ord General G for star cluster scenarios, the ranking is similar, from highest to lowest: (1) star H, (2) star LL, (3) star HL, (4) star L, and (5) star HH. However, the impact of clusters compared to the original scenario is different between Global Moran's I and Getis-Ord General G . For Global Moran's I , all clustering scenarios increase their value, whereas, for Getis-Ord General G , hotspots increase their value and coldspots reduce their value. This trend is similar to the theoretical interpretation of both metrics: adding more hotspots will increase both metrics, but adding more coldspots will increase Global Moran's I and reduce Getis-Ord General G . These findings also support our assumption that clustering scenarios with swapping node procedures for a hotspot could result in a more impactful coldspot in other locations, thereby reducing the Getis-Ord General G .

For the line cluster scenarios, the ranking of Getis-Ord General G is the opposite of that of Global Moran's I , and the effect of line clusters is the opposite of star clusters for Getis-Ord General G . This shows that the existence of both star and line clusters can cancel each other out, similar to how hotspots and coldspots cancel each other out.

Table 6 summarizes the univariate analysis of the APAM values for all scenarios. We calculated APAM with $\alpha = 0.5$, assuming that the importance of the topology of the network and traffic flow data are equal. We calculated kurtosis using Fisher's definition, with a positive kurtosis value representing leptokurtic, where the distribution has heavier tails and a higher peak. All the scenarios had positive skewness and kurtosis values. This means that the majority of the nodes have low APAM values, but some nodes have significantly higher APAM values. These nodes are highly important and can significantly affect the traffic networks. The variance of all clustering scenarios shows insignificant differences, and skewed distributions with high kurtosis render the variance of the distribution uninformative. Therefore, we did not further analyze the variance in the distribution.

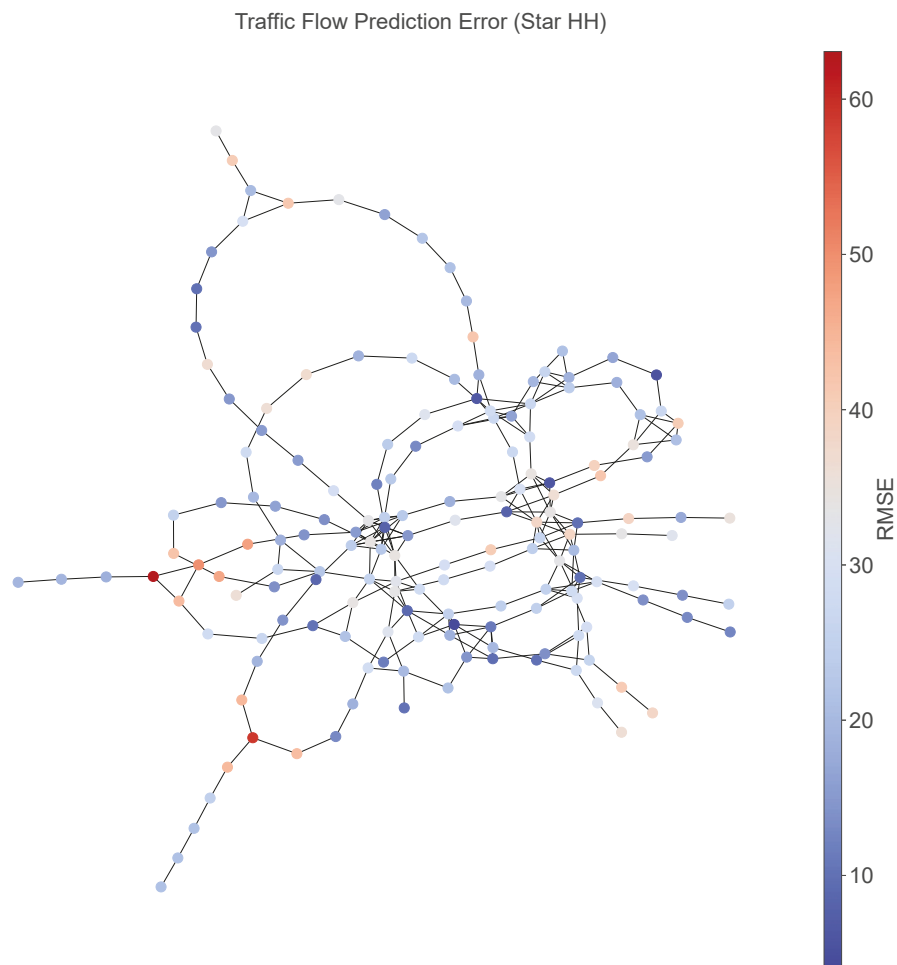


Figure 7. Network graph of Star HH scenario; the color of each node represents RMSE.

The star H is the most interesting scenario because of its significantly higher skewness and kurtosis. This indicates that the vast majority of nodes in star H have low importance, whereas a small minority have extraordinarily high importance. In the star H scenario, the hotspot is located within the center of the network, as shown in Figure 5. These nodes have high node value and centrality, resulting in significantly large APAM values, thereby increasing the skewness and kurtosis of the distribution. In other scenarios, the cluster is located in less connected areas, resulting in subtle changes in skewness and kurtosis values.

Table 6. APAM univariate analysis for each scenario.

Scenario	Variance	Skewness	Kurtosis
Original	0.0005	1.0067	0.5028
Star H	0.0006	1.4625	1.9287
Star L	0.0005	1.1108	1.2613
Star HH	0.0004	0.9179	0.3798
Star LL	0.0005	1.0307	0.5204
Star HL	0.0005	0.9666	0.5281
Line H	0.0004	0.9377	0.4688
Line L	0.0005	1.0362	0.4001
Line HH	0.0004	0.9680	0.5752
Line LL	0.0005	1.0025	0.3887
Line HL	0.0005	1.0278	0.7299

4.2. Comparison Between Different Traffic Prediction Methods

The Global Moran's I comparison between different methods is summarized in Figure 8. All methods have p_I -values lower than 0.05 and positive z_I -scores, which indicate that the null hypothesis of Global Moran's I can be rejected, and the resulting prediction error has positive spatial autocorrelation (similar values are spatially clustered). STSGCN and ASTGCN, which utilize the predefined adjacency matrix of the network, exhibit higher spatial autocorrelation than DDGCRN and STAEformer. DDGCRN, which learns dynamic graphs for spatial contexts, ranks third, whereas STAEformer, which has no graph modeling, ranks last. The differences between STSGCN, ASTGCN, and DDGCRN were subtle and less informative, whereas STAEformer showed a more apparent difference. A higher Global Moran's I in the context of traffic flow prediction error suggests that the model's prediction error is spatially structured, with nearby locations tending to have more similar values and not being distributed randomly.

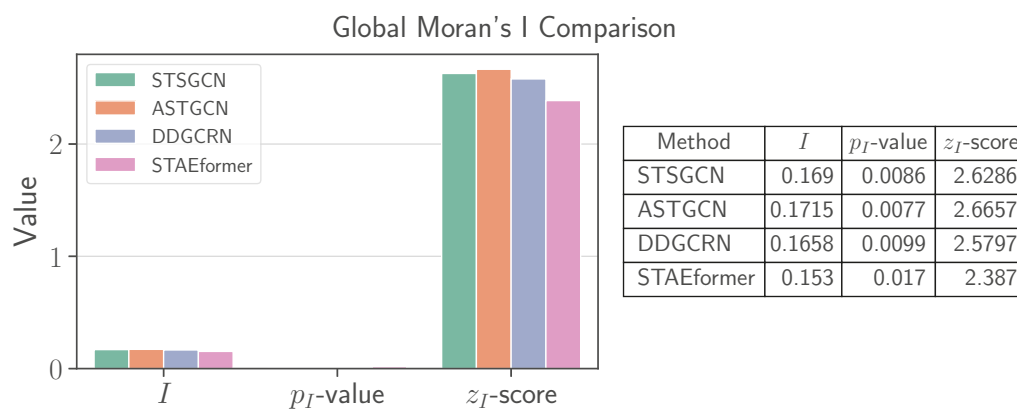


Figure 8. Comparison of Global Moran's I for different traffic flow prediction methods.

The value of z_I -score depends on I , $E[I]$, and $V[I]$ (Equation (4)). In Global Moran's I, the values of $E[I]$ and $V[I]$ depend only on the spatial weight matrix (from the adjacency matrix) and number of nodes. If we compare different methods in the same traffic network, the values of both p_I -value and z_I -score are solely dependent on the value of I .

In Figure 6, we can see that some nodes in STAEformer have a lower RMSE (deep blue color) but the remaining nodes are similar to other methods. This finding suggests that the lower RMSE of STAEformer could be caused by sporadic dispersive improvement, rather than global improvement, which reduces spatial autocorrelation. Such an improvement could be beneficial if the improved nodes are located at a critical location. However, if the improvement is in an isolated place, it could be less beneficial even though the average RMSE difference is large.

The Getis-Ord General G comparison between different methods is summarized in Figure 9. All methods except ASTGCN have p_G -values less than 0.05 with positive z_G -scores, indicating that the null hypothesis of Getis-Ord General G can be rejected and suggesting a spatial clustering of high-value nodes. In these methods, some spatially clustered areas have a higher RMSE, forming hotspots, and these methods struggle to predict traffic flow in those areas. As for ASTGCN, the null hypothesis cannot be rejected, suggesting no tendencies to cluster high or low values.

The G value of ASTGCN was the lowest among all the methods by a small margin, but the p_G -value and z_G -score were significantly different. The z_G -score was calculated using G , $E[G]$, and $V[G]$ (Equation (7)), as summarized in Table 7. The value of $E[G]$ is identical for all methods because it is the total sum of all spatial weights divided by the possible number of pairs of nodes, which are determined only by the adjacency matrix. Therefore, the z_G -score is dependent only on the values of G and $V[G]$. G measures the degree of the clustering of high or low values, depending on whether it is larger or smaller than $E[G]$. From Equation (7), the value of $V[G]$ determines the magnitude of $G - E[G]$.

required for the null hypothesis to be rejected. Unlike $V[I]$, the value of $V[G]$ depends on the value of the nodes, and the value of each method may differ.

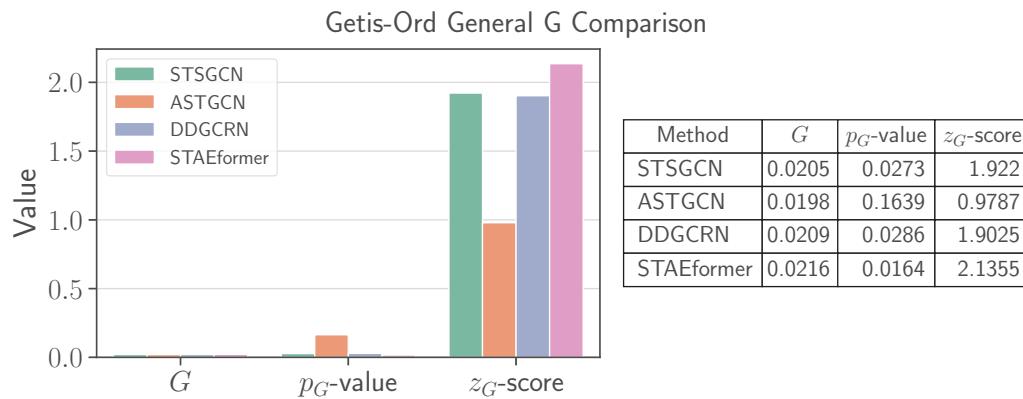


Figure 9. Comparison of Getis-Ord General G for different traffic flow prediction methods.

Interestingly, the $V[G]$ values of both STSGCN and ASTGCN are similar, and both utilize the adjacency matrix as their prior knowledge. Both of them had lower $V[G]$ values, suggesting higher confidence in the observed G value, compared to DDGCRN and STAEformer. However, the $G - E[G]$ value of ASTGCN was significantly lower than that of the other methods, resulting in a low z_G -score and insignificant p_G -value. Even though they had similar average RMSE values, the spatial clustering of high-value nodes on STSGCN was less preferable than that of ASTGCN, which had no tendencies. If we assume a similar number of star and line clusters, the insignificant p_G -value of ASTGCN suggests a more uniform performance across the network.

Table 7. G , $E[G]$, and $V[G]$ values for all traffic flow prediction methods.

Method	G	$E[G]$	$G - E[G]$	$V[G]$	$\sqrt{V[G]}$
STSGCN	0.0205	0.01907	1.43×10^{-3}	5.49×10^{-7}	7.41×10^{-4}
ASTGCN	0.0198	0.01907	7.26×10^{-4}	5.41×10^{-7}	7.35×10^{-4}
DDGCRN	0.0209	0.01907	1.83×10^{-3}	9.20×10^{-7}	9.59×10^{-4}
STAEformer	0.0216	0.01907	2.53×10^{-3}	1.37×10^{-6}	1.17×10^{-3}

The APAM univariate analysis comparison between different methods is summarized in Figure 10. We calculate APAM with $\alpha = 0.5$, assuming that the importance between the topology of the network and the traffic flow data is equal. The higher APAM value of a node indicates a higher importance, considering its centrality and node value.

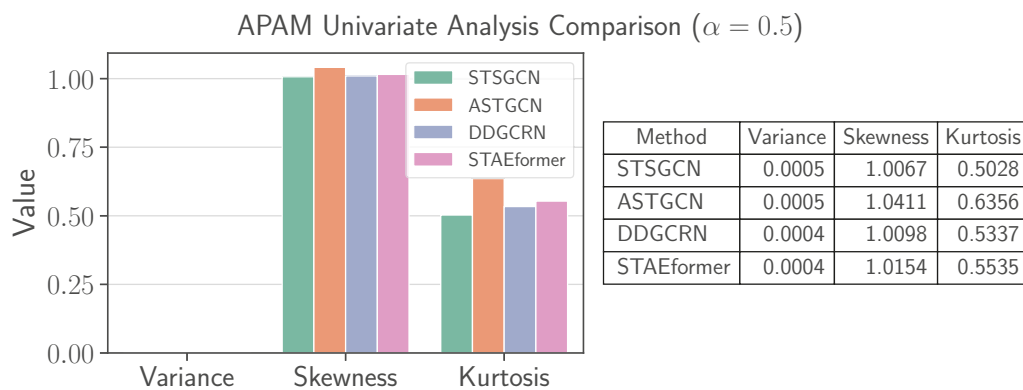


Figure 10. Comparison of APAM moment analysis for different traffic flow prediction methods.

All methods have positive skewness and kurtosis, indicating a distribution where most nodes have low importance, with some high-importance nodes. Similar to the clustering scenario, the variance of the distribution showed an insignificant difference and a skewed distribution with high kurtosis, rendering the variance of the distribution uninformative.

The ranks of skewness and kurtosis are identical, but kurtosis shows a more pronounced difference compared to skewness. The differences in the skewness and kurtosis of each method were small and less informative compared to the results in the clustering scenario. ASTGCN had a comparably higher kurtosis and STSGCN had a comparably lower kurtosis. STSGCN with the lowest kurtosis indicates a more uniform distribution and less pronounced extreme values, whereas ASTGCN with the highest kurtosis indicates a higher probability of extreme values. This finding is interesting because both STSGCN and ASTGCN use the same adjacency matrix as prior knowledge with similar average RMSE. Based on the analysis of clustering scenarios, the higher skewness and kurtosis of ASTGCN suggest that there are more nodes with higher APAM values, even though the majority of the nodes have lower APAM values. These nodes can be considered critical nodes and require more attention because of their high importance.

5. Discussion

In this study, we propose three different spatial KPIs that measure the performance of traffic flow prediction: (1) spatial autocorrelation (Global Moran's I), (2) spatial clustering of node values (Getis-Ord General G), and (3) node centrality measure (Adapted PageRank Algorithm Modified). We considered 10 clustering scenarios created by swapping node values to demonstrate the ability of spatial KPIs to evaluate traffic prediction methods that have identical average RMSE. We also validated these spatial KPIs against four different traffic prediction methods: (1) STSGCN [7], (2) ASTGCN [6], (3) DDGCRN [20], and (4) STAEformer [21] to predict traffic flow from the PeMSD8 dataset [19].

If we only consider the average RMSE (shown in Table 3), it is clear that STAEformer has the lowest average RMSE. However, the difference between STAEformer and DDGCRN is small, and the performance might vary from one network to another; hence, there is a need for other measures to evaluate traffic flow prediction methods. A similar case also occurs between STSGCN and ASTGCN, which have similar average RMSE values. For cases in which the standard prediction accuracy between different methods has negligible differences, our results show that spatial KPIs can provide extra information based on the spatial characteristics of the methods.

Global Moran's I results show that spatial clusters increased spatial autocorrelation, with hotspots giving a larger impact compared to coldspots. We also found that line clusters had a higher impact than star clusters. Based on this finding, a lower value of Global Moran's I is preferred, owing to less spatial clustering (especially hotspots) in the network. A prediction model with less spatial clustering (I close to zero) is preferred due to its consistent performance across the network. All traffic prediction methods showed positive spatial autocorrelation with subtle differences between the methods, which made this metric less informative in our case study. Traffic flow and RMSE have a linear relationship, so positive spatial autocorrelation is unavoidable. However, the results signal a relationship between spatial autocorrelation and spatial information utilized by traffic prediction methods.

In the clustering scenarios, Getis-Ord General G shows nuanced results, where the hotspot scenarios do not always increase G , and vice versa, because of swapping in the clustering scenarios. In general, a lower value of z_G -score is preferred from the traffic flow prediction error because it suggests spatial clustering of low RMSE nodes, which implies the prediction model performs well in connected areas. The results show that Getis-Ord General G can capture spatial clustering that is not easily discernible through visual inspection. For example, in the original scenario, the p_G -value is significant with a positive z_G -score, which indicates the spatial clustering of high node values. However, it is difficult to determine where the hotspot is located if we inspect Figure 6. It is important to

note that the results show that hotspots and coldspots cancel each other. This also occurs between star and line clusters. Getis-Ord General G was able to show a clear difference between ASTGCN and STSGCN, which have similar average RMSE and utilize the graph adjacency matrix, demonstrating the capability of this KPI to differentiate traffic prediction method. The results show that ASTGCN showed no spatial clustering tendencies, which is preferred over STSGCN, which has a spatial clustering of high node values.

For the APAM univariate analysis, extreme clustering scenarios such as Star H, a cluster consisting of highly important nodes with high node centrality and node values, can be detected from the skewness and kurtosis values. Nodes of high importance require attention owing to their significant effects on traffic networks. Traffic prediction methods with fewer numbers of such nodes were preferred. This translates into an APAM distribution with zero skewness and negative kurtosis values. All the traffic prediction methods in this study showed positive skewness and kurtosis values with subtle differences, making this KPI less informative for our case study. One interesting finding is that ASTGCN has comparably higher skewness and kurtosis than STSGCN, suggesting that more nodes have higher APAM values than the rest of the distribution.

All spatial KPIs showed comparable differences between the different clustering scenarios. Unfortunately, the comparison between different traffic prediction methods shows subtle differences, except for Getis-Ord General G, which makes it less informative. This is similar to the problem of standard accuracy KPIs, where the difference between the state-of-the-art methods is negligible. The subtle difference is because the difference between traffic prediction methods is not as extreme as the clustering scenarios demonstrate. However, ASTGCN showed a clear difference in Getis-Ord General G and noticeable differences in Global Moran's I and the univariate analysis of APAM. These results demonstrate the potential of spatial KPIs to differentiate methods that are less indistinguishable from standard accuracy KPIs.

Choosing a traffic prediction method that is evaluated by both the standard prediction accuracy and spatial KPIs will help the operation of traffic management systems. Spatial KPIs provide more confidence in traffic prediction methods. By considering both the standard prediction accuracy and spatial KPIs, stakeholders have more tools to compare different traffic prediction methods, ultimately leading to more reliable predictions and reduced operational risks.

Using spatial KPIs, we can infer whether the distribution of traffic flow prediction error and node importance is suitable for applications such as traffic signal control or route guidance. For example, in traffic signal control, some control algorithms such as model predictive control [33] require some knowledge of the future states, which we infer based on traffic prediction models. Traffic prediction models are assumed to be sufficiently accurate to represent traffic network dynamics and fail to do so, resulting in the degradation of network performance. A slightly higher RMSE traffic flow prediction method with a uniform error distribution and fewer hotspots is preferable for traffic signal control compared to other traffic flow prediction methods with a lower RMSE but more hotspots. Hotspots can degrade traffic signal control performance, resulting in traffic jams that propagate to neighboring locations. This information can be deduced from Global Moran's I and Getis-Ord General G. Similarly, the distribution of APAM values can infer the existence and distribution of influential nodes. This information is crucial for anticipating the propagation of errors because these influential nodes have high node centrality. In route guidance, the existence of hotspots can reduce the confidence level of a route passing through that area. Choosing a traffic prediction method with fewer hotspots can improve the confidence level of route guidance systems. Ultimately, route guidance systems can make informed decisions, potentially leading to more reliable and efficient route recommendations for users.

Compared to standard KPIs, spatial KPIs are not straightforward to evaluate and different traffic management applications may prioritize different aspects of spatial performance. We could draw some conclusions from the value of spatial KPIs between different

methods, but more caution is needed because factors such as different types of clusters (e.g., hotspots, coldspots, star clusters, and line clusters) could affect the evaluation measures, especially the Getis-Ord General G. The difference in spatial KPIs' values between the methods can also be negligible, leading to a problem similar to that of the standard accuracy KPIs.

6. Conclusions

This study presents spatial KPIs as a novel approach for evaluating traffic flow prediction methods, complementing the conventional average prediction accuracy metrics. Each of the proposed spatial KPIs offers unique capabilities for evaluating the traffic network prediction performance from a spatial perspective. Our study demonstrates that Global Moran's I, Getis-Ord General G, and the univariate analysis of Adapted PageRank Algorithm Modified (APAM) are sensitive to the synthetic clustering cases. However, the evaluation of the four traffic prediction methods showed less pronounced differences. We found Getis-Ord General G to be the most sensitive, as it can differentiate ASTGCN and STSGCN, two methods with similar average RMSE, and utilize the predefined adjacency matrix. This information helps to determine a traffic prediction method that has better spatial characteristics. The practical implications of this study are substantial and provide researchers and stakeholders with more nuanced measures for evaluating and selecting traffic prediction models, ultimately leading to more robust traffic management systems. There are several directions for improving the evaluation of traffic prediction methods in future studies. First, the integration of temporal KPIs, such as the propagation of errors over time, further enhances the evaluation of traffic prediction methods. Second, broader case studies and datasets that reflect real-world situations, such as validation in urban traffic network settings, the consideration of external factors (e.g., weather conditions and events), and larger traffic networks, will show whether spatial KPIs can be applicable as scalable general tools for traffic management systems. Finally, the investigation of other crucial traffic state predictions such as travel time and vehicle speed will broaden the application of spatial KPIs.

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Article

A Data-Driven Decision-Making Support Method for Priority Determination for an Intelligent Road Problem Reporting System

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Abstract: This paper presents a new decision support method aimed at prioritizing processing for an intelligent road problem reporting service. The proposed method uses advanced georeferencing technology to extract the longitude and latitude coordinates in the metadata of photos taken with the smartphone application to capture the complaint scene. This method not only maps out the processing times, but also applies a spatiotemporal clustering technique to link the complaint types and locations with the actual complaint processing times. A validation study of the frequency of reported locations per priority reveals that the complaint-processing prioritization method developed in this study aligns realistically with actual field complaint processing. Furthermore, recognizing the significance of location in processing complaints, the georeferencing technique appears suitable for identifying complaint locations for each report and incorporating this into the decision-making framework.

Keywords: decision-making support model; clustering; public complaint management; road problem reporting system

1. Introduction

The Road Problem Reporting Service (RPRS) was developed by the Korea Ministry of Land, Infrastructure, and Transport (MOLIT) to enable the public to report civil complaints on highways, national roads, and local roads quickly and conveniently using smartphones. Since its inception in 2013, the service received an average of more than 33,000 complaints annually [1]. These complaints are categorized into five types: poor road condition, poor drainage condition, poor road facility condition, roadkill and obstacles, and others/unclassified. In contrast to general inconvenience complaints, complaints related to road usage often require immediate action. For instance, potholes, animal carcasses (roadkill), and obstacles that directly endanger vehicle safety can lead to significant accidents, and poor drainage facilities can pose substantial risks during the rainy season. However, it is practically impossible to address all complaints promptly.

To address these constraints, Jeon et al. [2] utilized the equivalent property damage only (EPDO) technique, a comprehensive approach that assesses the severity of reported complaints and suggests methods for prioritizing them. Their method involved dividing each complaint into sub-items and assessing the severity of each sub-item using EPDO to calculate severity weights. These weights were determined by selecting indicators such as accident risk levels, driving and walking safety, convenience, and the visual impact on the traffic environment. Although the method by Jeon et al. [2] offers a comprehensive consideration of civil complaints in terms of safety, convenience, functionality, and environmental impact and has been noted for its remarkable effectiveness in providing objective

severity measurements, it does not adequately consider the geographic locations of the complaints. The severity assigned to potholes may vary significantly depending on their locations, i.e., a pothole on a busy highway lane poses a different level of risk compared to one on a less traveled local road shoulder, yet the previous method does not differentiate based on such criteria.

This study addresses the need to factor in geographic data by utilizing geotagging technology, a cutting-edge tool that records the longitude and latitude coordinates in the metadata of photos taken with smartphones. This allows for identifying complaint locations such as roads, buildings, neighborhood facilities, social overhead capital (SOC) facilities, and railways. The analysis of complaints processed in 2021 and 2022 utilizes these coordinates to further classify road-related complaints according to a detailed road hierarchy: highway/trunk road, general national road, local road, roads in city/county/district, residential road/back road, pedestrian road, farm road/forest road, service road, and unclassified road. By linking the complaint types and locations with the actual outcomes of complaint processing, this study not only maps out the processing times, but also applies clustering techniques to the data. This methodology facilitates the formulation of recommendations for complaint prioritization based on the understanding of complaint processing times (CPT) across different types of locations.

This paper is organized as follows: Following the introduction, the next section addresses a comprehensive review of relevant research efforts. The section of analysis presents an overview of the complaint data, providing both descriptive and comparative analyses to identify factors affecting the priorities of complaint processing. The details of the decision-making support model development are presented with the model results in the next section, followed by conclusions and recommendations.

2. Literature Review

This section summarizes the literature review, mainly focusing on data-driven approaches to prioritize and manage public complaints in various domains, from urban infrastructure to customer service and highway maintenance.

Mak and Jones [3] proposed a scoring-based methodology to determine the priority of highway improvement projects. Categorizing 26 parameters established for the project evaluation into six groups, such as need, deficiency, continuity, benefit-cost, local opinion, and social-economic and environmental consequences, the authors evaluated the parameters and assigned weight factors to each parameter group for each project. The weight factors were determined by state transportation board members, department of transportation (DOT) agencies, and local transportation planners, obtained from a state-wide panel survey in Georgia, USA. The final score for each project was estimated by summing the weight factors, and the priority is determined based on the estimated score: higher score, higher priority.

Minaei-Bidgoli and Akhondzadeh-Noughabi [4] adopted an association rule mining method to identify patterns in customer complaints and improve complaint management. The authors applied the a priori algorithm to a large dataset of complaints submitted to Tehran's municipality to identify relationships among factors such as season, complaint type, and citizen demographics. By analyzing these relationships, the proposed method prioritized responses and enhanced service quality by addressing frequent and region-specific complaints.

Akhondzadeh-Noughabi et al. [5] developed a novel urban management model to improve the quality of the response to citizen complaints in Tehran, Iran. To this end, the authors combined citizen relationship management (CiRM) and data mining techniques to better understand the primary needs of citizens and optimize municipal services. Employing key factors for identifying and prioritizing citizen needs, such as frequency, time interval, and satisfaction, the study categorized urban needs into primary, secondary, and uncommon groups by applying clustering methods to the key factors. The results demonstrate that the CiRM-clustering combined method can significantly enhance urban

management practices by allowing municipalities to better target and address citizens' most pressing concerns. This model also addressed potential applications in broader public sector customer relationship management (CRM), offering a structured, data-driven approach to improve service delivery and citizen satisfaction.

Bansal and Toshniwal [6] attempted to analyze urban civic complaints, such as pavement condition, traffic congestion, noise, and drainage, by applying clustering methods. The proposed analysis framework consisted of two components: (1) a dynamic grid-based clustering and (2) a location-based clustering. The dynamic grid-based clustering conducted complaints analysis based on spatial attributes of an urban area, taking into consideration the spatial connectivity of the urban street network. The location-based clustering focused on the types of complaints to group each complaint based on (1) density of complaints (DF) and (2) temporal patterns of complaints (TF). Utilizing the kernel density clustering method [5], DF was measured to quantify the concentration of a complaint to evaluate its significance. TF was employed to estimate the temporal correlation of each complaint group to determine the weighted scores. By combining DF and TF, the criticality score of each complaint group was estimated to finalize the priority. The proposed framework was applied to New York City, USA, and Bangalore, India. The results show that the proposed framework helped urban planning strategies increase civilians' satisfaction level with the service of complaints.

Ghodousi et al. [7] examined three clustering algorithms, such as K-means, fuzzy C-means (FCM), and independent component analysis (ICA), to assess public needs in terms of citizen relationship management (CiRM). Using data from public complaints in Bojnourd, Iran, the authors analyzed levels of satisfaction and classified citizen needs by identifying similar complaint patterns based on the frequency, recency, and satisfaction level of each reported complaint. The K-means algorithm was chosen for its straightforwardness, while FCM was utilized to capture overlapping clusters where complaints could belong to various categories. ICA was also applied to find hidden patterns that might be overlooked by conventional clustering methods. This analysis enabled city officials to pinpoint prevalent citizen complaints, assess satisfaction with resolutions, and prioritize issues according to urgency and public significance. The findings indicate that these clustering techniques could effectively categorize public needs and expose trends, assisting policymakers in prioritizing actions to enhance public services. This study underscored the real-world application of data science in urban management by demonstrating how clustering can help match public services with the changing needs of citizens, ultimately boosting community satisfaction and optimizing resource use.

Hubert et al. [8] presented a visual analytics model to support municipal authorities in managing citizen complaints. The tool was designed to perform map-based visualizations that help officials investigate patterns in citizen requests and complaints, particularly by leveraging geospatial clustering and heatmaps to identify highly affected areas within cities. By employing DBSCAN [9], the tool groups requests by location and frequency, identifying clusters where service issues are concentrated. It also supports hierarchical clustering to reveal subclusters within major complaint areas. By providing such features, the tool was envisioned to enable city officials to prioritize resources and improve response strategies based on visualized citizen feedback. The authors stated that this approach facilitates a better understanding of urban issues, thereby enhancing the decision-making process for public service improvements.

Lee et al. [10] conducted a study to prioritize service areas for urban safety and disaster management by analyzing civic complaints using big data analytics. The authors retrieved keywords related to safety and disaster management from unstructured text messages conveying civic complaints to identify major policy demands. They then filtered the dataset using these keywords and performed a panel analysis to investigate the effects of residents' policy demands on safety and disaster management in 16 local jurisdictions. According to the study, policy requirements varied depending on the socio-cultural factors, such as age, gender, economic status, and proportion of migrants. The conclusion was that

city governments should provide tailor-made services to address the specific needs of their residents.

Cerna et al. [11] proposed a decision support system (DSS) for managing complaints in Ethiopia's technical and vocational education and training (TVET) institutions. TVET institutions encountered various challenges in handling complaints due to limited resources and inefficient systems. The proposed DSS integrates a web-based interface and a mobile application, allowing users to submit complaints from anywhere and track their progress in real time. The system notifies users via SMS and enables administrators to prioritize and resolve issues more efficiently. It also includes reporting features for data analysis, helping decision-makers identify trends and improve service quality. The authors suggested that the DSS framework can enhance accountability and responsiveness in TVET institutions, supporting the goals of good governance and citizen satisfaction.

Ghodousi et al. [12] developed a framework to improve public service responses and understand community needs by utilizing 137 databases from Bojnourd, Iran, which track and classify citizen complaints. The proposed framework integrates (1) data mining techniques, such as the recency, frequency, and monetary value (RFM) model, and (2) clustering algorithms, including K-means [13] and the bees algorithm (BA) [14], to analyze complaint trends. While the K-means method provides a simple and popular clustering technique, BA, inspired by the foraging behavior of bees, offers a more refined approach to optimally cluster citizen needs. The comparison highlights the efficiency of BA in segmenting and prioritizing complaints for actionable insight. Using the framework, the authors were able to successfully identify key areas of public dissatisfaction and prioritize actions based on citizens' needs. The implementation results show that the proposed framework provides valuable feedback for city officials to streamline complaint resolution, enhance service quality, and ultimately boost citizen satisfaction by focusing resources on high-priority needs identified from the data. Such data-driven management approaches appeared to support better public engagement by addressing citizens' concerns more effectively.

In Taufiq et al. [15], a decision-support model powered by a simple additive weighting (SAW) technique for evaluating employee performance was presented. SAW is a multi-criteria decision-making approach that helps organizations assess employee performance by assigning weights to various criteria. SAW allows for a systematic and objective ranking of employees based on their performance across different metrics. The authors demonstrated the practical implementation of SAW in a performance appraisal system, where criteria such as attendance, work quality, and skills are assessed. By scoring and weighting each criterion, the model provides a ranking to identify top performers and those needing improvement, aiding managers in making promotion, training, or development decisions. The implementation results also reveal that the SAW-based model enhances transparency and consistency in evaluations, making it a valuable tool for human resource management in organizations aiming to foster productivity and employee development.

Similar to [15], Jumaryadi and Nugroho [16] also proposed a SAW-based decision-support model to prioritize customer complaints effectively. This study specifically focused on evaluating various complaint types by assigning weights to factors such as urgency and customer impact, allowing organizations to determine which complaints require immediate attention. The authors discovered that the SAW-based model provides a straightforward, quantifiable method for complaint prioritization, helping engineers and managers improve response times and increase customer satisfaction. This method also aligns with company goals by focusing on key performance indicators (KPIs) related to complaint resolution, ultimately fostering better customer service and operational efficiency in competitive business environments.

Lee et al. [17] proposed a framework to determine the service priority of pavement maintenance on rural highways by employing spatial big data analytics. The authors first datalized the past pavement maintenance records, including the location, duration, and traffic control of various roadworks, such as pothole repair, roadkill treatment, micro-

surfacing, and emergency infrastructure maintenance, to establish a database. The authors restructured the data to train a machine learning model to estimate the priority of pavement maintenance service. The proposed framework was expected to be deployed to practical uses in helping local governments establish short and mid-term pavement maintenance strategies in rural areas.

More recently, Helmy et al. [18] presented an advanced decision-support model designed to enhance how e-commerce businesses handle customer complaints, focusing on increasing customer satisfaction and trust. The authors integrated various tools and algorithms to categorize complaints, allocate resources efficiently, and monitor the effectiveness of complaint resolution strategies. In particular, by employing association rule mining [19], the model identifies common complaint patterns and trends, which help businesses proactively address recurring issues. Through case studies testing the proposed model, the authors proved that effective complaint management can significantly improve customer satisfaction and reduce negative word-of-mouth, which can damage a brand's reputation. The authors also demonstrated that effectively addressing complaints provides an opportunity for continuous improvement as businesses gain insights into potential areas for service and product enhancement. The authors addressed how e-commerce companies can foster trust, loyalty, and long-term customer relationships by systematically addressing customer complaints and using technology to streamline processes.

In summary, it is discovered that various methodologies utilize data-driven strategies to effectively address and manage public complaints across different areas, including urban infrastructure, customer service, and highway maintenance. Each examination applies distinct models and techniques, such as clustering, scoring, association rule mining, and decision-support systems, to analyze complaints and improve service responsiveness. These methods showcase the benefits of systematic, algorithm-based approaches in enhancing service quality, boosting citizen and customer satisfaction, and optimizing resource allocation. By recognizing complaint patterns and prioritizing needs based on data, organizations and municipalities can customize their responses to urgent issues, promoting a proactive, efficient, and transparent method of service management. The research highlights the promise of data-driven decision-making in positively influencing public satisfaction, operational efficiency, and strategic planning across various service domains.

3. Analysis

3.1. Complaint Processing Time Data Overview

This study analyzed 65,680 complaints recorded by the RPRS app from January 2021 to December 2022. The dataset includes various details such as the types of complaints, dates of complaint submission, action dates, addresses, and brief descriptions provided by the complainants. Additionally, it contains photos taken by the complainants, along with the longitude and latitude coordinates of each complaint location.

The date the service receives a complaint is automatically recorded by the app and referred to as the "complaint report date." The "action date," which marks the completion of complaint processing, is manually entered by the responsible official. The time between action dates and complaint report dates indicates the time required for processing the corresponding complaints, although differences from the actual processing time may exist due to manual entry.

Prior to analyzing the complaint processing time (CPT) data, 452 complaints that showed processing times exceeding five weeks (0.7% of the total dataset) were removed, as such lengthy durations are considered highly atypical. Additionally, 767 complaints processed in less than 4 h (1.2% of the dataset) were excluded, presuming that a minimum of 4 h is necessary for a complaint to be acknowledged and processed by an official. After these adjustments, the analysis proceeded with 64,461 valid complaint records.

In addition to analyzing CPTs, this study utilized longitude/latitude coordinates to determine the locations of complaints. Conducting a meaningful analysis with only these coordinates is not feasible. To enhance the utility of the geographic data, we employed the

Nominatim (Version 4.5.0) georeferencing application programming interface (API) [20], provided by OpenStreetMap [21], to obtain detailed information regarding the locations where individual complaints were reported. The specific locations of complaints are classified into the following categories: (1) areas around buildings, (2) neighborhood facilities, (3) roads, (4) social overhead capital (SOC) facilities, and (5) railways, as outlined in Table 1. Notably, roads are further divided into detailed sub-types. As appeared in the sub-types in Table 1, this research deals with complaints reported from any types of roads in and around the presented location types.

Table 1. Summary of complaint location type.

Complaint Location Types	Specific Sub-Types
Roads	Motorways, trunk roads, general national roads, local roads, roads in city/county/district, residential roads, residential streets, pedestrian roads, farm roads/forest roads, service roads, and unclassified roads.
Neighborhood facilities	Any types of roads in and around neighborhood facilities commonly used by tourists or residents, including toilets, public phones, banks, pharmacies, cafes, parking lots, schools, etc.
Buildings	Any types of roads near Individual or interconnected buildings, including offices and shops.
Railway	Includes railways and railroad crossings.
SOC facilities	Any types of roads near retaining walls, seawalls, harbor piers, harbor berth facilities, etc.

Finally, we measured the CPTs using the complaints data from 2021 to 2022, categorized by both complaint type and location type. We applied statistical analysis techniques to identify factors influencing the prioritization of complaints based on these categories. Considering the severity of different road sub-types, we also analyzed how each sub-type affects the processing time of complaints.

3.2. Descriptive Analysis of CPT

As shown in Table 2, over 91% of complaints were processed within two weeks. Notably, 4% of complaints were resolved within 24 h of receipt, while 2.2% of complaints, totaling 378, required more than four weeks to process. The average CPT was 246.3 h, approximately 10 days.

Table 2. Number of processed complaints.

	Less than 12 h	~1 Day	~2 Days	~4 Days	~1 Week	~2 Weeks	~3 Weeks	~4 Weeks	More than 4 Weeks	Total
Number of processed complaints	840	1768	4868	11,543	18,572	21,184	4276	1032	378	64,461
(%)	(1.3)	(2.7)	(7.6)	(17.9)	(28.8)	(32.9)	(6.6)	(1.6)	(0.6)	(100)

Figure 1 illustrates the distribution of CPTs by complaint type, revealing generally similar patterns across most categories, except for the roadkill/rockslide category. While the percentage of complaints processed within 12 h typically ranged from 0.4% to 1.5% across various complaint types, the roadkill/rockslide complaints were processed at a much higher rate of nearly 7%. Additionally, this category also exhibited higher processing rates within 1, 2, and 4 days compared to other types. This difference is attributed to the prioritization of roadkill/rockslide complaints, which are deemed urgent and thus processed more rapidly.

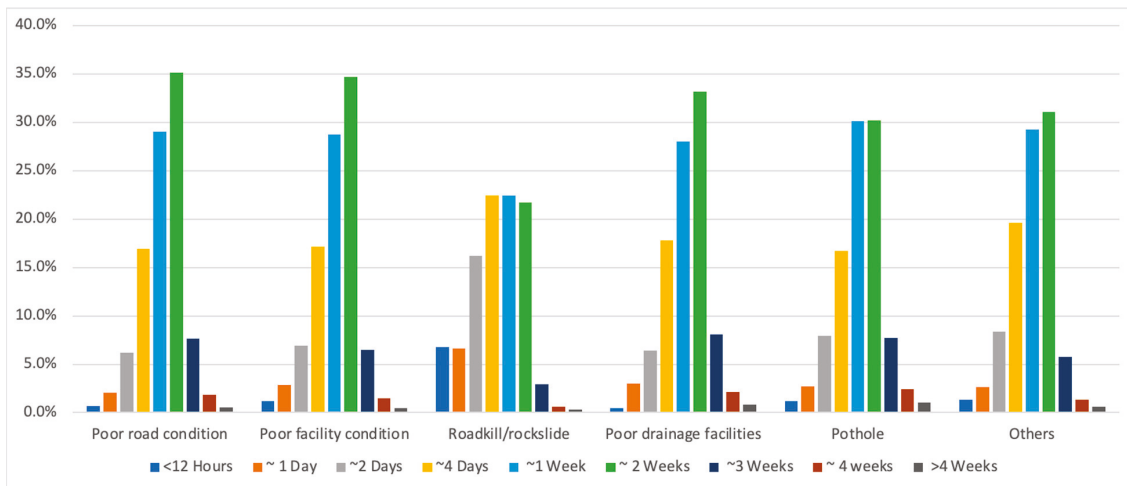


Figure 1. Distribution of CPTs by complaint types.

Table 3 presents the average CPTs organized by complaint location. We excluded roadkill/rockslide and drainage facilities from this analysis due to their low incidence (seven and three cases, respectively) when reported from SOC facilities and railways. The analysis revealed variability in average CPTs based on location and complaint type. For instance, SOC facilities exhibited the longest processing time for poor road condition complaints (232.8 h) but showed the shortest time for pothole complaints (174.8 h). Overall, this location type had the longest processing times for all complaint types, except for poor drainage facilities and potholes.

Table 3. Average CPTs by complaint location.

Civil Complaint Types	Average CPT (Unit: Hour)				
	Areas Around Buildings	Neighborhood Facilities	Road	SOC Facilities	Railway
Poor road condition	178.6	171.2	179.7	232.8	172.7
Poor facility condition	160.5	172.9	172.4	177.9	167.1
Roadkill/rockslide	106.6	127.3	117.7	-	-
Poor drainage facilities	168.4	167.7	182.4	174.8	-
Pothole	189.6	179.3	177.2	174.8	181.0
Others	156.6	163.1	162.9	172.5	147.6

3.3. Comparative Analysis of CPT

The comparative analysis of CPTs has thus far been based solely on average values, without considering the diversification effect per complaint type or reported civil complaint location. To address this, a one-tailed significance test was conducted for the average CPTs across various complaint types and locations, guided by the following null and alternative hypotheses:

$$\text{Null hypothesis (H}_0\text{): } \mu_1 - \mu_2 = 0, \quad (1)$$

$$\text{Alternative hypothesis (H}_1\text{): } \mu_1 - \mu_2 < 0, \quad (2)$$

where μ_1 and μ_2 represent the average CPTs for the comparison targets.

Table 4 presents the results from the one-tailed tests for the average CPTs of the reported complaint locations by complaint types. Firstly, the results indicate that the average processing times for poor road conditions in areas around buildings, neighborhood facilities, roads, and railways were not statistically significant. However, complaints categorized as poor road conditions in SOC facilities were processed statistically faster than those reported from other locations. Secondly, it was revealed that complaints regarding poor road conditions reported from areas around neighborhood facilities were processed significantly faster than those from areas around buildings or roads. Complaints pertaining to poor road facility conditions did not exhibit significant differences in processing times across most locations; however, complaints from areas around buildings were processed more quickly than those from neighborhood facilities, roads, and SOC facilities. Thirdly, for the complaints of roadkill/rockslide, location generally did not significantly influence the average processing time, although complaints from areas around buildings were processed quicker than those from neighborhood facilities. Fourthly, complaints regarding poor drainage facilities exhibited statistically shorter processing times when occurring in areas around buildings and neighborhood facilities compared to those reported from roads. In other cases, no significant differences were observed. Finally, complaints concerning potholes reported from roads were processed more quickly than those from areas around buildings, although similar processing times were noted in other comparisons. In addition, the complaint type categorized as “others” reported from areas around buildings had shorter processing times than when reported from neighborhood facilities, SOC facilities, and roads.

Table 5 shows test results on the differences in average CPTs per complaint type across various locations. Firstly, among the complaints reported from areas around buildings, roadkill/rockslide was processed more rapidly than all other complaint types at the 95% confidence level. On the other hand, complaints categorized as potholes were processed slower than all other types within the same confidence level. Notably, complaints related to road facilities were resolved quicker than those pertaining to poor road conditions. Secondly, with respect to complaints from neighborhood facilities and roads, roadkill/rockslide was addressed first compared to other types at the 95% confidence level. Furthermore, complaints concerning road facilities and those categorized as “others” reported from roads received prioritization over all other complaint types, except roadkill/rockslide. Thirdly, complaints reported from SOC facilities were statistically significant in general; however, none were processed particularly quickly, with poor road condition complaints requiring longer processing times on average compared to other types. Finally, no significant differences in CPTs were observed at the 95% confidence level for railways. However, at the 90% confidence level, the complaint type “others” was processed quicker than those related to poor road conditions.

Table 4. One-tailed *t* test results for the average CPTs.

Civil Complaint Types	Reported Civil Complaint Locations	Areas Around Buildings	Neighborhood Facilities	Road	SOC Facilities	Railway
Poor road condition	Areas around buildings		0.969	0.373	0.000 *	0.691
	Neighborhood facilities	0.031 *		0.004 *	0.000 *	0.448
	Road	0.627	0.996		0.000 *	0.718
	SOC facilities	1.000	1.000	1.000		0.998
	Railway	0.309	0.552	0.282	0.002 *	
Poor road facility condition	Areas around buildings		0.001 *	0.000 *	0.044 *	0.282
	Neighborhood facilities	0.999		0.565	0.330	0.678
	Road	1.000	0.435		0.309	0.669
	SOC facilities	0.956	0.670	0.691		0.755
	Railway	0.718	0.322	0.331	0.245	

Table 4. Cont.

Civil Complaint Types	Reported Civil Complaint Locations	Areas Around Buildings	Neighborhood Facilities	Road	SOC Facilities	Railway
Roadkill/rockslide	Areas around buildings		0.045 *	0.167	-	-
	Neighborhood facilities	0.955		0.822	-	-
	Road	0.833	0.178		-	-
	SOC facilities	-	-	-		-
	Railway	-	-	-	-	
Poor drainage facilities	Areas around buildings		0.528	0.079 **	0.410	0.481
	Neighborhood facilities	0.472		0.045 *	0.409	0.476
	Road	0.921	0.955		0.590	0.608
	SOC facilities	0.590	0.591	0.410		0.541
	Railway	0.519	0.524	0.392	0.459	
Pothole	Areas around buildings		0.878	0.975	0.781	0.612
	Neighborhood facilities	0.122		0.616	0.594	0.477
	Road	0.025 *	0.384		0.553	0.450
	SOC facilities	0.219	0.406	0.447		0.425
	Railway	0.388	0.523	0.550	0.575	
Others	Areas around buildings		0.046 *	0.024 *	0.066 **	0.778
	Neighborhood facilities	0.954		0.528	0.214	0.880
	Road	0.976	0.472		0.205	0.878
	SOC facilities	0.934	0.786	0.795		0.940
	Railway	0.222	0.120	0.122	0.060 **	

* Significance level: 0.05 ($\alpha = 0.05$); ** significance level: 0.1 ($\alpha = 0.1$).

Table 5. Differences in average CPTs by complaint locations and types.

Reported Civil Complaint Locations	Types of Civil Complaints	Poor Road Condition	Poor Road Facility Condition	Roadkill/Rockslide	Poor Drainage Condition	Pothole	Others
Areas around buildings	Poor road condition		1.000	1.000	0.875	0.038 *	1.000
	Poor facility condition	0.000 *		1.000	0.167	0.000 *	0.849
	Roadkill/Rockslide	0.000 *	0.000 *		0.000 *	0.000 *	0.000 *
	Poor drainage condition	0.125	0.833	1.000		0.025 *	0.930
	Pothole	0.962	1.000	1.000	0.975		1.000
	Others	0.000 *	0.151	1.000	0.070 **	0.000 *	
Neighborhood facilities	Poor road condition		0.331	1.000	0.675	0.109	0.979
	Poor facility condition	0.669		1.000	0.745	0.173	0.993
	Roadkill/Rockslide	0.000 *	0.000 *		0.001 *	0.000 *	0.001 *
	Poor drainage condition	0.325	0.255	0.999		0.125	0.719
	Pothole	0.891	0.827	1.000	0.875		0.993
	Others	0.021	0.007 *	0.999	0.281	0.007 *	

Table 5. Cont.

Reported Civil Complaint Locations	Types of Civil Complaints	Poor Road Condition	Poor Road Facility Condition	Roadkill/Rockslide	Poor Drainage Condition	Pothole	Others
Road	Poor road condition		1.000	1.000	0.198	0.876	1.000
	Poor facility condition	0.000 *		1.000	0.001 *	0.008 *	1.000
	Roadkill/rockslide	0.000	0.000		0.000	0.000	0.000
	Poor drainage condition	0.802	0.999	1.000		0.914	1.000
	Pothole	0.124	0.992	1.000	0.086 **		1.000
	Others	0.000 *	0.000 *	1.000	0.000 *	0.000 *	
SOC facilities	Poor road condition		0.998	-	0.912	0.988	0.999
	Poor facility condition	0.002 *	-		0.541	0.564	0.640
	Poor drainage condition	0.088 **	0.459	-		0.500	0.530
	Pothole	0.012 *	0.436	-	0.500		0.547
	Others	0.001 *	0.360	-	0.470	0.453	
Railway	Poor road condition		0.631	-		0.390	0.933
	Poor facility condition	0.369		-	-	0.314	0.883
	Pothole	0.610	0.686	-	-		0.896
	Others	0.067 **	0.117	-	-	0.104	

* Significance level: 0.05 ($\alpha = 0.05$); ** significance level: 0.1 ($\alpha = 0.1$).

4. Development of Decision-Making Support Method

4.1. Overview

Based on the analysis of average complaint processing times by type, location, and required time intervals, this section proposes a method for prioritizing complaint processing. This study employs a data clustering technique, specifically the density-based spatial clustering of applications with noise (DBSCAN) [9] method, to organize and analyze the complaint data. The DBSCAN algorithm is a non-parametric technique for clustering spatial data with noise. The algorithm detects clusters of data points that are closely grouped together, using a predefined number of neighboring points. It also identifies any data points that are significantly different from the rest and located in locations with low density. This clustering approach is capable of effectively handling clusters with different forms and noise, unlike other methods such as K-means [13] and hierarchical clustering, which are more suitable for compact and well-separated spherical clusters. DBSCAN relies on two main parameters, including (1) neighborhood radius: a small value classifies more outliers, while a large value merges clusters; and (2) a minimum number of points within the neighborhood radius to form a cluster: at least one more than the number of dimensions in the dataset with a minimum dimension of 3. By subdividing the entire set of complaint processing times using the suggested methods, we constructed the dataset, applied the DBSCAN technique, and identified clusters with optimal priority.

Initially, this study categorized the road type among complaint locations more finely, as road-related complaints constitute the majority of cases, approximately 81%. The characteristics of each sub-category within the road types are markedly distinct. As shown in Table 1, the current road type sub-categories include highways, general national roads, local roads, urban road, residential roads, residential streets, pedestrian roads, unclassified roads, farm/forest roads, and service roads. When prioritizing complaint processing within these sub-categories, issues arise, such as complaints concerning potholes on highways and service roads potentially being assigned the same priority. To preemptively address these potential discrepancies, we refined the subdivision of road types among complaint locations. Other location types, such as areas around buildings, neighborhood facilities, so-

cial overhead capital facilities, and railways, were not further subdivided after determining that their sub-categories do not significantly impact the prioritization process, as reviewed in Table 1.

4.2. Prioritization Decision

This section presents the data-driven complaint-processing prioritization decision method. Figure 2 illustrates a high-level stepwise procedure for conducting the proposed prioritization method. This study utilizes the required complaint processing time classifications suggested in Table 2.

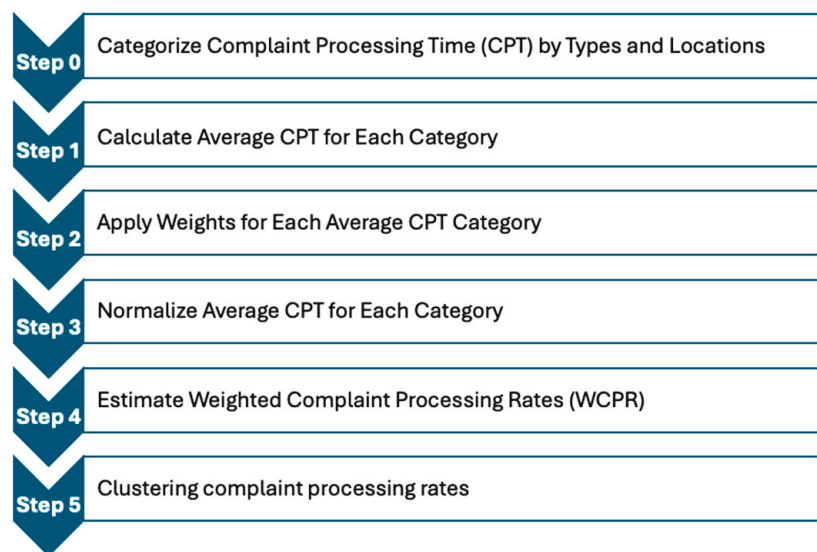


Figure 2. Overall distribution of weight average CPR.

4.2.1. Average CPT

Average CPT, measured in hours per complaint, is calculated with reported civil complaint locations and types. This includes using the subdivided road type in addition to the existing reported civil complaint location types. The comprehensive list of reported civil complaint locations now includes buildings, neighborhood facilities, social overhead capital facilities, railways, highways (motorway + trunk road), general national roads, local roads, urban road, residential roads, residential streets, other roads, unclassified roads, pedestrian roads, and service roads. In classifying Korea's road hierarchy, the OpenStreet Map differentiates roads into motorways and trunk roads based on the Korean Road Act [22]. However, this study merges motorways and trunk roads into highways for clearer classification.

4.2.2. Apply Weights for Each Required Complaint Processing Time Section

Weights are applied to the complaint processing rates (CPRs) for each complaint type and location across each required processing time section. This approach reflects the assumption that complaint type–location combinations with shorter processing times should be prioritized higher in the decision-making process. Various methods can determine these weights. Initially, we experimentally assigned values ranging from 100 to 1 based on the required complaint processing time sections, as outlined in Table 6. As indicated, combinations requiring more than four weeks to process were assigned a weight of 1, and those processed within 12 h received a weight of 100. This weighting implies that complaints resolved within 12 h are considered 100 times more urgent than those taking more than four weeks, aligning with the observed ratio of the average processing times—approximately 95.7 ($=746.5/7.9$). By applying different weights to each required processing time section, we ensure that the actual processing time is factored into the prioritization of complaints.

Table 6. Weighs by CPT section.

	Less than 12 h	~1 d	~2 d	~4 d	~1 Week	~2 Weeks	~3 Weeks	~4 Weeks	More than 4 Weeks
Weight	100	90	70	50	30	10	5	3	1

4.2.3. Normalize Average CPT

The weights assigned to each required CPT section as shown in Table 6 are applied to every complaint type–location combination, thereby producing the weighted average CPT (WACPT).

WACPT for each required processing time is normalized based on complaint types and locations. That is, the normalized WACPT indicates the weighted complaint processing rate (CPR) in processed complaints per hour, as it is calculated by taking the reciprocal of each WACPT. Consequently, combinations of complaint types and locations with shorter required processing times are prioritized over others.

4.2.4. Clustering Complaint Processing Rates

Data clustering was performed based on the weighted processing rates calculated for each complaint type–location combination. Figure 3 presents the overall distribution of weighted average CPR for these combinations (e.g., poor road condition on highway, road-kill/rockslide on local road). Although different rates were observed across combinations, consistent groupings emerged. Among various clustering techniques, this study employed DBSCAN algorithm to capture the groups. The DBSCAN algorithm is a non-parametric technique for clustering spatial data with noise. The algorithm detects clusters of data points that are closely grouped together, using a predefined number of neighboring points. It also identifies any data points that are significantly different from the rest and located in locations with low density. This clustering approach is capable of effectively handling clusters with different forms and noise, unlike other methods method, and hierarchical clustering, which are more suitable for compact and well-separated spherical clusters.

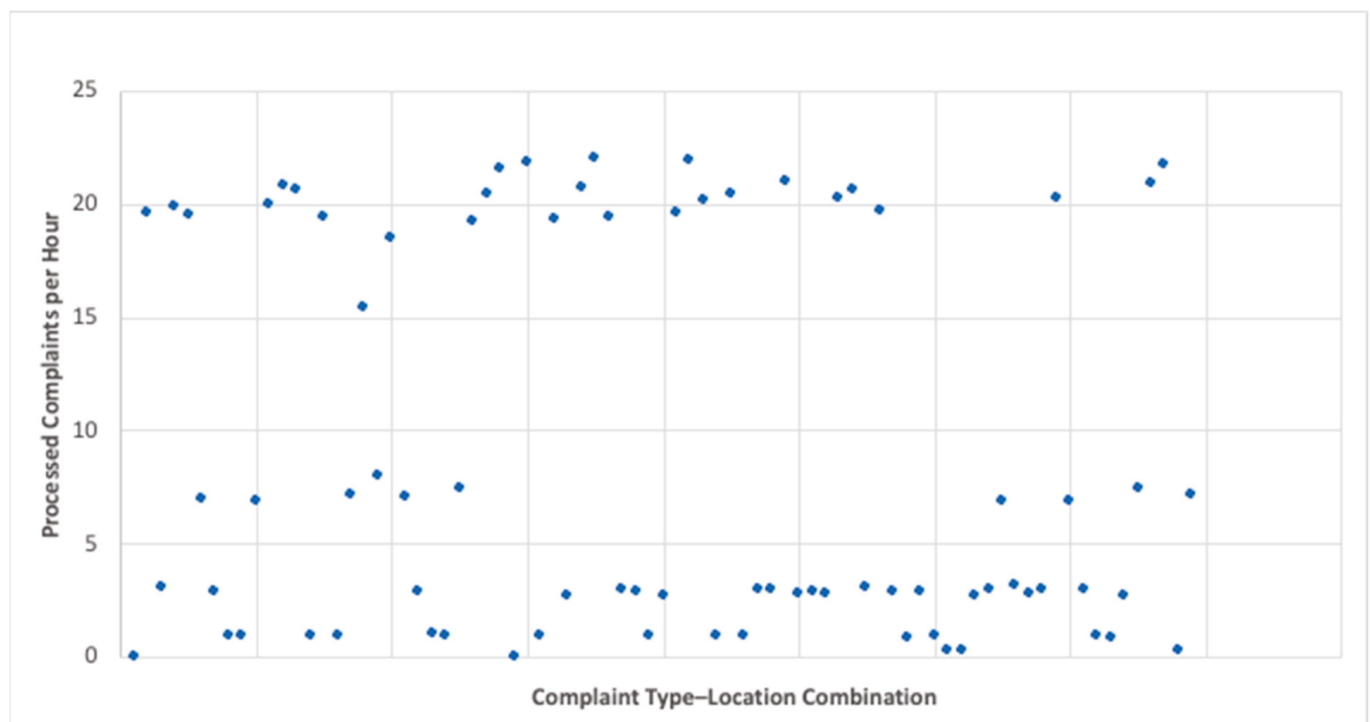


Figure 3. Overall distribution of weight average CPR.

In contrast to other clustering techniques that require a pre-set number of clusters, DBSCAN allows for flexibility in this aspect. However, as there is no established basis for arbitrarily determining the number of clusters, we experimented with numbers ranging from 2 to 10. It is worth noting that 10 more clusters would not be practically applicable; we decided to apply 10 as the maximum number of clusters. Clustering was performed for each scenario, and the optimal number of clusters was determined using the silhouette score technique [23]. To verify the robustness of the DBSCAN results, we also applied the K-means clustering technique [13] for comparison.

5. Results

After implementing the DBSCAN technique with the number of clusters ranging from 2 to 10 as input variables, the silhouette score for each cluster was estimated, as depicted in Figure 4. In general, silhouette scores range from -1 to 1 , with values closer to 1 indicating a more optimal cluster configuration. The analysis revealed that with four (4) clusters, the silhouette score reached a peak value of 0.91 . This optimal clustering was confirmed through parallel analysis using the K-means clustering technique, which yielded the same result.

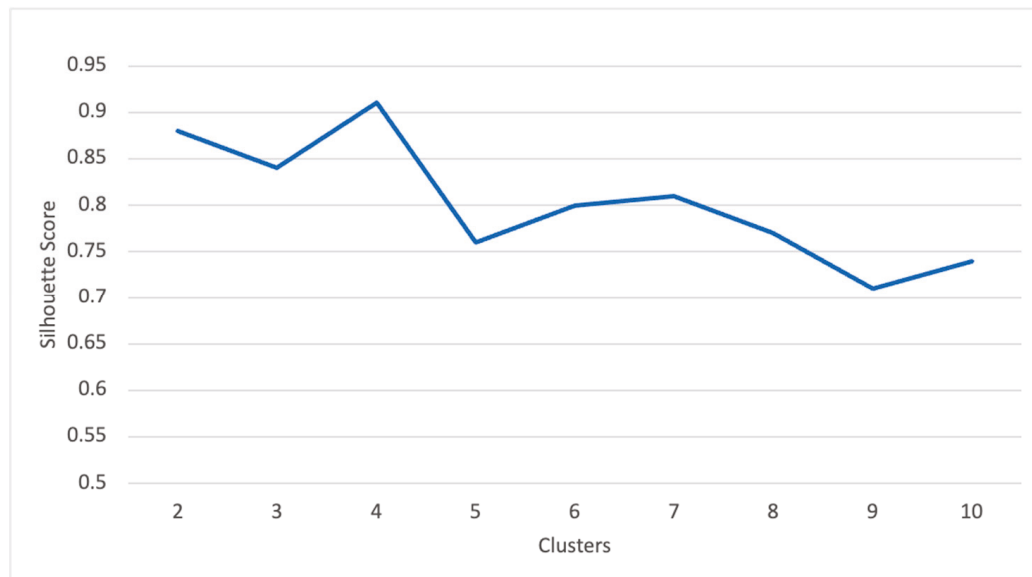


Figure 4. Silhouette score for each cluster.

Choosing the four (4) clusters as the final priority group based the silhouette score result, the boundary values for each cluster, representing the minimum and maximum complaint processing rate totals, are summarized in Table 7. Clusters were evaluated based on their complaint processing rate totals, with corresponding priority levels of high, neutral, low, and very low assigned to clusters 1–4, respectively, as detailed in Table 7. Table 8 further delineates the types of complaint locations associated with each complaint type according to their designated priority level.

Table 7. Boundary Values for Each Priority Level.

Cluster	Minimum Value	Maximum Value	Priority Levels
1	15.45	22.543	High
2	6.868	7.477	Neutral
3	2.698	3.138	Low
4	0.045	1.019	Very low

Table 8. Priority level by complaint locations and types.

Priority Level	Civil Complaint Types	Reported Civil Complaint Locations (Sum of Complaint Processing Rates)
High	Poor road condition	Highway (22.5); local road (21.8); residential road (21.5); general national road (20.5); city road (19.2); neighborhood facilities (18.5)
	Poor road facility condition	Neighborhood facilities (22.0); general national road (21.9); Local road (20.5); highway (20.3); residential road (20.2); urban road (19.6); other roads (19.4); buildings (19.3)
	Roadkill/rockslide	Highway (21.0); general national road (20.6); urban road (20.2); local road (19.7)
	Pothole	Residential road (21.7); general national road (20.9); highway (20.3)
	Others	General national road (20.8); residential road (20.7); urban road (20.0); highway (19.7); buildings (19.6); neighborhood facilities (19.5); local road (19.5)
Neutral	Poor road condition	Service road (7.4); buildings (7.1); other roads (7.0)
	Poor drainage facilities	Residential road (6.9)
	Pothole	City road (7.5); local road (7.2); neighborhood facilities (6.9)
	Others	Other roads (6.9); service road (6.9)
Low	Poor road condition	Unclassified roads (2.9)
	Poor road facility condition	Unclassified roads (3.0); pedestrian roads (2.9); service road (2.7)
	Roadkill/Rockslide	Residential road (3.1); buildings (3.0); other roads (2.9); unclassified roads (2.8); neighborhood facilities (2.8)
	Poor drainage facilities	Local road (3.1); general national road (3.0); neighborhood facilities (2.9); buildings (2.9); city road (2.7)
	Pothole	Other roads (3.00); buildings (2.8); service road (2.8)
	Others	Unclassified roads (2.9)
Very Low	Poor road condition	Pedestrian roads (1.0); railway (0.9); social overhead capital facilities (0.9); residential streets (0.0)
	Poor road facility condition	Residential streets (1.0); social overhead capital facilities (1.0); railway (0.9)
	Poor drainage facilities	Other roads (1.0); highway (0.9); unclassified roads (0.3); service road (0.3)
	Pothole	Unclassified roads (1.0); social overhead capital facilities (0.9); residential streets (0.3)
	Others	Residential streets (1.0); pedestrian roads (1.0); railway (0.9); social overhead capital facilities (0.9)

To validate how closely the calculated complaint-processing priorities align with actual complaint-handling practices, we analyzed the frequency of reported civil complaint locations for each priority level. As depicted in Figure 5, locations categorized with a

“high” priority predominantly include high-traffic and high-speed roads such as highways, national roads, and local roads. Conversely, the “very low” priority category frequently encompasses SOC facilities, residential streets, and railways. This distribution suggests that the data-based complaint-processing prioritization method proposed in this study aligns well with established social conventions and reflects practical traffic management needs effectively.

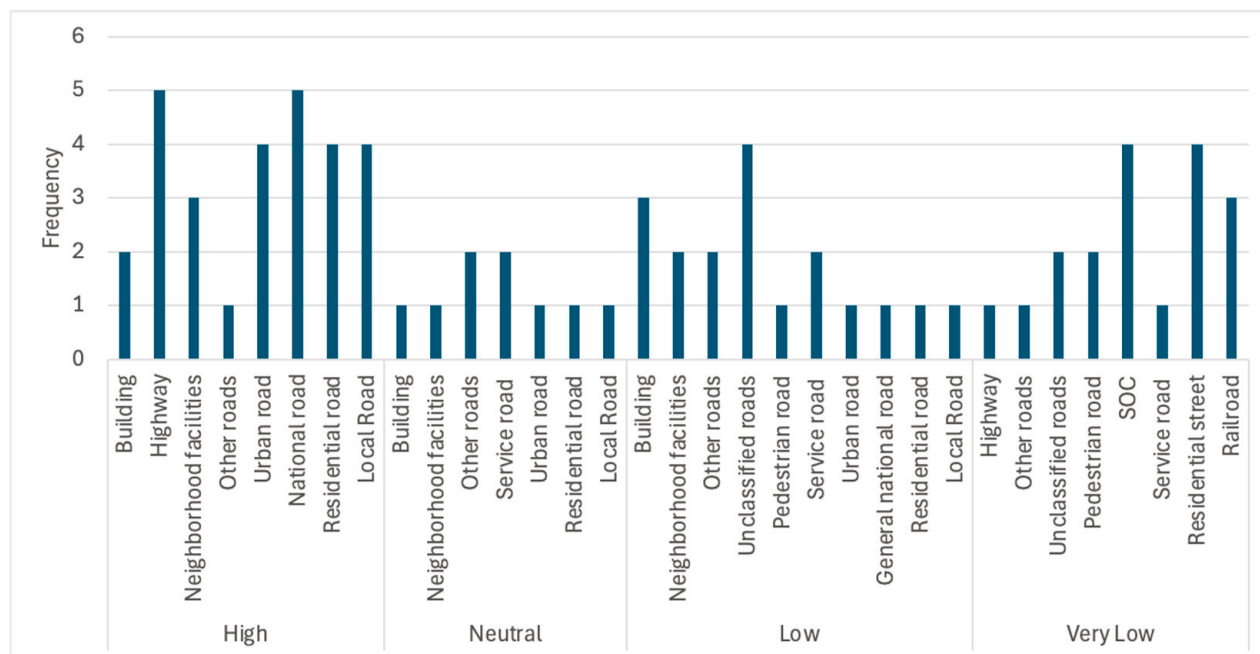


Figure 5. Frequency of reported civil complaint locations by each priority level.

6. Conclusions and Recommendations

This study presents a data-driven decision-making support method aimed at improving the quality of public service to efficiently handle various public complaints about road use. To achieve this goal, this study first examined complaint processing times categorized by type (such as poor road facility condition, poor road condition, roadkill/rockslide, pothole, inadequate drainage facilities, and others) and by location (including areas around buildings, neighborhood amenities, roads, social overhead capital facilities, and railways) utilizing two years of data from the road problem reporting service. We determined processing rates for complaints (the number of civil complaints addressed per hour) for each type–location combination, applied weights between 1 and 100 based on the necessary processing time, and aggregated these weighted rates. A validation study assessing the frequency of reported locations by priority showed that the proposed method accurately reflects actual field processing of complaints. Additionally, given the importance of location in complaint handling, the georeferencing technique seems appropriate for pinpointing complaint locations for each report and integrating this into the decision-making framework.

The DBSCAN clustering technique was used to organize complaint types and locations into groups, resulting in four final priority clusters (high, neutral, low, and very low), determined via the silhouette score test. Additionally, we applied the K-means clustering technique to the same data, cross-validated the results with those obtained from the DBSCAN technique, and confirmed their consistency. Additionally, understanding the importance of location in handling complaints, we applied georeferencing methods to pinpoint civil complaint locations for every report, integrating this into our analytical and decision-making system. This strategy, particularly if integrated into future complaint-processing prioritization techniques, has the potential to greatly improve the usefulness and relevance of georeferencing methods.

Despite the possibility of containing minor errors identified during the analysis, the dataset used in this research was direct observations from complaint processing sites and may include minor data entry errors. Nevertheless, the dataset is considered highly valuable as it reflects a variety of real-world situations encountered during complaint handling.

Previous research in this field proposed a method for automatically extracting issues from complaint-related photos and assigning priority rankings using machine learning techniques. Enhancing this model by integrating reported civil complaint locations could lead to the development of more precise artificial intelligence (AI)-based prioritization decision models, representing a promising direction for future research.

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Article

LGTCN: A Spatial–Temporal Traffic Flow Prediction Model Based on Local–Global Feature Fusion Temporal Convolutional Network

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Abstract: High-precision traffic flow prediction facilitates intelligent traffic control and refined management decisions. Previous research has built a variety of exquisite models with good prediction results. However, they ignore the reality that traffic flows can propagate backwards on road networks when modeling spatial relationships, as well as associations between distant nodes. In addition, more effective model components for modeling temporal relationships remain to be developed. To address the above challenges, we propose a local–global features fusion temporal convolutional network (LGTCN) for spatio-temporal traffic flow prediction, which incorporates a bidirectional graph convolutional network, probabilistic sparse self-attention, and a multichannel temporal convolutional network. To extract the bidirectional propagation relationship of traffic flow on the road network, we improve the traditional graph convolutional network so that information can be propagated in multiple directions. In addition, in spatial global dimensions, we propose probabilistic sparse self-attention to effectively perceive global data correlations and reduce the computational complexity caused by the finite perspective graph. Furthermore, we develop a multichannel temporal convolutional network. It not only retains the temporal learning capability of temporal convolutional networks, but also corresponds each channel to a node, and it realizes the interaction of node features through output interoperation. Extensive experiments on four open access benchmark traffic flow datasets demonstrate the effectiveness of our model.

Keywords: traffic flow prediction; spatial–temporal feature; local–global feature fusion; probabilistic sparse self-attention; temporal convolutional network

1. Introduction

The growing number of automobiles has created many challenges for urban transportation, including traffic congestion and traffic environment pollution [1,2]. The failure to divert congested traffic results in a lot of wasted travelers' time and fuel consumption, which has been troubling urban transportation managers [3]. The development of Intelligent Transportation Systems (ITSs) offers promising solutions to this challenge [4]. In particular, high-precision spatial and temporal prediction of regional traffic flow prediction is important reference information of the ITS, which can provide support for traffic control and management and improve the efficiency of urban traffic operation [5].

In the past few decades, scholars have proposed a large number of traffic flow prediction models and achieved excellent prediction results. These models mainly include statistical methods, traditional machine learning, and deep learning methods. Statistical methods include the history average (HA) [6], autoregressive integrated moving average (ARIMA) [7], seasonal autoregressive integrated moving average (SARIMA) [8], Kalman filter model [9], etc. These models are simple, efficient, and easy to compute, but it is difficult

to capture the nonlinear temporal correlation of traffic flow and the traffic spatial correlation in the city. To solve this problem, machine learning methods have been proposed and widely used, including k-nearest neighbor (KNN), support vector regression (SVR) [10], gradient boosting machine (GBDT) [11], etc. These methods can be applied to nonlinear traffic flow data, but they rely on manually setting parameters, and the feature extraction capability is still insufficient. Deep learning methods solve the above problems well. For example, Long Short-Term Memory Networks (LSTMs) and Gated Recurrent Units (GRUs) can learn long-term temporal dependencies [12,13], and Temporal Convolutional Networks (TCNs) can realize a larger sensory field by expanding the convolution [14]. Furthermore, the topology of the road network can be modeled by advanced graph neural networks [15]. These models have achieved good results in traffic flow prediction, but it is always difficult to be satisfied with the improvement brought by simple models [16,17].

Focusing on the spatial characteristics of urban transportation networks is considered to be a significant contribution to the improvement of prediction accuracy [18–20]. Early research project constructed traffic information as a spatio-temporal matrix and achieved good prediction results using convolutional neural networks (CNNs) [21–23]. However, it is applicable to standard Euclidean data, while real traffic spatial relationships (i.e., road networks) are usually non-Euclidean structured. The Graph Convolutional Network (GCN) proposed later introduces a spatially structured graph to represent road network nodes and connectivity relationships, and it shows excellent performance in predicting spatio-temporal traffic [2,24,25]. However, previous studies on traffic network graphs have overlooked the important fact that the nodal impacts of traffic flows can propagate not only in the forward direction, but also in the reverse direction. Specifically, a congested traffic flow not only affects subsequent moments at the next node of the roadway, but it also spreads to the previous node. In addition, nodes with the same land use attributes may have similar change patterns due to commuting behavior, even though these nodes are non-adjacent in terms of road topology, as shown in Figure 1. Note that Figures 1–3 illustrate the observational or experimental results in our dataset. Previous CNN and GCN studies could only extract long-distance features by deepening the number of layers, but they are prone to overfitting and difficult to obtain global features [26]. For classical CNNs and GCNs, information can only be propagated in neighboring vectors or nodes on the graph. A multilayered propagation structure may introduce ambiguity or the overfitting of information. How to effectively learn the global correlation of urban road networks has been a hot and challenging research topic [27,28].

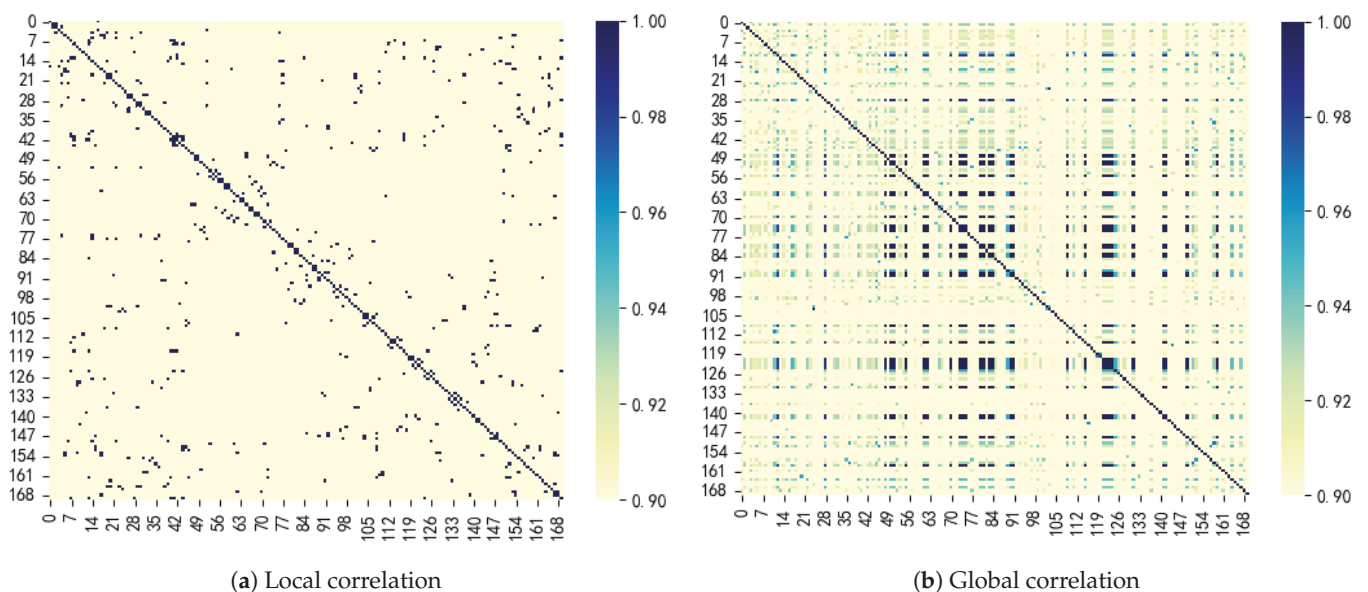


Figure 1. Spatial correlations. (a) Spatial relationship according to prior graph structure. (b) Pearson correlation coefficient for all nodes.

As shown in Figure 2, the patterns of each node have not only certain commonalities but also heterogeneity. Specifically, node 1 has two traffic peaks, node 2 has only one traffic peak, and nodes 3 and 4 show strong similarity. Previous spatio-temporal studies of traffic prediction, whether they choose convolutional, recurrent neural networks, or advanced transformers, have only considered the nodes of the whole city as a whole to learn the temporal features, and they ignore the independence [29,30]. A temporal module that can learn multinode heterogeneous features, while the loss of commonality is still lacking.

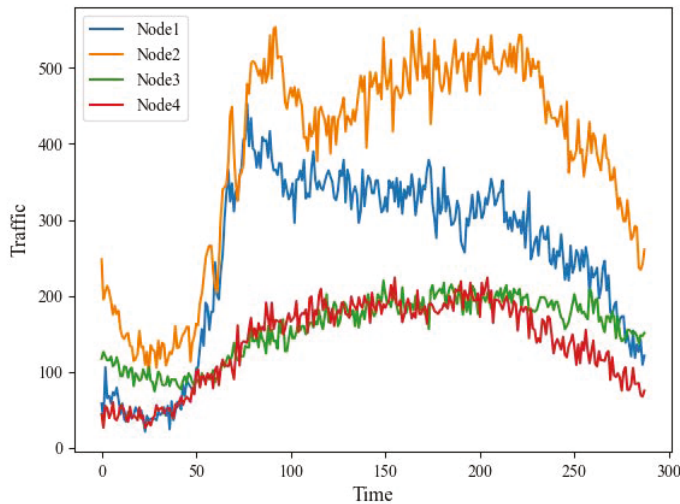


Figure 2. Heterogeneity in temporal dimension.

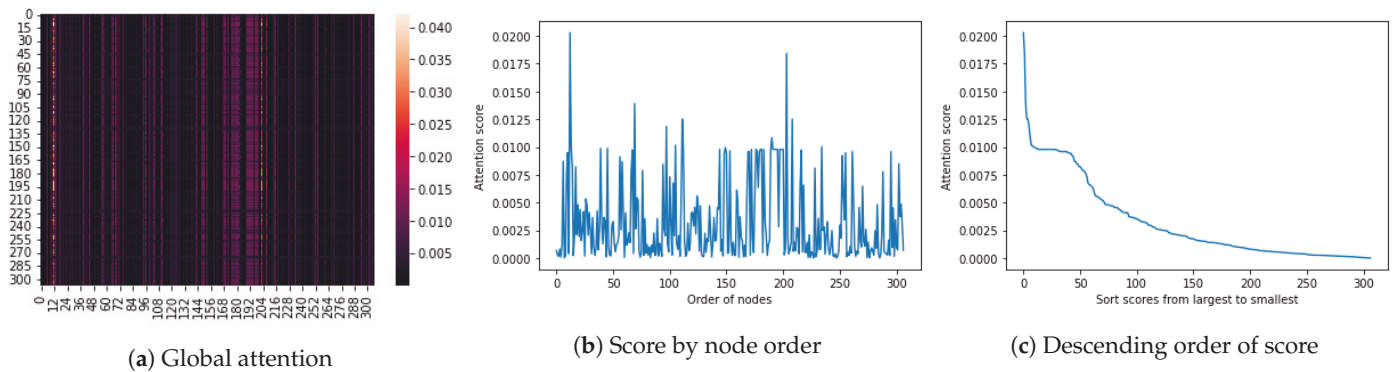


Figure 3. Feature distribution learned by self-attention. (a) The distribution of global attention values. (b) A node attention score in node order. (c) The attention score of a node is sorted from high to low.

To address the above challenges, we propose a local–global features fusion temporal convolutional network (LGTCN) for accurate spatial–temporal traffic flow prediction, which incorporates the bidirectional graph convolutional network, probabilistic sparse self-attention, and multichannel temporal convolutional network. Specifically, we employ bidirectional graph convolution to extract the bidirectional propagation of local road networks, as well as a probabilistic sparse self-attention mechanism to efficiently extract global features. Furthermore, we propose a multichannel temporal convolutional network to refine and extract temporal heterogeneity features without the loss of commonality; Finally, multilayer perceptron is used to integrate the hidden states and output predictions. Extensive experiments are conducted on four open access benchmark traffic datasets to evaluate the proposed model, and the experimental results demonstrate the effectiveness of our model.

The main contributions of this paper are as follows:

- We propose an innovative spatio-temporal traffic flow prediction scheme, which addresses the research difficulties in spatial and temporal dimensions.

- In the spatial local dimension, we propose bidirectional graph convolution to extract local traffic characteristics with bidirectional propagation. It is more in line with the reality of traffic flow compared to previous graph neural network studies.
- In the spatial global dimension, we express spatial nodes as spatial sequences and employ a probabilistic sparse self-attention mechanism for node interaction computation. Our method can reduce the computational complexity while maintaining the effectiveness of feature extraction.
- In the temporal dimension, we propose a multichannel temporal convolutional network to extract temporal heterogeneity features without the loss of commonality. We set the number of nodes equal to the number of channels to realize the fine extraction of multinode temporal features. Moreover, we utilize the dilated causal convolution, which can expand the sensory field to effectively extract the temporal features of long-term sequences while avoiding information leakage.

The rest of this paper is organized as follows: Section 2 summarizes the literature review related to our topic; Section 3 introduces the problem studied in this paper; Section 4 introduces the proposed spatio-temporal traffic flow prediction method; Section 5 presents the experiments in four benchmark datasets, including descriptions of the datasets, results of the experiments, and findings. Finally, Section 6 concludes the paper and discusses possible future work.

2. Related Work

2.1. Deep Learning for Traffic Flow Prediction

The rapid development of deep learning provides a new research method for the spatial-temporal prediction of traffic flow [31–33]. Stacking autoencoders (SAEs) deepen the network layers to learn the latent traffic spatial-temporal relationships and employ a greedy layerwise unsupervised algorithm to pretrain the model [34]. CNN-MLP can extract local spatial correlations and is less sensitive to data noise [18]. By abstracting network traffic into images, CNNs can be employed to learn large-scale spatio-temporal information [19]. Some scholars extracted traffic spatial-temporal information through Conv-LSTM and then used a Bi-LSTM to obtain temporal periodicity features of traffic flow [21]. The Conv-LSTM conforms to the attention mechanism optimization module to extract spatio-temporal features and then uses the BiLSTM module to efficiently capture daily and weekly periodic features [23]. T-GCN adopts a GCN to obtain the spatial dependence of urban roads and then introduces a GRU to obtain the temporal dependence of dynamic changes [35]. ST-ResNet uses convolutional and residual networks to extract spatial correlations, as well as residual networks to extract temporal features [36]. FCL-Net uses Conv-LSTM network to extract spatial-temporal correlation, as well as an LSTM network to extract external weather features [37]. However, a CNN is usually suitable for grid data. In reality, traffic flow data are often non-Euclidean structural data, so a GCN is introduced into traffic prediction. The STGCN employs the GCN and temporal gated convolutions to model spatial and temporal dependencies [38]. The DCRNN adopts the bidirectional random walk mechanism on the graph to model the spatial dependence, uses the Gated Recurrent Units (GRUs) to capture the temporal dependence, the overall model adopts the encode-decode structure, and the scheduled sampling technique to improve the prediction accuracy [39]. Further, a study used advanced deep learning models to accomplish multitask learning and prediction on missing traffic data [40].

2.2. Attention Mechanism

The self-attention mechanism is an important component of the Transformer [41]. The self-attention mechanism can reduce the maximum length of network signals traveling paths to the theoretical shortest $O(1)$ [42], so it has the potential to capture the global dependencies of spatial nodes compared to CNN and GCN. The attention mechanism is validated in traffic flow prediction to capture long-range dependencies [27,43–46].

However, the quadratic computational complexity of the self-attention mechanism affects the efficiency of the model. The Longformer attention mechanism reduces the computational complexity through the combination of local self-attention and global attention, and it realizes the modeling application of long text sequences [47]. Faster attention operations can be achieved by constructing a sparse transformer by dividing the complete attention computation into several blocks [48]. Logsparse Transformer reduces computational complexity to $O(L(\log L)^2)$ [49]. Reformer also achieves the complexity of $O(L(\log L)^2)$ by replacing the dot product attention with locality-sensitive hashing [50].

In addition, the self-attention mechanism makes all nodes perform weight calculation, which will cause the final weight to show a long-tailed distribution [51–53] and introduces too much noise from unrelated nodes. We used a self-attention mechanism to extract global spatial correlations for a dataset, which can be learned from long-range correlations from Figure 3a, and the prior graph structure can be ignored. We selected a point in the dataset for attention score distribution analysis, and it can be seen from Figure 3b that the attention distribution is unstable. And as shown in Figure 3c, according to the attention score from high to low, it obviously shows a long-tailed distribution, and a few nodes contribute to the main utility.

3. Preliminaries

In this paper, the task of traffic flow prediction is to predict the traffic flow in future time periods based on the historical traffic flow and the spatial relationship of nodes. This is defined as follows:

Nodes Graph: We use $G = (V, E, A)$ to represent the graph of nodes, V to represent the sequence of nodes, E to represent the edges of nodes, and adjacency matrix A to represent the connection between nodes.

Feature Matrix: Graph signal vector $X_N^t \in R^N$, where t denotes the time step. X_N^t represents the observed traffic flow of the nodes at time step t .

Prediction Problem: The prediction problem can be described as follows: given the spatial–temporal data τ time steps in the past, learn a nonlinear mapping function to predict the data Q time steps in the future. The formula is as follows:

$$\left(X_N^{(t+1)}, \dots, X_N^{(t+Q)} \right) = f \left(G; \left(X_N^{(t-\tau+1)}, \dots, X_N^{(t)} \right) \right) \quad (1)$$

where f is the nonlinear mapping function to be learned, and τ denotes the number of look back intervals.

4. Methodology

We proposed a prediction model that fuses temporal convolutions with the local–global feature, as shown in Figure 4. In the spatial dimension, the bidirectional graph convolutional network was used to extract the spatial local features, and the probability sparse self-attention mechanism was used to extract the spatial global features. In the temporal dimension, the multichannel temporal convolutional network was used to extract the temporal features.

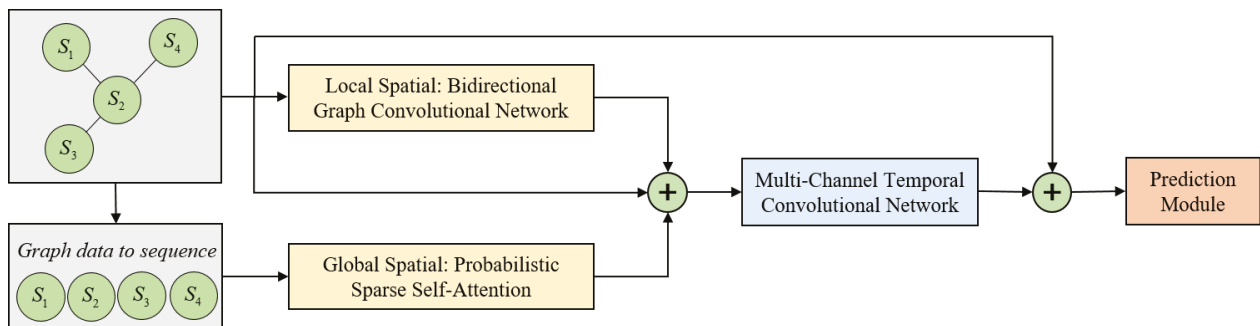


Figure 4. Overall framework of the model.

4.1. Bidirectional Graph Convolutional Network

For local node relationships, we considered nodes with physical road connections to be neighbors on actual road network. The graph convolutional network aggregates neighborhood information according to the spatial graph structure [54], which can be effectively used for spatial feature extraction of traffic flow. Traffic nodes have upstream and downstream relationships in a physical sense, but because traffic flow has the characteristics of backward propagation, traffic events at downstream nodes will also affect upstream traffic status. Therefore, forward and backward propagation studies on traffic graph are more applicable [39,55]. The bidirectional message propagation function in the first-order approximation ChebNet is defined as follows:

First, we calculate a adjacency matrix $\tilde{A}$ with a self-connected structure.

$$\tilde{A} = A + I \quad (2)$$

where A denotes the adjacency matrix without self-connected information, and I is the unit diagonal matrix. More specifically, $A_{ij} = 1$ stands for node i and node j being connected. And same below.

Then, a degree matrix $\tilde{D}$ can be obtained accordingly as below:

$$\tilde{D} = \sum_j \tilde{A}_{ij} \quad (3)$$

Then, the normalized adjacency matrix $\hat{A}$ can be calculated as below:

$$\hat{A} = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{\frac{1}{2}} \quad (4)$$

Finally, we can calculate the hidden feature matrix H^l of the l th graph convolutional layer as below:

$$H^l = \hat{A} H^{l-1} W + \hat{A}^T H^{l-1} W \quad (5)$$

where $\hat{A}^T$ is the matrix transposed after normalization, and W is a learnable parameter matrix.

4.2. Probabilistic Sparse Self-Attention

4.2.1. Canonical Self-Attention

The self-attention mechanism is an important structure of the Transformer, which effectively demonstrates the ability to extract features [41]. Transformer maps the input into query, key, and value, and the attention is calculated by the scaled dot product that then uses Softmax to obtain the weights. The formula is as follows:

$$A(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \quad (6)$$

where $Q, K, V \in R^{L \times d}$, and d define the input dimension. Softmax is an activation function that allocate attention to each feature. After Softmax calculation, the sum of attention weights of features was 1.

4.2.2. Multihead Self-Attention

The multihead attention mechanism divides the model into subspaces, which allows the model to learn information representing different subspaces at different locations. By mapping the linear mapping matrices of Q , K , and V to h in the dimension of d_s , $d_s = d/h$, and then performing the attention operation, and finally concatenating the h attentions together for linear mapping to obtain the output. The multihead attention mechanism expands the model's ability to learn different positions, and the parameters of the linear mapping can be learned, which improves the model fitting ability. The mechanism first

computes the attention information of multiple heads independently and then fuses the multidimensional features through a linear mechanism. The formula is as follows:

$$head_i = A(QW_i^Q, KW_i^K, VW_i^V) \quad (7)$$

$$MA(Q, K, V) = \text{Concat}(head_1, \dots, head_h)W^O \quad (8)$$

where MA stands for mutihead attention function, h is the number of heads, Concat means to concatenate the high-dimensional feature matrices of multiple heads, W is a learnable linear mapping matrix, $W_i^Q, W_i^K, W_i^V \in R^{d \times d_s}$, and $W^O \in R^{d \times d}$.

4.2.3. Probabilistic Sparse Measurement

The self-attention mechanism usually forms a long-tailed distribution, where a few dot products contribute the main attention, and other dot products contribute less, so the computational complexity can be simplified by capturing the main contribution of dot products. Those elements of the long-tailed distribution that deviate from the uniform distribution have a better chance of being the dominant contribution, so the Informer uses a variant of the KL divergence formulation to filter out the more important dot product pairs, known as the max-mean measurement [42], and the formula is as follows:

$$M(q_i, K) = \max_j \left\{ \frac{q_i k_j^T}{\sqrt{d}} \right\} - \frac{1}{L_K} \sum_{j=1}^{L_K} \frac{q_i k_j^T}{\sqrt{d}} \quad (9)$$

where q_i is the i th element in Q , and k_j represents the j th element of K .

The Informer achieves sparse self-attention by allowing each key to focus only on u dominant queries [42].

$$A(Q, K, V) = \text{Softmax} \left(\frac{\bar{Q}K^T}{\sqrt{d}} \right) V \quad (10)$$

where $\bar{Q}$ is a sparse matrix, including only the top- u dominant queries. Note that softmax is an activation function to determine the attentional weights of the features. First, randomly sample the quantitative key for each query; Second, calculate the M value of each query; Then select u queries with the highest M value, $u = L \cdot \ln L$, other dot-product pairs are filled with 0; Finally, only calculate the dot product of u queries and all keys. The score corresponding to the other query is to average the input of the self-attention layer.

4.3. Multichannel Temporal Convolutional Network

4.3.1. Temporal Convolutional Network

The TCN adopts structures such as dilated causal convolution and residual blocks, which can obtain a larger receptive field with fewer layers and maintain the stability of the model.

Dilated Causal Convolution: Causal convolution does not use recurrent connections, so it can achieve a faster network training speed with parallel input of time series data. However, standard causal convolution needs to stack many layers or use many large convolution kernels to increase the receptive field of neurons when dealing with large sample time series. The dilated causal convolution can improve the receptive field without significantly increasing the computational cost through the skip operation [14]. The formula is as follows:

$$DCC(i) = \sum_{j=0}^{k-1} h(j)x(i-dj) \quad (11)$$

where $DCC(i)$ is the convolution result of the i th element in the sequence $(x_0, \dots, x_t)$; $h(j)$ is the convolution kernel, and the size of the convolution kernel of the one-dimensional sequence is $K = 1 \times k$; d is the expansion factor, when $d = 1$ is the standard causal convolution.

The dilated causal convolution structure is shown in Figure 5, and the parameters $K = 1 \times 2$, and d are 1, 2, 4, and 4, respectively. Under the same number of network layers, a very large receptive field can be achieved.

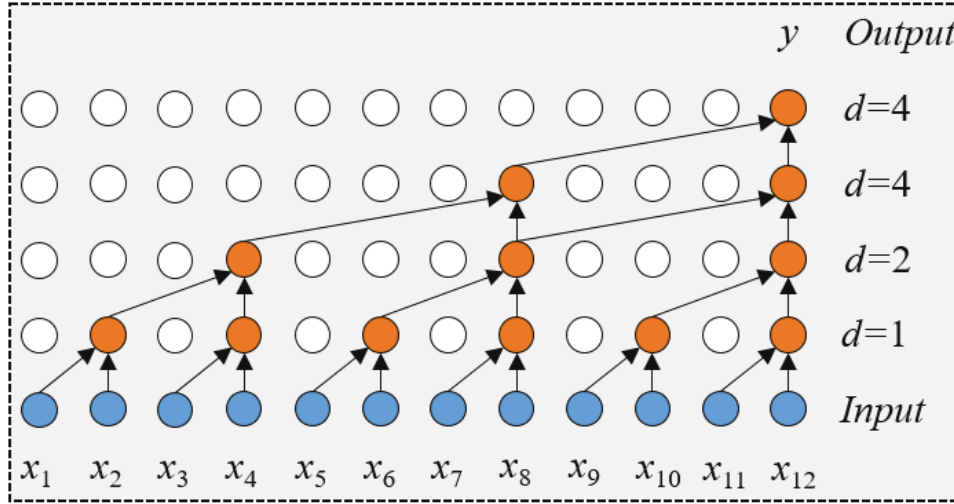


Figure 5. Structure of dilated causal convolution.

Residual Block: The residual block can maintain the stability of model features by introducing the operation of skip connection and solving the problem of deep learning network degradation [56]. The input x of the residual block is added to the features extracted by the dilated causal convolution module, and the final output result o is obtained through the activation function. The formula is as follows:

$$o = \text{ReLU}(x + D(x)) \quad (12)$$

where ReLU is an activation function; $D(\cdot)$ is the dilated causal convolution block.

4.3.2. Multichannel Mechanism

Traffic flow spatial-temporal prediction can also be regarded as a multivariate time series forecasting problem, which consists of multiple one-dimensional time series. The variation laws of each sequence are not the same, so a more refined extraction on the scale of temporal features can improve the prediction accuracy. We regard different nodes as different channels and let the input channel c_i and output channel c_o equal the number of nodes N ; then each channel is regarded as a response to the temporal varying of different nodes. For each output channel, its convolution kernel is $c_i \times K$, and the total number of convolution kernels is $c_o \times c_i \times K$.

4.4. Prediction Module

The prediction module of our model was used to improve nonlinear prediction ability and is a fully connected neural network architecture [41]. The formula is as follows:

$$FFN(X) = (XW_1 + b_1)W_2 + b_2 \quad (13)$$

where W_1 and W_2 are learnable parameter matrices, b_1 and b_2 are biases.

5. Experiments

5.1. Datasets Description

We evaluated the prediction performance of LGTCN on four public traffic flow datasets: PEMS03, PEMS04, PEMS07, and PEMS08 released by STSGCN [57]. The data were collected from four regions in California and aggregated into discrete data at 5 min

intervals, and each node generated 288 data per day, and the detailed description is shown in Table 1.

Table 1. Datasets description [58,59].

Datasets	Nodes	Days	Time Steps	Missing Rate
PEMS03	358	91	26,208	0.672 %
PEMS04	307	59	16,992	3.182 %
PEMS07	883	98	28,224	0.452 %
PEMS08	170	62	17,856	0.696 %

We normalized the data using max-min scaling:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (14)$$

where X_{min} is the smallest values in X , and X_{max} is the largest values in X .

5.2. Baseline Methods

- FC-LSTM: The Long Short-Term Memory Network is suitable for dealing with long-term dependencies in time series [60].
- DCRNN: The Diffusion Convolutional Recurrent Neural Network uses bidirectional random walks on the graph to capture spatial correlations and an encoder–decoder architecture with predetermined sampling to capture temporal correlations [39].
- STGCN: The Spatial–Temporal Graph Convolutional Network employs a temporal gated convolutional module to capture temporal correlations and a graph neural network to capture spatial correlations [38].
- ASTGCN(r): The ASTGCN constructs recent, daily, and weekly modules. A spatial–temporal attention module is used to capture spatial–temporal dynamic features, a graph convolution module is used to capture spatial features, and a standard convolution is used to capture temporal features. The comparison algorithm has recently adopted the recent modules in the model [32].
- STSGCN: The Spatial–Temporal Synchronous Graph Convolutional Networks construct a spatial–temporal synchronization graph to capture spatial–temporal relationships simultaneously and obtain prediction results by stacking multiple modules to aggregate long-range spatial–temporal relationships and heterogeneity [57].
- STFGNN: The Spatial–Temporal Fusion Graph Neural Networks constructs a temporal graph based on time series similarity that can learn long-range dependencies, and it employs a gated dilated convolution module whose large dilation rate can capture long-range dependencies [59].

The spatial-temporal feature extraction methods used by different baseline models are shown in Table 2.

Table 2. Methodology used in the baseline model.

Model	Spatial Global	Spatial Local	Temporal
FC-LSTM	-	-	RNN
DCRNN	-	Bidirectional random walks	RNN
STGCN	-	GCN	TCN
ASTGCN(R)	-	GCN	TCN
STSGCN	-	Synchronization graph	
STFGNN	Temporal graph	-	Gated dilated convolution
LGTCN	Probabilistic Sparse Self-Attention	Bidirectional GCN	Multi-Channel TCN

5.3. Experiment Settings

We split the original datasets into the training set, validation set, and test set in a ratio of 6:2:2. We used the past one hour data to predict the future one hour data, which means $P = Q = 12$.

We implemented the LGTCN model on the Pytorch platform, and the hyperparameters of the model were determined on the validation set. We used the same model architecture to conduct experiments on each of the four datasets. Among them, the number of multi-head of the probability sparse self-attention mechanism is 4, and $d = 12$. Multi-channel temporal convolutional network adopts dynamic expansion coefficients of 1, 2, 4, and 4 respectively. The hidden layer neurons of the prediction module are 128.

We adopted three validation metrics for model performance evaluation, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Their formulas are presented as follows:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i^p - y_i| \quad (15)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i^p - y_i)^2} \quad (16)$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \frac{|y_i^p - y_i|}{y_i} \quad (17)$$

where n is the number of all values, y_i is the ground values, and y_i^p is the predicted values at time i .

5.4. Experiment Results

5.4.1. Model Prediction Effects Comparison

The comparison of the prediction effects of various models is shown in Table 3. The LGTCN has achieved in ten out of the twelve indicators and has superior prediction performance. On all four datasets, our experimental results performed consistently well. Our proposed model, LGTCN, consistently outperformed the other baseline models on its MAE and RMSE. In the MAPE, our model took the lead on two datasets, but slightly fails on two datasets. One of the reasons for this is the presence of 0 and tiny values in the data, which leads to the nonapplicability of the MAPE. Another reason is that the loss function of the model is the MAE, and the model is optimized in the direction of minimum MAE value. Nonetheless, we argue that our model achieves an important improvement in prediction performance compared to the baseline models.

The FC-LSTM can only use temporal correlation and cannot use spatial correlation, so the prediction effect is the worst. The DCRNN, STGCN, and ASTGCN(r) can use different modules to utilize the temporal and spatial correlation of data, so the prediction accuracy has improved. The STSGCN can simultaneously extract temporal and spatial information, and the STFGNN model can take into account long-range spatial correlations, so it exhibits excellent predictive performance.

Our model can extract global spatial correlations with a small computational cost and then use a multichannel temporal convolutional network to achieve refined extraction of temporal correlations, and the comprehensive prediction performance is the best.

Table 3. Performance comparison of different models in traffic flow dataset prediction.

Datasets	Metrics	FC-LSTM [60]	DCRNN [39]	STGCN [38]	ASTGCN(r) [32]	STSGCN [57]	STFGNN [59]	LGTCN
PEMS03	MAE	21.33 ± 0.24	18.18 ± 0.15	17.49 ± 0.46	17.69 ± 1.43	17.48 ± 0.15	16.77 ± 0.09	15.21 ± 0.04
	MAPE(%)	23.33 ± 0.23	18.91 ± 0.82	17.15 ± 0.45	19.40 ± 2.24	16.78 ± 0.20	16.30 ± 0.09	14.79 ± 0.20
	RMSE	35.11 ± 0.50	30.31 ± 0.25	30.12 ± 0.70	29.66 ± 1.68	29.21 ± 0.56	28.34 ± 0.46	24.11 ± 0.07
PEMS04	MAE	27.14 ± 0.20	24.70 ± 0.22	22.70 ± 0.64	22.93 ± 1.29	21.19 ± 0.10	19.83 ± 0.06	19.58 ± 0.09
	MAPE(%)	18.20 ± 0.40	17.12 ± 0.37	14.59 ± 0.21	16.56 ± 1.36	13.90 ± 0.05	13.02 ± 0.05	15.92 ± 0.31
	RMSE	41.59 ± 0.21	38.12 ± 0.26	35.55 ± 0.75	35.22 ± 1.90	33.65 ± 0.20	31.88 ± 0.14	31.37 ± 0.14
PEMS07	MAE	29.98 ± 0.42	25.30 ± 0.52	25.38 ± 0.49	28.08 ± 2.34	24.26 ± 0.14	22.07 ± 0.11	22.03 ± 0.13
	MAPE(%)	13.20 ± 0.53	11.66 ± 0.33	11.08 ± 0.18	13.92 ± 1.65	10.21 ± 1.05	9.21 ± 0.07	9.96 ± 0.14
	RMSE	45.94 ± 0.57	38.58 ± 0.70	38.78 ± 0.58	42.57 ± 3.31	39.03 ± 0.27	35.80 ± 0.18	34.83 ± 0.16
PEMS08	MAE	22.20 ± 0.18	17.86 ± 0.03	18.02 ± 0.14	18.60 ± 0.40	17.13 ± 0.09	16.64 ± 0.09	16.20 ± 0.08
	MAPE(%)	14.20 ± 0.59	11.45 ± 0.03	11.40 ± 0.10	13.08 ± 1.00	10.96 ± 0.07	10.60 ± 0.06	10.56 ± 0.20
	RMSE	34.06 ± 0.32	27.83 ± 0.05	27.83 ± 0.20	28.16 ± 0.48	26.80 ± 0.18	26.22 ± 0.15	25.22 ± 0.12

5.4.2. Horizon Analysis

As can be seen from the Figure 6 and Table 4, as the horizon increased, the prediction error increased steadily. The model had higher prediction accuracy for the near-term and lower prediction accuracy than for the long-term. Different evaluation indicators were not completely consistent with the direction of model validation. For example, the model achieved the minimum value of the MAPE on the PEMS07 dataset, while the MAE and RMSE were always at the highest values.

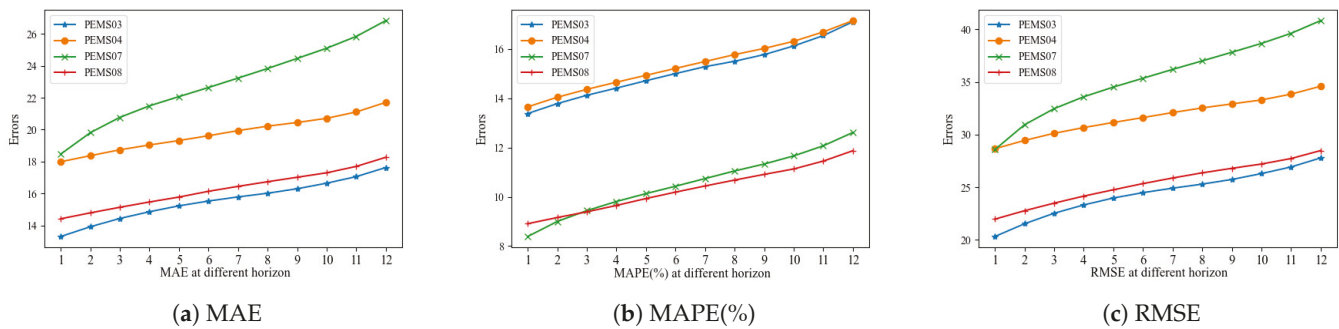


Figure 6. Prediction errors on different datasets. (a) MAE at different horizon. (b) MAPE(%) at different horizon. (c) RMSE at different horizon.

Table 4. Comparison of errors in different prediction horizons on four datasets.

Datasets	Metrics	1	2	3	4	5	6	7	8	9	10	11	12
PEMS03	MAE	13.31	13.92	14.44	14.86	15.23	15.53	15.79	16.02	16.30	16.65	17.06	17.63
	MAPE(%)	13.38	13.78	14.12	14.41	14.71	15.00	15.28	15.50	15.77	16.12	16.54	17.10
	RMSE	20.32	21.53	22.53	23.32	23.98	24.49	24.91	25.30	25.74	26.30	26.93	27.79
PEMS04	MAE	17.99	18.37	18.74	19.04	19.32	19.62	19.94	20.22	20.45	20.71	21.11	21.71
	MAPE(%)	13.65	14.04	14.36	14.65	14.93	15.21	15.49	15.77	16.02	16.31	16.69	17.15
	RMSE	28.66	29.45	30.13	30.67	31.16	31.62	32.10	32.54	32.92	33.30	33.85	34.60
PEMS07	MAE	18.47	19.81	20.77	21.49	22.07	22.64	23.23	23.83	24.46	25.10	25.84	26.83
	MAPE(%)	8.39	9.00	9.44	9.81	10.13	10.43	10.74	11.05	11.33	11.66	12.07	12.61
	RMSE	28.58	30.94	32.47	33.60	34.52	35.36	36.20	37.01	37.83	38.67	39.63	40.84
PEMS08	MAE	14.42	14.79	15.14	15.47	15.78	16.14	16.45	16.74	17.02	17.30	17.70	18.27
	MAPE(%)	8.91	9.16	9.39	9.65	9.93	10.19	10.44	10.68	10.91	11.13	11.45	11.87
	RMSE	21.97	22.77	23.49	24.16	24.76	25.35	25.88	26.37	26.80	27.21	27.73	28.49

5.4.3. Ablation Experiment

To verify the role of each module of the model in prediction, we fixed the random seed and conducted a series of ablation experiments on the four datasets, which are the following: NO-PSA: remove the probability sparse self-attention; NO-MCTCN: remove the multichannel temporal convolution network; NP-PM: remove the prediction module; NO-RES: Remove residual connections.

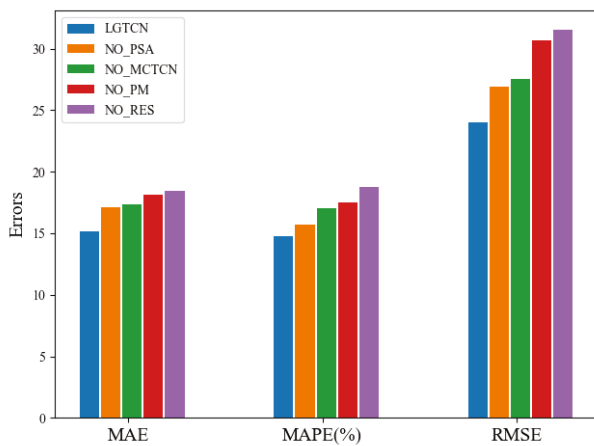
The experimental results are shown in Table 5 and Figure 7, and each module plays a role in the prediction. As shown in Figure 7d, the verification errors of different modules on the PEMS08 datasets, in the evaluation function of MAE, the errors of NO-PSA, NO-MCTCN, NO-PM, and NO-RES were increased by 3.91%, 20.84%, 16.09%, and 24.18% compared to the LGTCN, respectively. In the evaluation function of MAPE, the errors of NO-PSA, NO-MCTCN, NO-PM, and NO-RES were increased by 8.63%, 20.07%, 12.30%, and 23.52% compared to the LGTCN, respectively. In the evaluation function of the RMSE, the errors of NO-PSA, NO-MCTCN, NO-PM, and NO-RES were increased by 3.28%, 20.54%, 14.44%, and 25.02% compared to the LGTCN, respectively.

After removing the PSA module, the model still showed strong predictive ability, because the multichannel mutual operation of the MCTCN module can also achieve the

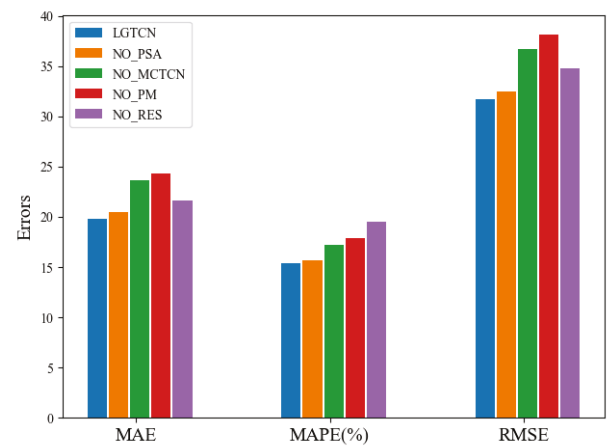
extraction of spatial relationships. The multichannel mechanism in the MCTCN module can achieve refined extraction for each node. Although the PM and RES modules are relatively simple, they have a very important effect on the stability of the model.

Table 5. Ablation experiment.

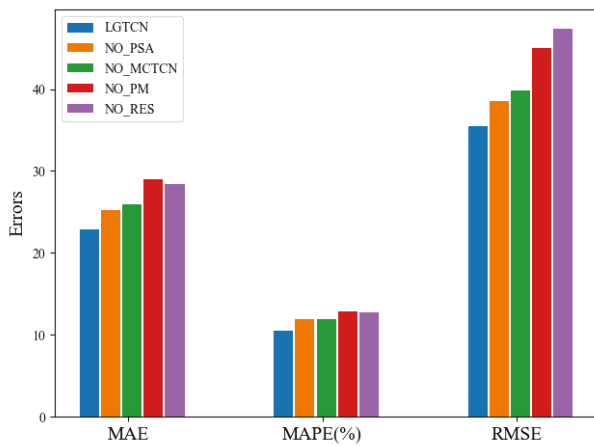
Method	MAE	PEMS03 MAPE(%)	RMSE	MAE	PEMS04 MAPE(%)	RMSE	MAE	PEMS07 MAPE(%)	RMSE	MAE	PEMS08 MAPE(%)	RMSE
LGTCN	15.14	14.73	24.00	19.77	15.36	31.75	22.88	10.56	35.47	16.27	10.31	25.41
NO-PSA	17.14	15.67	26.90	20.47	15.72	32.44	25.26	11.97	38.52	16.90	11.20	26.25
NO-MCTCN	17.31	17.05	27.54	23.61	17.17	36.66	25.98	11.89	39.77	18.89	11.58	29.08
NO-PM	18.15	17.50	30.69	24.28	17.87	38.18	29.00	12.84	45.00	19.66	12.38	30.63
NO-RES	18.45	18.73	31.53	21.60	19.51	34.80	28.36	12.80	47.35	20.20	12.73	31.77



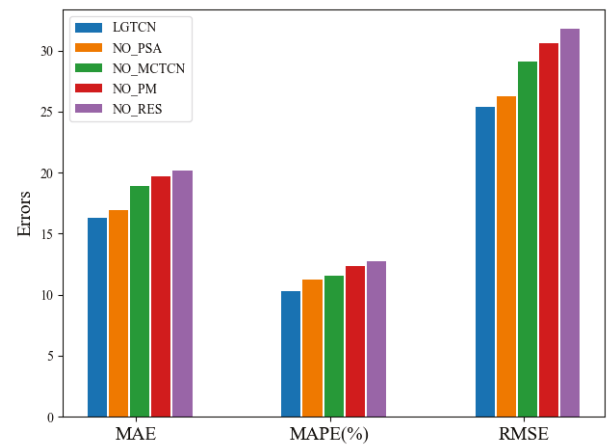
(a) PEMS03



(b) PEMS04



(c) PEMS07



(d) PEMS08

Figure 7. Comparison of ablation experiment results.

6. Conclusions

In this paper, we propose a traffic flow prediction model based on a local–global features fusion temporal convolutional network. First, we used a forward and backward graph convolutional network to obtain spatial local features, and we used a probabilistic sparse self-attention mechanism to efficiently extract spatial global features. Then, we used a multichannel temporal convolutional network to extract the temporal feature, and fine-grained extraction could be achieved by making each channel correspond to a node. Finally, the prediction result was obtained through the prediction module. Extensive experiments demonstrate the overall better performance of our model, and ablation experiments demonstrate that each module plays a role in prediction.

In the future, we will study the simultaneous extraction of spatially local and global features. At the same time, due to the cross-correlation operation of the multichannel convolution output, the model could not realize the independent extraction of complete temporal features, which inspires us to construct a series of independent time extraction sub-modules in the future. In addition, we need to embed real-time data from multiple sources (e.g., weather) into the model to further improve the prediction accuracy of the model. We also hope to implement the model in more urban spatio-temporal data mining areas, such as parking demand analysis. Downstream applications, including congestion information dissemination system, dynamic navigation, etc., are also yet to be developed.

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Article

Factors Affecting Rear-End Collisions in Underground Road Junctions Using VISSIM

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Abstract: Due to urban overcrowding, available land is limited and traffic congestion has increased. Underground roads are being built to mitigate traffic congestion as an alternative. Studies associated with underground roads are needed because these roads are dark and closed and have a high risk of accidents compared to surface roads. In particular, there is limited study on junctions that connect two or more underground roads. In this study, an underground road network including junctions was constructed to analyze the factors behind rear-end collisions at underground road connections. To reflect the driving behavior on underground roads, the scenario analysis was conducted by applying the speed distribution of underground roads in Korea. The results of the analysis showed that variables such as acceleration standard deviation and lateral position standard deviation are crucial for accidents on underground roads. Thus, this study can be used as a basis for traffic management and safety improvement in the operation of underground road junctions in the future.

Keywords: underground road junction; rear-end collisions; traffic safety; microscopic traffic simulation

1. Introduction

Cities provide numerous opportunities, services, and facilities to their citizens, but at the same time, their growth results in negative impacts [1], such as land-use changes and increasing population mobility. Thus, cities face problems like traffic congestion and population imbalance [2]. In dense cities, traffic problems can be exacerbated by insufficient road capacity. In particular, Asian cities such as Seoul—the capital of Republic of Korea—experience more severe problems than Western cities because of their extremely dense environment [3]. Roads in dense areas cannot meet demand because of the rapidly decreasing road capacity per person [4].

Underground spaces serve an important role in the sustainability of cities as a means of making more rational use of scarce land [5]. In particular, underground roads are the easiest way to access the saturated surface space, making them ideal for solving problems that exist in cities and their transportation systems [6]. In the 2000s, many underground highways were opened, such as the Big Dig in Boston, the A86 West Beltway Tunnel in France, and Södra Länken in Sweden, which helped regenerate cities by reducing traffic congestion on urban road networks [7].

On the other hand, underground roads are dark, closed environments, and have a higher risk of accidents than aboveground roads [8,9]. Liu et al. [10] argued that it is not reasonable to apply the design criteria for surface roads to underground roads because of their environmental differences. In addition, Qin et al. [11] showed that the visual

information inside a tunnel, which is a similar environment to an underground road, affects driver perception. The lack of visibility leads to a higher risk of accidents [12].

Because underground road junctions are designed to be curved, unlike mainline roads, they have even less visibility. Thus, it is crucial to prevent incidents through traffic management. Despite these risks, there are limited studies on the determinants of accidents within underground junctions that enable access between two or more underground roads. Most of the underground roads that have been opened so far are single roads, and none of them have yet implemented junctions. However, a study considering junctions in future underground networks is necessary.

The objective of this study was to analyze the factors that influence the possibility of rear-end collisions on underground road junctions. For this purpose, a network was constructed using VISSIM version 11, a microscopic traffic simulation program. Traffic information such as the speed and acceleration of individual vehicles and surrogate safety measures (SSM) were considered among the factors that influence the occurrence of accidents at the junction of underground roads.

The paper is organized as follows. Section 2 reviews the research related to risk factors and SSM, while Section 3 describes the network and methodology used. Section 4 summarizes and presents the results, and Section 5 concludes with a final discussion of the results.

2. Literature Review

Currently, underground road junctions are not being constructed, making it challenging to analyze real-world data. Simulation-based studies are particularly useful in evaluating the safety of roads that have not yet been constructed, as they are more cost-effective than actual road construction and allow for the assessment of safety issues in advance. Numerous studies on underground roads have been conducted using simulation tools.

2.1. Evaluating the Effectiveness of Underground Roads

Driving simulators are an effective method for collecting data from subjects driving in a virtual environment to analyze behavioral patterns based on different driving conditions [13]. Several researchers have employed driving simulators to observe driver behavior in underground roads or tunnel environments similar to underground roads, focusing on how design factors influence driver behavior [10,14–16]. Driving simulators have also been utilized to evaluate safety under varying conditions, including weather, lighting, and human factors [17–19].

However, analyzing complex interactions between drivers can be challenging with driving simulators, as it typically involves one or two users at a time. In contrast, microscopic traffic simulation is well suited for analyzing intricate interactions between vehicles [13]. Therefore, traffic simulation is necessary to evaluate complex systems, such as underground road junctions.

Some studies have employed traffic simulation to assess operational effectiveness in underground roads, and many others have used it to evaluate safety in underground roads and tunnels [20–25]. Factors such as speed variance, traffic volume, travel time, and queue length have been analyzed to assess safety [20–23]. Existing research has significantly contributed to understanding underground road safety, including aspects like road design, lighting, and secondary crash risks. However, there remains a gap in research concerning the safety and operation of junctions, which are crucial components of the underground road network. Therefore, this study aims to conduct an in-depth analysis of underground road junctions and their related safety factors using traffic simulation, focusing on assessing accident risk through surrogate safety measures (SSMs) such as time-to-collision (TTC), crash potential index (CPI), and deceleration rate to avoid the crash (DRAC).

2.2. Safety Evaluation Studies with SSMs

SSMs allow for the estimation of accidents without relying on actual accident data, making them a valuable tool for safety evaluation through simulation [24,26–29]. Upon reviewing the literature, TTC, CPI, and DRAC emerged as commonly used metrics for estimating accident risk. CPI and DRAC, in particular, can be assessed when vehicle information is collected within a connected vehicle environment that enables information exchange between vehicles.

TTC is especially useful for predicting rear-end collisions by measuring the time [30] until a collision occurs, assuming that two vehicles in the following situation maintain their current speeds. In this study, we considered TTC as an SSM to identify the crash risk at road junctions.

3. Methodology

The accident risk analysis was conducted through a microscopic traffic simulation and involved setting up an analysis network on VISSIM [31], running simulations for each scenario, generating data for analysis, and performing logistic regression analysis. Figure 1 explains the research framework and shows how the study was conducted.

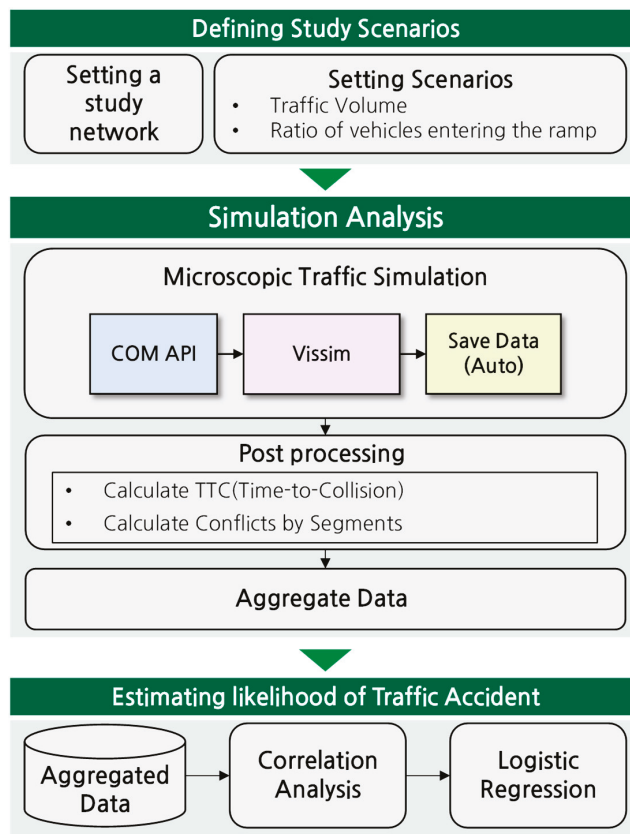


Figure 1. Research framework.

3.1. Simulation Network and Scenario

Because there are currently no existing three-dimensional intersections in operational underground roads in Republic of Korea, a virtual simulation network was constructed. The simulation network was set up according to the Highway Capacity Manual [32], Explanation of the Rules for Structural and Facility Standards for Roads [33], and Design Guidelines for Underground Roads in Urban Areas [34], which are the Korean design guidelines. The network consisted of a diamond-shaped underground-underground junction with a main line of 10 km and connections of 1 km.

Underground roads and the surrounding areas, including ramp, diverge areas, and merge areas, were selected as the studied area. Figure 2 shows the simulation network used in the study and the scope of the studied area where the data were analyzed. Table 1 describes the simulation network components.

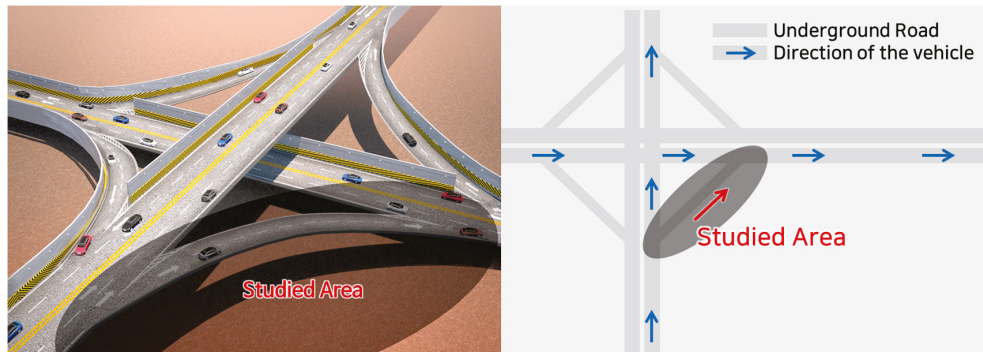


Figure 2. Simulation network (left: design of network, Right: Analysis Section of Network).

Table 1. Description of the simulation network.

Component	Content
Lane	Main road: 2 lanes one way Connection road: 1 lane
Vehicle composition	Underground road: Car only Ground road: All vehicle
Link Length	Main road: 10 km Connection road: 1 km
Designed speed	Main road: 80 km/h Connection road: 60 km/h
Gradient of link	Main road: 8% Connection road: 10%
Lane width	Main road: 3.5 m Connection road: 3.5 m
Capacity	Main road: 4000 pcph (veh/hour) ¹ Connection road: 1800 pcph (veh/hour) ¹
Acceleration and deceleration lane	Acceleration: 205 m Deceleration: 180 m
Separation distance between JC	Main road: 2 km
Curve radius	Main road: 450 m Connection road: 250 m

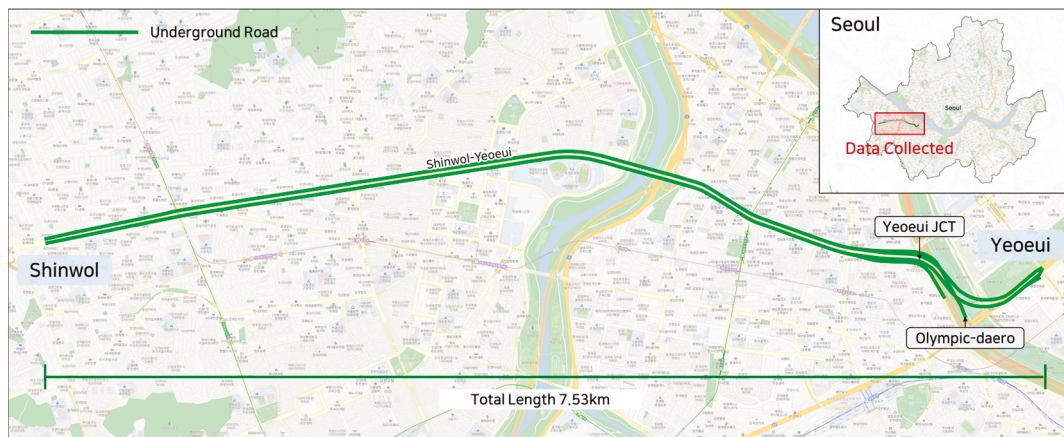
¹ pcph: passenger cars per hour.

Table 2 describes the simulation scenarios set up for the analysis. The simulation was conducted by dividing the analysis into cases with and without driving speed distribution in the underground road. To collect individual vehicle information through the simulation, we set up scenarios according to the mainline traffic volume and the rate of vehicles entering the connecting road. In the case of the mainline R1 and R2 in Figure 2, the traffic volume varied from 1600 pcph (LOS B) to 4000 pcph (LOS E) depending on the level of service, and in the case of the connecting ramp, the percentage of vehicles entering the connecting ramp from the mainline varied from 15% to 40% in 5% increments. Each scenario was simulated 30 times, and 1 h of individual vehicle driving data (not including the first 600 s as a warm-up period) was used for analysis.

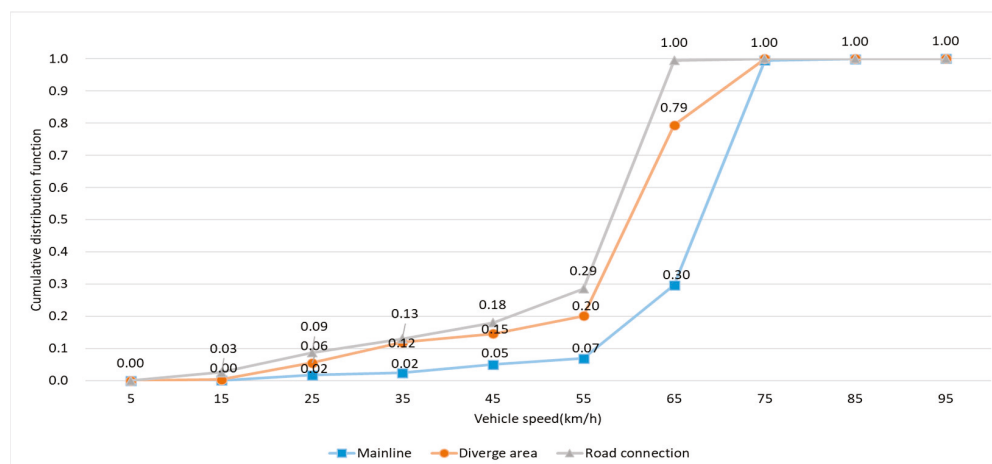
Table 2. Description of the simulation scenarios.

Speed Distribution	Volume of R1	Volume of R2	Access Rate to Ramp	
Speed on surface roads (Without)	LOS B	LOS B	15% of R1 traffic	30% of R1 traffic
	LOS C	LOS C	20% of R1 traffic	35% of R1 traffic
Speed on underground (With)	LOS D	LOS D	25% of R1 traffic	40% of R1 traffic
	LOS E	LOS E		

To construct the speed distribution, we used data from the Shinwol-Yeoui underground road in Seoul. Figure 3 shows the Shinwol-Yeoui underground road in Seoul. The Shinwol-Yeoui underground road is a 7.53 km long road that connects Shinwol-dong, Yangcheon-gu district to Yeouido-dong, Yeongdeungpo-gu district. The road has a speed limit of 80 km/h from the Shinwol direction to Yeoui JCT and 60 km/h after Yeoui JCT. There are also two off-ramps from Yeoui JCT to Yeoui-daero and Olympic-daero, and the off-ramp to Olympic-daero is a single lane, which is similar to the simulation network in this study.

**Figure 3.** Shinwol–Yeoui underground road in Seoul.

VDS (vehicle detection system) data collected for two months from 1 September 2021 to 31 October 2021 were used. Figure 4 shows the speed distribution set up for the underground road environment. Based on the average hourly section speed and traffic volume, we created speed distributions for the main line, diverging area, and road connection and applied them to VISSIM.

**Figure 4.** Speed distribution on Sinwol-Yeoui.

3.2. Data Processing

After data collection, TTC and density were estimated based on speed, location, and link information. The TTC was calculated using the speed and location information of the lead vehicle and the target vehicle, employing Equation (1).

$$TTC_i(t) = \frac{X_{i-1}(t) - X_i(t) - L_i}{V_i(t) - V_{i-1}(t)} \leq 1.5 \quad (1)$$

where X: $V(t)$: vehicle speed;
 $X(t)$: vehicle position;
 L_i : subject vehicle's length;
 $X_{i-1}(t) - X_i(t)$: relative distance;
 $V_i(t) - V_{i-1}(t)$: relative speed.

The Surrogate Safety Assessment Model (SSAM) (version 3.0), a road safety performance analysis software provided by the Federal Highway Administration (FHWA) of the United States, sets 1.5 s as the threshold for TTC. Thus, in this study, the threshold for TTC was set to 1.5 s to classify cases with a $TTC \leq 1.5$ s as conflict situations and cases with $TTC > 1.5$ s as non-conflict situations [35].

The processed data were aggregated by segment and time for analysis. The analysis area was divided into 50 m segments, with a total of 116 segments. The aggregation time interval was 1 s, and the information of 250 m worth of vehicles, including the center segment (k) and the two segments before and after it, was aggregated and used for the analysis, as illustrated in Figure 5 (i.e., the information was aggregated from 116 segments every second). Table 3 shows the final variables after data processing, and Table 4 presents a sample of the collected data.

Table 3. Description of the study variables.

Variable	Description	Variable	Description
Time frame	Simulation seconds	DensityMean	Acceleration average
Segment	Analysis points (No.)	AccelerationStd	Standard deviation of acceleration
Conflict	Conflict or not at segment m (conflict: 1, non-conflict: 0)	SpeedStd	Standard deviation of speed
AccelerationMean	Average of acceleration	PosLatStd	Standard deviation of lateral position
SpeedMean	Average speed	SpacingStd	Standard deviation of distance between vehicles
PosLatMean	Average of lateral position	DensityStd	Standard deviation of density
SpacingMean	Average of distance between vehicles		

Table 4. Aggregated data sample.

Time Frame	Segment	Conflict	Acceleration Mean	Speed Mean	PosLat Mean	Spacing Mean	Density Mean	Acceleration Std	Speed Std	PosLat Std	Spacing Std	Density Std
601	83	0	−0.1	78.3	0.5	30.9	48.6	0.2	1.0	7.8	0.1	12.8
601	84	0	−0.1	77.9	0.5	28.4	47.6	0.2	1.1	7.7	0.1	10.1
601	85	0	−0.1	77.0	0.5	33.0	46.4	0.1	1.0	7.5	0.1	22.5
601	86	0	0.3	79.8	0.5	35.9	46.6	0.1	0.6	4.7	0.2	26.9
601	87	0	0.1	74.1	0.5	33.6	30.5	0.0	0.7	13.4	0.2	31.0
⋮						⋮						
4200	112	1	−1.4	57.0	0.5	61.8	34.4	0.0	3.2	21.7	0.1	40.9
4200	113	0	−1.4	57.0	0.5	61.8	34.4	0.1	3.2	21.7	0.1	40.9
4200	114	0	−1.2	58.8	0.5	64.9	35.7	0.1	3.4	22.7	0.1	43.1
4200	115	0	0.1	80.7	0.5	90.3	29.5	0.1	0.5	9.1	0.0	31.7
4200	116	0	−0.1	77.0	0.5	65.5	24.3	0.0	0.3	11.7	0.0	55.9

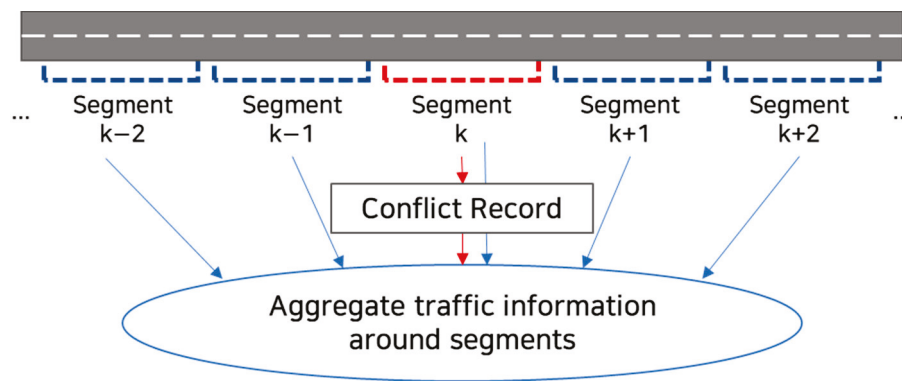


Figure 5. Aggregate traffic information around segments by time interval.

3.3. Logistic Regression

Logistic regression analysis was performed using the processed data. Logistic regression is a methodology used to estimate the probability of an accident by considering the variables that affect the risk of it occurring. Because we categorized conflict and non-conflict situations based on the TTC in Section 3.2, logistic regression can be used to identify factors that affect the probability of an accident.

The log odds of observing an incident ($Y = 1$) are estimated with each combination of explanatory variables, and the goodness of fit of the variables can be increased through Pearson residual values. The parameter estimates, standard errors, odds ratios, and confidence intervals of the logistic can also be visualized [36,37].

4. Results

4.1. Simulation Result

Table 5 shows the percentage of accidents with and without speed distribution. When the average number of conflicts was determined, a total of 108,000 pieces of information were collected per hour of simulation. In the scenario without speed distribution, 36.8% of the total (39,783 on average) were conflicts, whereas in the scenario with speed distribution, 52.5% of the total (56,702 on average) were conflicts.

Table 5. Conflict rates by scenario.

	Without		With	
Non-conflict	68,217	63.2%	51,298	47.5%
Conflict	39,783	36.8%	56,702	52.5%
Total	108,000	100%	108,000	100%

Figure 6 illustrates the difference in conflict rates by location between the without and with scenarios. It shows that diverge area, merge area, and ramp are the most common conflicts, with the with scenario having the highest conflict rates. This suggests that the proportion of conflicts on underground roads is higher than that on surface roads, and it is thus necessary to identify and manage variables that have a substantial effect on the safety of underground road junctions.

Table 6 presents the changes in the values according to whether speed distribution was applied as well as the R1 LOS change. When comparing the results by LOS, the average acceleration and average speed were found to gradually decrease as the traffic situation worsened. As spacing decreased, the acceleration standard deviation and density increased. When evaluating the changes in the variables depending on whether speed information was applied, we confirmed that the number of conflicts increased, speed and acceleration decreased, and density increased.

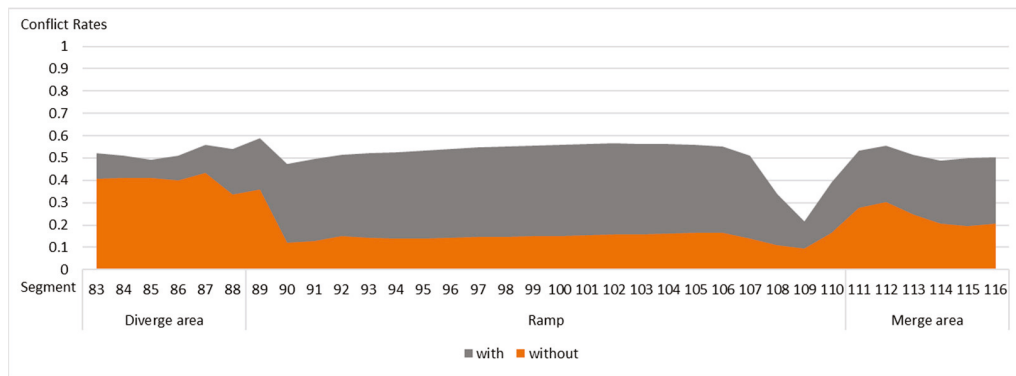


Figure 6. Conflict rate by scenario by location.

Table 6. Analysis results by scenario.

		Mean	LOS B	LOS C	LOS D	LOS E
Without	AccelerationMean [m/s ²]	−0.1	−0.1	−0.1	−0.1	−0.1
	SpeedMean [km/h]	61.6	70.0	68.9	63.0	47.8
	PosLatMean [m]	314.9	332.6	339.5	332.7	266.8
	SpacingMean [m]	55.9	66.2	64.2	55.6	41.4
	DensityMean [veh/km]	40.3	18.4	21.3	36.6	76.0
	AccelerationStd [m/s ²]	1.1	0.7	0.8	1.0	1.6
	SpeedStd [km/h]	16.6	12.6	12.8	15.9	23.2
	PosLatStd [m]	316.5	329.7	331.1	324.2	288.1
	SpacingStd [m]	54.6	65.2	60.8	51.6	43.5
	DensityStd [veh/km]	30.3	15.6	17.0	27.4	55.0
With	AccelerationMean [m/s ²]	−0.1	0.0	−0.1	−0.1	−0.1
	SpeedMean [km/h]	32.2	40.7	34.0	27.1	27.0
	PosLatMean [m]	0.5	0.5	0.5	0.5	0.5
	SpacingMean [m]	29.6	40.3	31.1	23.5	23.4
	DensityMean [veh/km]	75.6	48.9	65.0	93.9	94.7
	AccelerationStd [m/s ²]	1.8	1.4	1.7	2.0	2.0
	SpeedStd [km/h]	21.7	22.6	22.4	21.0	20.9
	PosLatStd [m]	0.0	0.1	0.1	0.0	0.0
	SpacingStd [m]	35.5	45.7	37.9	29.4	29.1
	DensityStd [veh/km]	35.8	26.4	32.0	42.5	42.5

4.2. Logistic Regression Result

To identify accident factors in the “with” scenario, logistic regression analysis was performed using Python’s `sklearn.linear_model` tool. Sixteen variables, including traffic dummy variables, were used in the logistic regression analysis. The variance inflation factor (VIF) test was performed to check for multicollinearity problems between the variables [38]. VIF is used to test whether the correlation between predictor variables affects the accuracy of the model and reflects the severity of multicollinearity. VIF measures the effects on model accuracy by evaluating the correlation between predictor variables (which reflects the severity of multicollinearity). Typically, a VIF value ≥ 5 means high collinearity. If $VIF > 10$, the correlation between variables is high, affecting the prediction accuracy of the model [39].

Here, the VIF values of all variables were < 1 , indicating a low correlation. The VIFs of the average speed and average lateral position variables were 0.347 and 0.001, respectively, demonstrating a very low correlation.

Table 7 presents the estimated coefficients, Wald Chi-square, odds ratio, and p -value. The Wald Chi-square statistic and p -value were used to test the significance of variables used in the logistic regression analysis. The odds ratio is a measure that shows how many times the accident frequency increases when the unit of a variable increases by 1, assuming

that the values of all variables, except for that one variable, are the same. The odds ratio was used to determine the effects of variables on accidents.

Table 7. Statistic results of logistic regression models.

Variable	Coefficient	Odds Ratio	<i>p</i> -Value
Intercept	0.0213	1.022	<0.01
AccelerationMean	0.0742	1.077	<0.01
SpeedMean	−0.0106	0.989	<0.01
PosLatMean	−0.469	0.626	<0.01
SpacingMean	−0.0134	0.987	<0.01
DensityMean	0.0114	1.011	<0.01
AccelerationStd	0.6599	1.935	<0.01
SpeedStd	−0.0032	0.997	<0.01
PosLatStd	2.2134	9.147	<0.01
SpacingStd	−0.0075	0.993	<0.01
DensityStd	−0.0034	0.997	<0.01
R1_C	0.0321	1.033	<0.01
R1_D	0.0595	1.061	<0.01
R1_E	0.0638	1.066	<0.01
R2_C	−0.0028	0.997	<0.01
R2_D	−0.0362	0.964	<0.01
R2_E	−0.0474	0.954	<0.01

(Pseudo R-square: 0.267, log-likelihood: −131,270,000).

The logistic regression analysis revealed that the variables that affected the increase in accidents were the average acceleration, average density, acceleration standard deviation, and lateral standard deviation. In R1, where the diverging area exists, the possibility of an accident was found to increase from LOS B to LOS D. By contrast, the variables that affected the decrease in accidents as their value increased were the average speed, average lateral position, average distance between the vehicles, speed standard deviation, standard deviation of the distance between the vehicles, and density standard deviation. In R2, which includes the merging area, accidents were found to decrease from LOS B to LOS D, but the effect was small.

As a result of the odds ratio analysis, the variables that have a large impact per unit are the standard deviation of the lateral position and the standard deviation of acceleration. When one unit increases, the occurrence of accidents increases by 8.147 times in the standard deviation of the lateral position, and increases by 0.935 times in the standard deviation of acceleration.

The simulation results revealed that the accident rate increases when a speed distribution is applied to the underground road, compared to when it is not applied. As the traffic flow increased, the average acceleration and average speed decreased, while the standard deviations of acceleration and density increased.

When the factors affecting accidents were estimated through logistic regression analysis, variables such as acceleration, speed, lateral position, and density were found to be related to accidents. In particular, the odds ratio of the lateral position and acceleration standard deviation is higher than other variables, suggesting that special management measures are needed to manage acceleration and lateral position standard deviation.

Previous studies have shown that lateral position [10,14,40–42] and acceleration [14,43–47] are variables that directly affect accidents in various environments. On surface roads, lateral position has been shown to be managed through management of edgelines, guardrail design, etc., and speed management policies have been shown to be enforced through automated speed enforcement.

5. Conclusions

Logistic regression analysis was used to examine accident risk factors in the VISSIM network. This is a proactive method for safety management and operation of underground

road junctions that do not exist yet. We aimed to simulate the underground road environment by reflecting the speed and traffic volume of an actual underground road. To realize the underground road environment, we specifically configured the simulation based on VDS data of Korean underground roads.

To predict the risk of accidents in a large-depth environment, the analysis was conducted using VISSIM data, and the speed and traffic volume of the Shinwol-Yeoeui underground road were reflected in the speed distribution. Time to collision (TTC) was used as the surrogate safety measure (SSM) to determine whether there was a conflict, and each datum was aggregated by segment to collect the traffic information of the surrounding segments depending on whether there was an accident in the target segment.

Speed, acceleration, and density decreased when underground road speed information was applied and when the level of service (LOS) of the access road was worsened in the underground road environment. In addition, the simulation results show that the proportion of conflicts is higher than that of non-conflicts in scenarios that reflect the speed distribution of underground roads. Thus, it is necessary to manage accidents in underground road junctions. The analysis revealed that the acceleration standard deviation and lateral standard deviation were the main contributing factors to the accident. Variables such as acceleration and lateral position are affected when driving in a tunnel environment similar to an underground road, so management of these variables is particularly necessary when operating on an underground road.

For example, it is expected that improving lane markings in underground roads to encourage drivers to keep their lane, and maintaining uniform speeds through speed enforcement, will reduce the risk of accidents in underground roads. In the future, a more detailed analysis will be required to analyze the effects of different management strategies in underground roads.

In addition, when the LOS of road R1 with a classifier increases from B to C and from C to D, the accident risk increases considerably, so it seems that traffic operation management should be performed before LOS D. In addition, the probability of an accident decreases when driving close to the left on a junction with a right-hand curve, so installing a sufficiently wide shoulder is expected to have a positive effect on accident reduction.

Notwithstanding, this study has some limitations. Due to data acquisition difficulties, only two months of VDS data were used to adjust the simulation parameters, making it difficult to understand long-term traffic patterns and accident risk. It is expected that more detailed traffic conditions can be constructed through long-term data analysis. And the data also do not reflect the visual elements of underground roads and differ from the real environment. Therefore, future studies should further utilize driving simulator-based data to reflect lighting conditions and underground roads components. Data that reflect driver behavior are expected to provide more realistic results.

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Article

A Backpropagation-Based Algorithm to Optimize Trip Assignment Probability for Long-Term High-Speed Railway Demand Forecasting in Korea

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Featured Application: (1) The concept of trip assignment probability was used to simulate passenger behavior of selecting different HSR stations in a zone, unlike the existing all-or-nothing-based optimal strategy algorithm. (2) By optimizing the trip assignment probability using a backpropagation-based algorithm, the accuracy and time efficiency of long-term HSR demand forecasting were improved compared with the existing calibration process using a trial-and-error approach. (3) The estimation accuracy of the backpropagation-based algorithm was especially superior when applied to an area with multiple accessible HSR stations, such as the Seoul metropolitan area, as well as non-metropolitan areas with a single accessible HSR station.

Abstract: In Korea, decisions for high-speed railway (HSR) construction are made based on long-term demand forecasting. A calibration process that simulates current trip patterns is an important step in long-term demand forecasting. However, a trial-and-error approach based on iterative parameter adjustment is used for calibration, resulting in time inefficiency. In addition, the all-or-nothing-based optimal strategy algorithm (OSA) used in HSR trip assignment has limited accuracy because it assigns all trips from a zone with multiple accessible stations to only one station. Therefore, this study aimed to develop a backpropagation-based algorithm to optimize trip assignment probability from a zone to multiple accessible HSR stations. In this algorithm, the difference between the estimated volume calculated from the trip assignment probability and observed volumes was defined as loss, and the trip assignment probability was optimized by repeatedly updating in the direction of the reduced loss. The error rate of the backpropagation-based algorithm was compared with that of the OSA using KTDB data; the backpropagation-based algorithm had lower errors than the OSA for most major HSR stations. It was especially superior when applied to areas with multiple HSR stations, such as the Seoul metropolitan area. This algorithm will improve the accuracy and time efficiency of long-term HSR demand forecasting.

Keywords: high-speed railway (HSR); long-term demand forecasting; trip assignment probability; calibration; optimization; backpropagation; access trip pattern

1. Introduction

High-speed railway (HSR) networks are significantly expanding on a global level. The length of HSRs was about 44,000 km in 2017, increasing by more than 30% to about 59,000 km in 2022 [1]. The HSR network in Korea has also expanded to about 893 km since it opened in 2004, as shown in Figure 1 [2], and the number of passengers has increased from 37,394 thousand persons in 2009 to 89,420 thousand persons in 2019 [3]. HSRs are used for operations of at least 250 km/h by UIC [4], but in Korea they have a maximum speed of over 300 km/h. In response to increasing demand, projects to build several HSR lines have been undertaken by the Korean Government. The impacts of these projects need to be evaluated using preliminary feasibility studies to secure part of the national budget, and the impacts are quantified based on long-term demand-forecasting results.

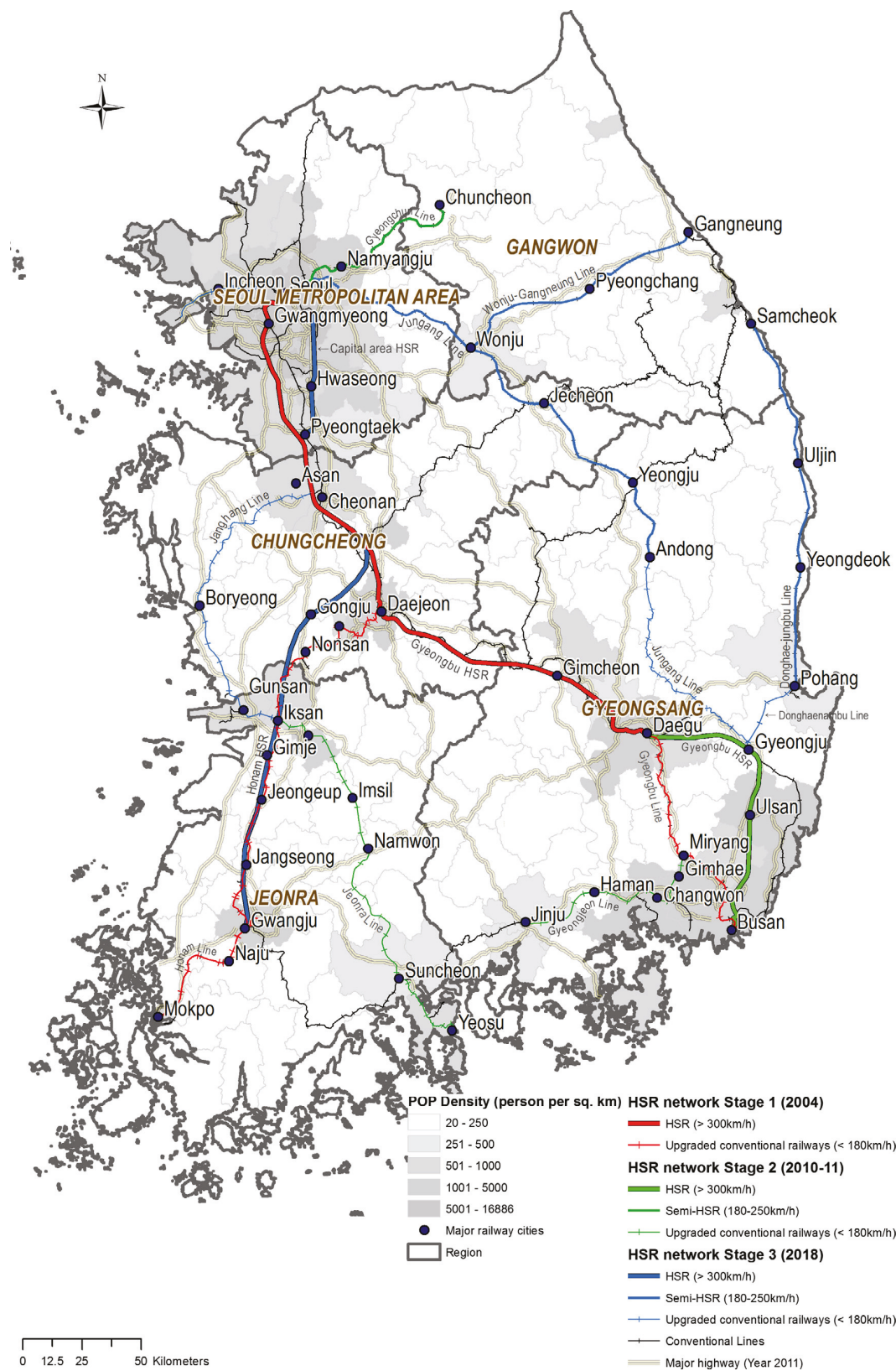


Figure 1. The HSR network in Korea [2].

The standard procedure for long-term demand forecasting in preliminary feasibility studies is included in a guideline published by the Korea Development Institute, which is a national research institute [5]. According to the guideline, the long-term demand for

HSR is predicted based on the premise that the current trip patterns will be maintained in the future. Therefore, the calibration process to simulate the current trip patterns is one of the most important steps in the long-term demand forecasting procedure. However, the guideline does not provide a specific methodology for calibration; therefore, analysts apply a trial-and-error approach to correct the error between the observed volume and estimated volume using a trip assignment model. This approach causes a large amount of time loss in long-term demand-forecasting analysis. Therefore, it is necessary to develop a time-efficient long-term demand-forecasting algorithm.

A variety of machine learning (ML)-related algorithms have been used to improve accuracy and time efficiency. In railway demand forecasting, ML is mainly focused on short-term forecasting. Short-term demand forecasting estimates the daily/hourly demand and establishes train operation plans. It aims to improve service quality and to reduce operating costs by adjusting operation plans. The most recent research on short-term passenger flow prediction has used the long short-term memory (LSTM)-based model or a combined model to capture the spatiotemporal features of historical passenger flow data in Chinese urban railway networks [6–16]. Han et al. proposed a novel deep-learning-based passenger flow (inflow and outflow) volume prediction approach using graph convolutional neural networks to capture spatiotemporal dependencies [17]. Hao et al. proposed a sequence-to-sequence model with an embedded attention mechanism to predict the alighting passenger volume at each Singapore metro station in the near future given the boarding passenger volume at each station in the last few short-term periods [18]. Wang et al. predicted the weekly periodicity and nonlinearity characteristics of short-term (5 min) ridership using a support vector machine (SVM) combined online model at two stations of the Nanjing Metro [19]. Roos et al. forecasted short-term passenger flows in the urban rail network of Paris with incomplete data based on dynamic Bayesian networks [20]. Sun et al. proposed a novel hybrid model Wavelet-SVM to predict different kinds of passenger flows (high frequency and low frequency) in the Beijing subway [21]. Wei and Chen developed a hybrid EMD-BPN forecasting approach that combines empirical mode decomposition (EMD) and backpropagation neural networks (BPNs) to predict short-term passenger flow in Taipei's rapid transit [22]. In addition, several research works have predicted abnormal or irregular congested passenger flow [23–26], and a few scholars have established models to predict short-term HSR demand. Zhao and Mi proposed a hybrid model that predicts short-term demand for an HSR by combining singular spectrum analysis, a convolutional neural network (CNN), and support vector regression [27]. Jiang et al. developed a hybrid approach combining the ensemble empirical mode decomposition (EEMD) and gray support vector machine (GSVM) for the short-term prediction of HSR flows [28]. When planning and constructing a new railway line or station, the influencing factors of demand become the variables for long-term demand forecasting. Du et al. proposed several factors affecting long-term passenger flow in rail transit, constructing a prediction model based on a class neural network [29]. Lin et al. focused on investigating the relationship between the built environment around the station and its passenger flow, developing a passenger flow prediction model using a multilayer perceptron (MLP) that could be applied to new railway stations without historical passenger flow data [30]. Lin et al. used mathematical and neural network methods to predict metro passenger flow based on land use around stations [31]. Yu et al. divided a city into multiple regions with similar internal traffic properties and a moderate spatial size to obtain more accurate factors affecting passenger flow, proposing a new prediction model based on the fuzzy processing method and Xgboost [32]. He et al. proposed a passenger flow prediction model based on station attributes affecting passenger flow regularity and predicted the passenger flow of a new line or station using its own attributes [33]. Cao et al. presented a new system with deterministic and probabilistic forecasting capacities based on residual component disposing for HSR demand forecasting [34]. Using long-distance elasticities, Börjesson investigated the prediction performance of two state-of-the-art Swedish HSR demand-forecasting models: the nested logit-based Sampers long-distance model and the newly

developed Box-Cox transformation-based model [35]. Thus, a large number of researchers are engaged in this topic on all continents.

The optimal strategy algorithm has been widely used not only academically but also practically in railway trip assignment models [36,37]. This algorithm assigns origin–destination (O/D) trips to the route that minimizes passenger travel time among various route options. The procedure is as follows [38]:

1. Define a departure node (station or stop);
2. Move to and board the vehicle that arrives first at the departure node among the competing routes;
3. Get off at the intermediate node (station or stop) that was determined according to the optimal strategy;
4. End if the passenger arrives at their destination; otherwise, define the alighting node as the departure node and repeat from step 1.

This approach is limited when simulating access trip patterns from each zone to diverse railway stations because this algorithm is based on an all-or-nothing trip assignment approach assigning all trips to only one railway station that minimizes the generalized cost. Tavassoli et al. proposed a practical procedure that automatically calibrates and validates large-scale transit assignments based on the optimal strategy [36]. They used smart card data and adopted a particle swarm optimization (PSO) algorithm as an optimization technique. De Cea and Fernandez [39] and Wu et al. [40] improved the optimal strategy algorithm to simulate congestion and delay by considering capacity constraints in the optimal strategy, but they did not overcome other limitations.

There are many access modes to HSR stations, and those selected by passengers will vary depending on the preferred access modes in a zone. Furthermore, in an HSR trip, the proportion of access time compared with in-vehicle time in the total travel time is higher than that of other public transportation. Therefore, it is necessary to develop a trip assignment algorithm that can reflect the diverse passenger preferences for accessibility to HSR stations.

In this study, we developed a backpropagation-based algorithm to optimize trip assignment probability from each zone to accessible HSR stations. This improves the accuracy and time efficiency of long-term HSR demand forecasting by reflecting the various access patterns of HSR passengers and using an optimization-based calibration algorithm.

The remainder of this paper is organized as follows: Section 2 reviews the standard long-term HSR demand forecasting methodology in Korea. Section 3 explains the trip assignment probability and optimizing algorithm for HSRs. Section 4 describes the data used and discusses the case study results. Section 5 presents conclusions and ideas for future research.

2. Standard Long-Term HSR Demand-Forecasting Methodology in Korea

This section introduces the standard long-term HSR demand-forecasting method in Korea. A preliminary feasibility study is a system in which government agencies review the feasibility of a project in advance. A preliminary feasibility study must be conducted for projects costing USD 35 million (KRW 50 billion) or more. The guideline for a preliminary feasibility study presents a long-term demand-forecasting methodology. The guideline provides a conventional four-step method of trip generation, trip distribution, mode split, and trip assignment for long-term demand forecasting, as shown in Figure 2 [5]. The O/D trip and network data included in the Korea Transport Database (KTDB) are used in this process. Since the KTDB includes O/D data by mode, the first three steps (trip generation, trip distribution, and mode split) in the conventional four-step method are omitted when predicting long-term demand. Therefore, the accuracy of the long-term demand forecasting varies according to the trip assignment algorithm. An optimal strategy algorithm without capacity constraints is applied for long-term railway demand forecasting using macrosimulations, such as Emme or TransCAD. To simulate the current trip pattern of a trip assignment algorithm, a calibration process based on a trial-and-error approach is

iteratively performed to correct the error between the volume estimated by the algorithm and the observed volume. After the calibration process, the long-term demand is predicted by applying the calibration results to the future network.

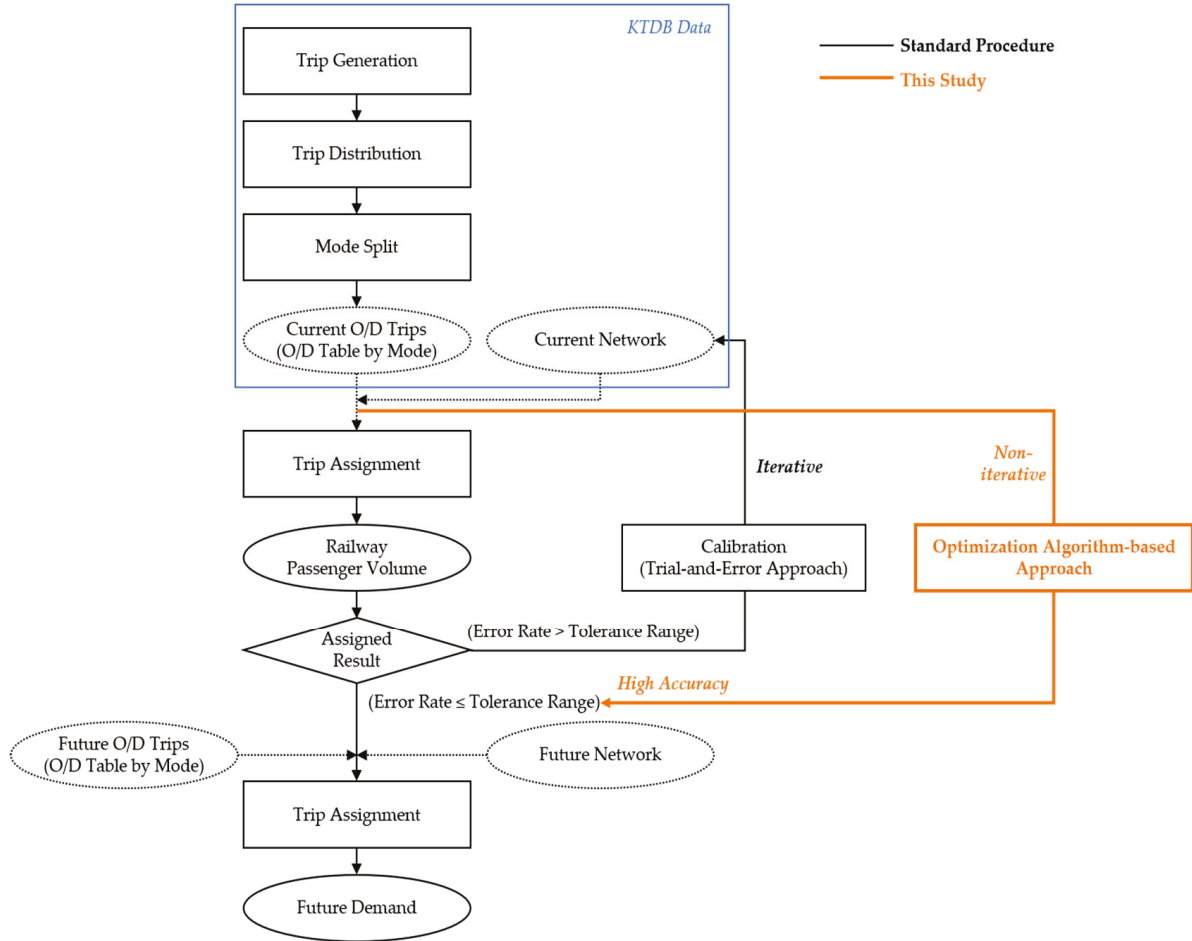


Figure 2. Standard long-term HSR demand-forecasting procedure in Korea.

The calibration reference value in railway trip assignment is the error rate between the estimated and observed boarding/alighting volumes at major stations, calculated as Equation (1) [5]. The guideline suggests that the error rate must be under 30% for stations but does not provide specific calibration methods. Accordingly, the analyst repeats the calibration process, such as by adjusting the network parameter, to satisfy the 30% critical error rate; however, there are limits to improving this accuracy due to the temporal inefficiency and limitations of the all-or-nothing-based optimal strategy algorithm:

$$\text{Error rate } \varepsilon(\%) = 100 \times \frac{f^{est} - f^{obs}}{f^{obs}} \quad (1)$$

where f^{est} is the estimated number of passengers at each station using the trip assignment model, and f^{obs} is the observed number of passengers at each station.

3. Methods

3.1. Trip Assignment Probability

The trip assignment probability is calculated by extracting the accessible HSR stations for each zone by route. The trip assignment probability concept is shown in Figure 3. Unlike the optimal strategy algorithm, this method can simulate the passenger behavior of selecting different HSR stations in a zone. For zone i , stations s_A and s_B within the

accessible distance are considered accessible stations, and station s_C is excluded because it is outside the accessible distance. Thus, the HSR trips from zone i are assigned to s_A and s_B . The passengers are assigned in the same way for the departure and arrival zones. If the departure and arrival stations are on the same line, then $X = 1$; otherwise, $X = 0$, and the passenger volume between the two stations equals zero. For example, in Figure 3, $X_{s_A \rightarrow s_D} = 1$, but $X_{s_A \rightarrow s_C} = 0$. The inter-station passenger volume, $V_{s_A \rightarrow s_D}$, is equal to the sum of all stations multiplied by P_{is_A} , the probability of using station s_A in zone i ; P_{js_D} , the probability of using station s_D in zone j ; and T_{ij} , the O/D trips from zone i to zone j . If s_A and s_D are not connected on the same line ($X_{s_A \rightarrow s_D} = 0$), $V_{s_A \rightarrow s_D}$ becomes 0.

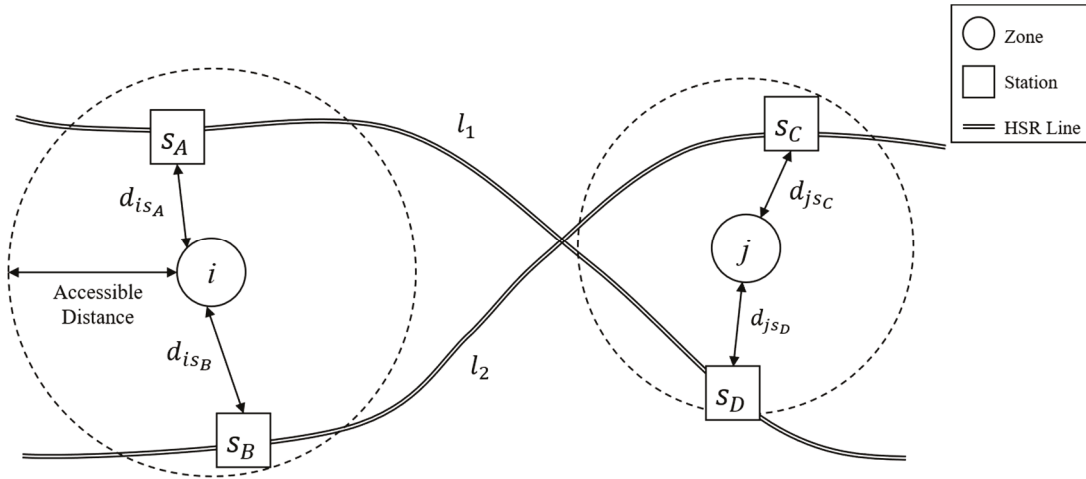


Figure 3. The trip assignment probability concept.

Passengers can access different stations, even within the same zone, based on impedances experienced in traveling to the station or the service level of the station. Yao and Morikawa found that induced demand increases with decreased travel time, travel costs, and access time, and increased service frequency [41]. Choi et al. used walking distance to the station as an influential factor for metro ridership [42]. Moreover, the vehicle frequency of public transportation is the most crucial factor of the trip assignment in the optimal strategy algorithm [38]. Therefore, we considered d_{is} , the Euclidean distance from zone i to station s , to be a travel impedance factor, and f_{sl} , the train frequency at station s , to be a travel attractiveness factor.

3.2. Optimization Algorithm

The HSR trip assignment model outputs the predicted demand for each station when influencing factors are input. An artificial neural network algorithm that has recently been used in many ways owing to its high prediction performance could be applied to this problem. This algorithm learns the relationship between inputs and outputs based on collected data and then highly accurately outputs the results by optimizing the weight using a backpropagation algorithm [43]. The backpropagation algorithm optimizes the weight to minimize loss, which is the error margin between a prediction and the actual target value. After a gradient is obtained for each weight, the weight is updated in the opposite (negative) direction. In this study, we used the trip assignment probability concept, but the probability could not be used as an output in the modeling because of limitations in data acquisition. When we applied backpropagation to this problem, the trip assignment probability could be recognized as the weight optimized in the artificial neural network. In other words, it could be approached as an optimization problem: finding a trip assignment probability that minimizes loss, that is, the difference between the estimated volume based on this probability and the observed volume. Therefore, the trip assignment probability was estimated using an optimization technique based on backpropagation.

In addition, considering that accessible stations may vary depending on the line, the trip assignment probability was estimated using a combination of zones and lines, not just zones. We assumed that there were n accessible stations for each combination of zones and lines; thus, n probabilities for each combination were estimated using the optimization algorithm. If there were N combinations and n accessible stations for each combination, $(N \times n)$ probabilities needed to be estimated. The sum of the probabilities for n accessible stations is 1. The trips provided as a combination of zones and lines were assigned to each accessible station, along with their probabilities, and the assigned trips were added up for each station to calculate the boarding/alighting volume at each station.

However, to apply this backpropagation concept, the loss calculation process must be differentiable. In this study, PyTorch 1.11 [44] was used, a deep learning framework used for artificial neural network learning, and it provided the loss value using only differentiable calculations. Backpropagation is the basic principle for weight updates, and several optimization algorithms exist depending on how backpropagation is applied. In this study, the AdamW algorithm [45] was applied as the optimization algorithm, and MSELoss (mean squared error loss) was used as the loss function as shown in Figure A1. The procedure is shown in Figure 4, and its detailed codes are presented in Figure A2 for readers to better analyze and repeat the experiment.

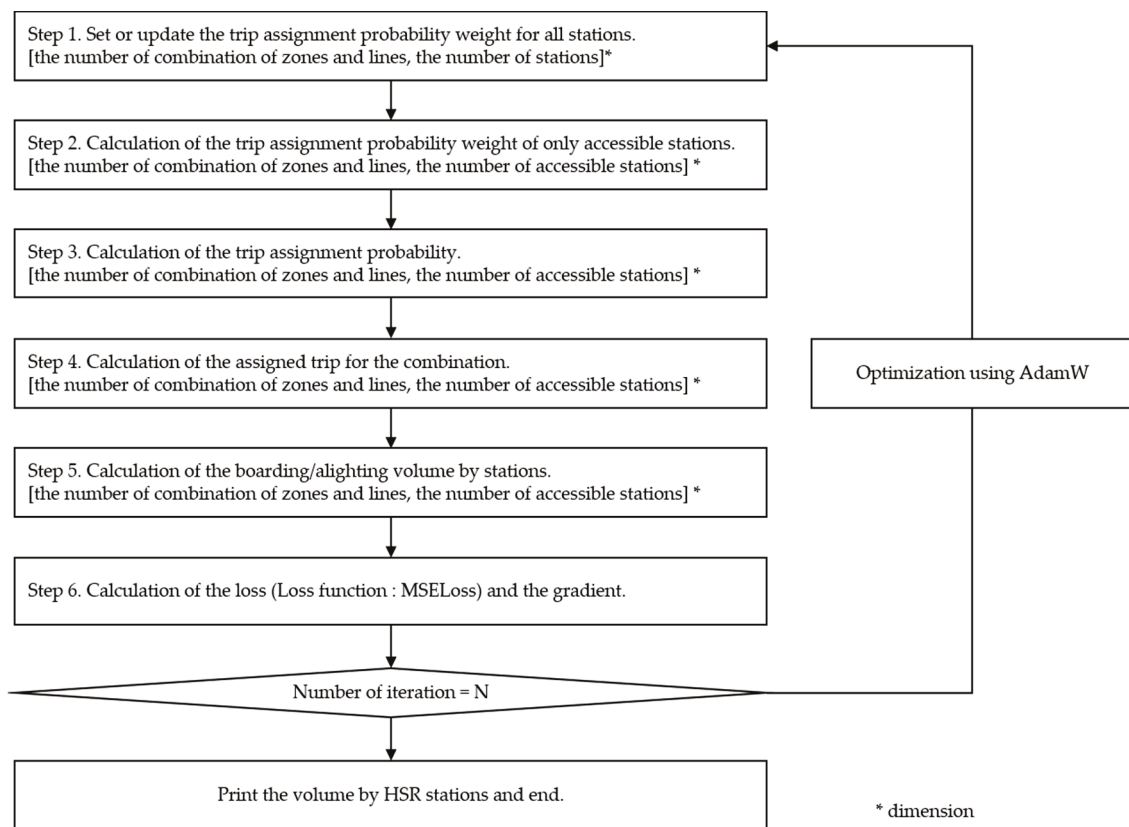


Figure 4. The backpropagation-based optimization algorithm in this study.

The optimization calculation process is explained based on an example with a smaller dataset than the actual dataset used. The initial value of the trip assignment probability weight was constructed to be inversely proportional to the square of the Euclidean distance from zones to stations and proportional to the train frequency at the station, with reference to the gravity model [46]. The accessible stations were set to the three nearest stations.

First, to obtain the trip assignment probability weight tensor of only accessible stations, the probability weight tensor for all stations (T_a) with each combination of zones and lines is multiplied by the accessible station tensor (T_b), where each entry has a value of 1 if

the station is accessible; otherwise, it is 0 (a tensor refers to any data structure with a scalar, vector, matrix, or more dimensions). Accordingly, a trip assignment probability weight tensor (T_c) with only three accessible stations in its combinations remains, and the probability weights for all other stations become 0, as shown in Figure 5. This allows only three accessible stations for each combination to be included in the loss calculation and the probability weight updating process.

$$\begin{array}{c}
 \text{Probability Weight Tensor} \\
 \text{for All Stations} \\
 (T_a) \\
 \text{Stations} \\
 \begin{array}{c} \text{┌───┐} \\ \text{└───┘} \end{array} \\
 \text{Combinations of Zones and Lines} \left\{ \begin{array}{l} \text{(Zone 1, Line 1)} \\ \text{(Zone 1, Line 2)} \\ \text{(Zone 1, Line 3)} \end{array} \right. \begin{bmatrix} 1.5 & 2 & 3.5 \\ 4 & 5 & 6 \\ 7 & 8.5 & 9 \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1.5 & 0 & 3.5 \\ 0 & 5 & 0 \\ 7 & 0 & 0 \end{bmatrix}
 \end{array}$$

Figure 5. Calculation of probability weight tensor (T_c).

Since the probability weight tensor does not represent a probability, it must be converted into one using a normalization process, as shown in Figure 6. A row of the probability weight tensor (T_c) represents a combination of zones and lines, and a probability weight sum tensor (T_d) is created by extending a row-wise sum of the probability weight tensor. A probability tensor (T_e) is calculated by dividing the previous two tensors.

$$\begin{array}{c}
 \text{Probability Weight} \\
 \text{Tensor} \\
 (T_c) \\
 \begin{bmatrix} 1 & 1 & 2 \\ 2 & 6 & 2 \\ 5 & 10 & 5 \end{bmatrix}
 \end{array}
 \begin{array}{c}
 \text{Probability Weight Sum} \\
 \text{Tensor} \\
 (T_d) \\
 \begin{bmatrix} 4 & 4 & 4 \\ 10 & 10 & 10 \\ 20 & 20 & 20 \end{bmatrix}
 \end{array}
 /
 \begin{array}{c}
 \text{Probability} \\
 \text{Tensor} \\
 (T_e) \\
 \begin{bmatrix} 0.25 & 0.25 & 0.5 \\ 0.2 & 0.6 & 0.2 \\ 0.25 & 0.5 & 0.25 \end{bmatrix}
 \end{array}$$

Figure 6. Calculation converting the probability weight to the probability.

The following is the step used to assign the total trip from each combination of zones and lines to each station using the probability. The total trip tensor (T_f) is a tensor that contains the total trip information for each combination, and it is multiplied by the probability tensor (T_e) to obtain the assigned trip tensor (T_g) for the accessible stations. This is represented in Figure 7.

$$\begin{array}{c}
 \text{Probability} \\
 \text{Tensor} \\
 (T_e) \\
 \begin{bmatrix} 0.25 & 0.25 & 0.5 \\ 0.2 & 0.6 & 0.2 \\ 0.25 & 0.5 & 0.25 \end{bmatrix}
 \end{array}
 \cdot
 \begin{array}{c}
 \text{Total Trip} \\
 \text{Tensor} \\
 (T_f) \\
 \begin{bmatrix} 10.6 & 10.6 & 10.6 \\ 400.36 & 400.36 & 400.36 \\ 150.4 & 150.4 & 150.4 \end{bmatrix}
 \end{array}
 =
 \begin{array}{c}
 \text{Assigned Trip} \\
 \text{Tensor} \\
 (T_g) \\
 \begin{bmatrix} 2.65 & 2.65 & 5.3 \\ 80.072 & 240.216 & 80.072 \\ 37.6 & 75.2 & 37.6 \end{bmatrix}
 \end{array}$$

Figure 7. Calculation used to assign the total trip values for each station using their respective probabilities.

The boarding/alighting volume for each station must be estimated using the assigned trip tensor to calculate the loss compared with the observed volume. This is calculated by adding the entries in each column in the assigned trip tensor, as shown in Figure 8.

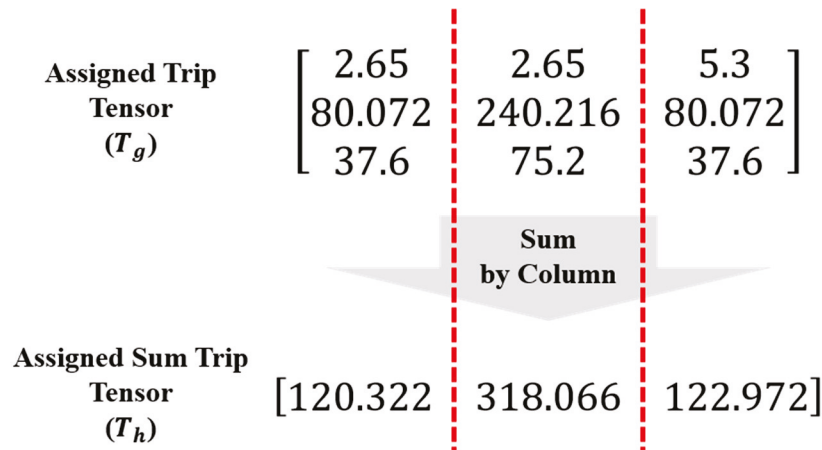


Figure 8. Calculation of the boarding/alighting volume by stations.

The difference between the assigned sum trip tensor and the observed trip tensor is calculated with a predefined loss function. Finally, by calculating the gradient using backpropagation to reduce the loss, the probability weight tensor is updated until the end of the algorithm as shown in Figure A3. The optimization codes were implemented based on Python 3.8 and PyTorch 1.11, and the PC specifications were CPU: Intel Core i5 11400 (2.60 GHz), memory: 32 GB, and GPU: NVIDIA GeForce RTX 2070 SUPER.

4. Case Study

4.1. Data Description

In Korea, the Korea Transport Institute (KOTI), a government-funded institute, periodically distributes KTDB data, including O/D trip and network data, to increase public confidence in long-term demand predictions. The KTDB data consist of 250 zones defined by local governments, and 247 zones were used in this study, as shown in Table 1; Jeju, Seogwipo, and Ulleung were excluded since they are islands that do not have HSR lines, and thus have zero trips.

Table 1. Summary of zones in the KTDB data used in this study.

Region	No. of Zones	Region	No. of Zones	Region	No. of Zones	Region	No. of Zones
Seoul	25	Gwangju	5	Gangwon	18	Jeonnam	22
Busan	16	Daejeon	5	Chungbuk	14	Gyeongbuk	24
Daegu	7	Ulsan	5	Chungnam	16	Gyeongnam	22
Incheon	10	Gyeonggi	42	Jeonbuk	15	Sejong	1

The O/D trip frequency in Korea's HSR was 225,495 trips/day in 2018, and the number of inter-region (16 metropolitan local governments) O/D trips is shown in Table 2. There were no O/D trips between Gangwon and North/South Chungcheong, North/South Jeolla, and North/South Gyeongsang, as well as between North/South Jeolla and North/South Gyeongsang, in the KTDB. This is because travel between these regions is not directly connected by HSR, and thus travel time and distance between these regions is so long. Therefore, it was assumed that there was no transfer demand in the HSR network and only trips between stations connected by the same line.

Table 2. Inter-region O/D trips in KTDB data.

O/D	Seoul	Busan	Daegu	Incheon	Gwangju	Daejeon	Ulsan	Gyeonggi
Seoul	16	10,480	7938	237	4493	7529	2865	1418
Busan	10,030	15	1849	712	0	1724	656	4220
Daegu	7953	2021	0	593	0	1461	956	3311
Incheon	729	737	585	0	295	570	243	2
Gwangju	4511	0	0	295	0	30	0	1761
Daejeon	7597	1925	1527	577	38	0	681	2527
Ulsan	2939	741	844	251	0	678	55	1329
Gyeonggi	1324	4468	3404	3	1763	2619	1292	304
Gangwon	3406	0	0	128	0	0	0	573
North Chungcheong	2467	339	250	185	179	220	113	754
South Chungcheong	4766	905	742	364	329	1241	423	1538
North Jeolla	3882	0	0	286	500	94	0	1393
South Jeolla	3886	0	0	328	324	66	0	1386
North Gyeongsang	3914	547	1244	340	0	992	119	1437
South Gyeongsang	2482	55	817	261	0	593	0	868
Sejong	2642	363	268	198	191	40	121	808
O/D	Gangwon	North Chungcheong	South Chungcheong	North Jeolla	South Jeolla	North Gyeongsang	South Gyeongsang	Sejong
Seoul	3435	2385	5141	3811	3847	3876	2419	2554
Busan	0	320	801	0	0	517	47	343
Daegu	0	244	679	0	0	1318	781	262
Incheon	118	187	411	287	333	338	256	200
Gwangju	0	169	299	509	438	0	0	181
Daejeon	0	10	1231	128	93	1049	559	275
Ulsan	0	114	403	0	0	117	0	122
Gyeonggi	594	782	1787	1373	1388	1496	871	838
Gangwon	531	0	0	0	0	0	0	0
North Chungcheong	0	0	208	216	194	127	83	0
South Chungcheong	0	144	101	390	397	355	312	64
North Jeolla	0	213	317	702	816	0	0	228
South Jeolla	0	194	326	755	257	0	0	208
North Gyeongsang	0	137	334	0	0	97	84	147
South Gyeongsang	0	58	222	0	0	78	239	62
Sejong	0	10	0	232	208	136	89	0

The HSR network consists of railway stations and lines. There are 51 HSR stations and three major lines in Korea: Gyeongbu (Seoul–Busan), Honam (Seoul–Gwangju), and Gangneung (Seoul–Gangneung). Figure 9 shows HSR network data schematized using EMME, where the pink boxes represent the zones (centroids), and the blue lines represent the HSR lines.

Two influential variables, namely the access distance from the zones to stations and the train frequency at the stations, were considered in this study. The access distance from zones to stations was calculated using the Euclidean distance from the centroid (a point representing each zone) to the station node. The KTDB network data used a local coordinate system (Bessel ellipsoid, Korean 1985 datum) to express the geographical location, and the coordinate system unit was in meters. Therefore, the Euclidean distance from zones to stations was calculated using Equation (2) [47]. The Euclidean distances were calculated by extracting only the information of the 51 HSR station nodes and 247 centroids in the KTDB network data.

$$d_{is} = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2} \quad (2)$$

Here,
 i : zone ($\forall i \in Z$);
 s : HSR station ($\forall s \in S$);
 d_{is} : Euclidean distance from zone i to station s ;
 x, y : x -coordinate and y -coordinate.

Sets

- Z : The set of zones;
- S : The set of HSR stations.



Figure 9. HSR network data in the KTDB.

The train frequencies at the HSR stations were calculated by extracting the stop stations for each HSR train from the transit line data in the KTDB. Although both the skip and stop stations were presented in the transit line data, skip stations were excluded in the train frequency calculation, and the daily train frequency by line at the stations was calculated based on information for the line to which the train belonged.

4.2. Results

The trip assignment probability weight was updated 2000 times with a learning rate of 0.01 in the backpropagation-based algorithm. The loss had a downward trend with each update, and dropped sharply within about 200 iterations, as shown in Figure 10. Furthermore, it almost converged to the final value after about 200 iterations. When the probability weight was updated once, the loss was 36,624,504, and the final value decreased to 97,344 after 2000 iterations. This means that the difference between the estimated volume using the backpropagation-based algorithm and the observed volume significantly decreased.

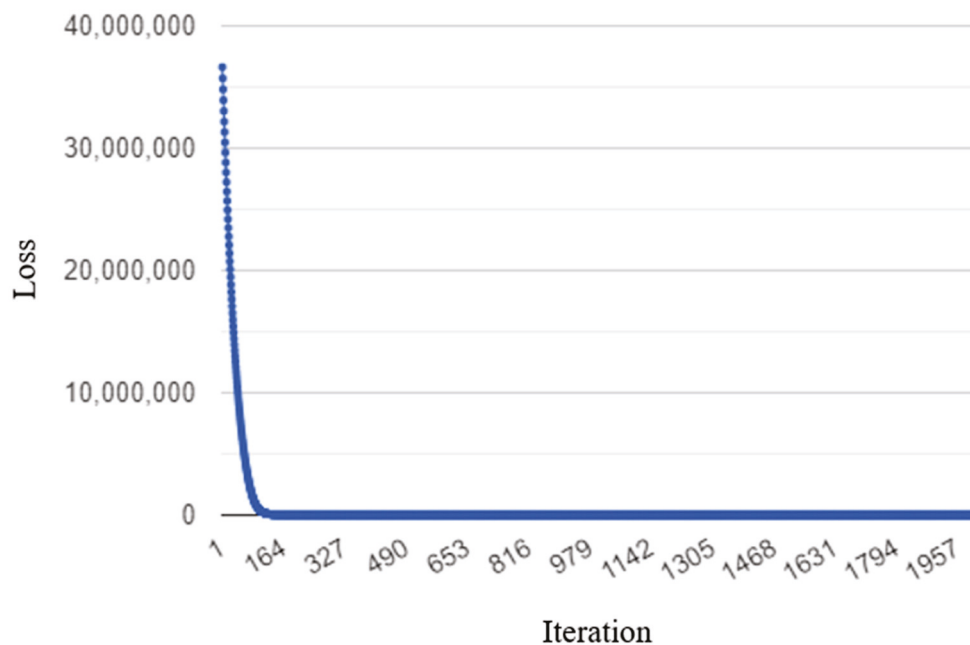


Figure 10. The loss changes in the backpropagation-based algorithm by iteration.

The trip assignment results for each HSR station using the backpropagation-based algorithm are presented in Table 3. The results for major HSR stations with more than 1000 passengers are presented by dividing the regions into the Seoul metropolitan area, which had a relatively high concentration of HSR stations, and non-metropolitan areas, which did not. To verify the algorithm's prediction performance, we compared the results found using the optimal strategy algorithm based on the volume at each HSR station. Moreover, the error rate presented in Equation (1) and the mean absolute error (MAE) and mean absolute percentage error (MAPE), expressed as Equation (3) [48], were chosen as the key performance indicators.

$$MAE = \frac{\sum_i^n |f_{est} - f_{obs}|}{n}, MAPE = \frac{\sum_i^n \frac{|f_{est} - f_{obs}|}{f_{obs}} \times 100}{n} \quad (3)$$

Table 3. Trip assignment results for the major HSR stations.

Region	HSR Station	Observed Volume (Persons/Day)	The Backpropagation-Based Algorithm		Optimal Strategy Algorithm	
			Estimated Volume (Persons/Day)	Error Rate (%)	Estimated Volume (Persons/Day)	Error Rate (%)
Seoul metropolitan area	Seoul	37,867	38,907	0.6	21,103	−44.3
	Suseo	19,509	19,742	1.2	22,743	16.6
	Yongsan	13,488	13,720	1.7	15,092	11.9
	Gwangmyeong	12,867	13,096	1.8	12,709	−1.2
	Dontan	3682	3916	6.4	4933	34.0
	Cheongnyangni	2617	2847	8.8	8478	224.0
	Hangsin	2111	2239	6.1	5567	163.7
	Suwon	1598	1735	8.6	1100	−31.2
	Jije	1546	1411	−8.7	1428	−7.6
	MAE (MAPE)	-	153	3.5	3310	53.6
Non-metropolitan area	Busan	24,062	24,066	0.0	21,690	−9.9
	Dongdaegu	23,564	23,246	−1.3	22,856	−3.0
	Daejeon	17,634	17,500	−0.8	19,025	7.9
	Cheonan-Asan	11,568	11,430	−1.2	11,283	−2.5
	Osong	10,061	9925	−1.4	10,218	1.6
	Gwangju-Songjeong	9474	9496	0.2	9184	−3.1
	Ulsan	6770	6776	0.1	8073	19.2
	Iksan	5461	5403	−1.1	4704	−13.9
	Gangneung	4478	3922	−12.4	3914	−12.6
	Singyeongju	4396	4401	0.1	2541	−42.2
	Gimcheon-Gumi	3182	3284	3.2	3463	8.8
	Pohang	3057	3057	-	3050	−0.2
	MAE (MAPE)	-	123	1.8	831	10.0

Here,

i : HSR station ($\forall i \in Z$);

n : the number of HSR stations;

f_{est} : the estimated number of passengers at each station using the trip assignment model;

f_{obs} : the observed number of passengers at each station.

The trip assignment results from the backpropagation-based algorithm show that all stations had an error rate of less than 30%, the reference value stated by the guideline. However, the results from the optimal strategy algorithm show that many stations had an error rate exceeding 30%. The backpropagation-based algorithm results presented a very low error rate, less than 2% for the major stations with more than 10,000 passengers and less than 10% for the minor stations with less than 10,000 passengers. The high error rate at Gangneung Station could be attributed to the PyeongChang Olympic Winter Games. During the Winter Olympics, additional temporary trains that directly connected Incheon International Airport to Gangneung were operated. Accordingly, the observed volume at Gangneung Station was higher than usual; thus, the predicted demand was underestimated because it used the KTDB O/D trip data, estimated based on the average weekday trips.

The estimation accuracy using the backpropagation-based algorithm was relatively high compared with the estimation results from the optimal strategy algorithm for stations in both areas, i.e., the Seoul metropolitan area and the non-metropolitan area. However, the results for the Seoul metropolitan area show that the backpropagation-based algorithm's accuracy was overwhelmingly higher than the optimal strategy algorithm's accuracy. In the optimal strategy algorithm, the trip distribution among the adjacent stations was

unbalanced, resulting in a large error rate. For example, in the Seoul metropolitan area, an error rate of more than 40% was found for Seoul, Cheongnyangni, and Haengsin Stations. Furthermore, in the non-metropolitan area, the demand that should have been assigned to Singyeongju Station was assigned to Ulsan Station, so the error rates were 19.2% and −42.2%, respectively, because the optimal strategy algorithm based on the all-or-nothing trip assignment was able to simulate the diverse access trip patterns of passengers in areas with multiple HSR stations, such as the Seoul metropolitan area. Therefore, after the initial assignment from the optimal strategy algorithm, it was necessary to reduce the error rate within the reference value using a parameter calibration process by adjusting the network parameters. The analyst's arbitrary judgment was involved in this process, and much time and effort were required.

For stations in the Seoul metropolitan area, the MAE and MAPE indicators were 153 and 3.5%, respectively, when using the backpropagation-based algorithm, and those when using the optimal strategy algorithm were 3310 and 53.6%, respectively. Moreover, for the stations in the non-metropolitan area, the MAE and MAPE values were 123 and 1.8%, respectively, when using the backpropagation-based algorithm, and those when using the optimal strategy algorithm were 831 and 10.0%, respectively. Therefore, the estimation accuracy of the backpropagation-based algorithm developed in this study was superior to that of the optimal strategy algorithm.

5. Conclusions

We developed a backpropagation-based algorithm to optimize the trip assignment probability, and probability simulations of the access trip pattern from each zone to accessible HSR stations were undertaken. Backpropagation was used when training the artificial neural network; in this problem, the probability could be recognized as the weight optimized in the artificial neural network. Accordingly, the initial value in the backpropagation-based algorithm was a function of the access distance from zones to accessible HSR stations and the train frequency at HSR stations for each zone and line combination. The difference between the estimated volume from the probability and the observed volume was defined as the loss in the optimization process, and the weight was updated in the direction of minimizing this loss. To apply this backpropagation concept, we obtained the loss value using only differentiable calculations provided by PyTorch, a deep learning framework used for artificial neural network learning.

To verify the prediction performance of the backpropagation-based algorithm, its trip assignment results were compared with those of an optimal strategy algorithm using network and O/D trip data from the KTDB. A total of 225,495 trips/day generated from 247 zones were assigned to 51 stations on the three HSR lines. The results for 19 major HSR stations with more than 1000 passengers were presented by dividing the regions into the Seoul metropolitan area, which had a relatively high concentration of HSR stations, and a non-metropolitan area, which did not. The backpropagation-based algorithm results show that all stations had an error rate of less than 30%, the reference value stated in the guideline. Furthermore, the results present a very low error rate, less than 2% for major stations with more than 10,000 passengers and less than 10% for minor stations with less than 10,000 passengers. On the other hand, the optimal strategy algorithm results show that many stations had an error rate exceeding 30%. For the stations in the Seoul metropolitan area, the MAE and MAPE indicators found using the backpropagation-based algorithm were 153 and 3.5%, respectively, and those found using the optimal strategy algorithm were 3310 and 53.6%, respectively. This means that the backpropagation-based algorithm was especially superior when applied to an area with multiple HSR stations, simulating the passenger access trip pattern from each zone to multiple stations. Therefore, the backpropagation-based algorithm will improve the accuracy and time efficiency of long-term HSR demand forecasting.

A limitation of this study was that the access distance from each zone to the HSR stations was calculated using the Euclidean distance, which was used owing to data

acquisition issues and the complexity problem of calculating using input data, such as applying the shortest path algorithm. If it were possible to obtain access distance or time data for each access mode to HSR stations, the algorithm's accuracy would be improved by reflecting more realistic conditions. Lastly, it is necessary to examine the extendibility of the backpropagation-based algorithm by applying it to various HSR networks with different conditions from those in Korea.

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Data Availability Statement: The data are available upon request from the author.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

The main codes for optimizing the trip assignment probability weight are presented below. They consist of two steps: (1) variable initialization and (2) optimization.

(1) Variable initialization

- Line 105: "opt_target_tensor" is the trip assignment probability weight tensor for all stations (T_a) in Figure 5.
- Line 106: "prob_mask_tensor" is the accessible station tensor (T_b) in Figure 5.

```

100  def optimize():
101      print('===== Optimize Params =====')
102      global actual_demand_tensor, param_tensor
103      global optimized_probs, optimized_demand_list
104
105      opt_target_tensor = param_tensor.clone().detach().requires_grad_(True)
106      prob_mask_tensor = param_tensor.clone().detach()
107      param = [opt_target_tensor]
108
109      lr = 0.01
110      n_iter = 2000
111      optimizer = optim.AdamW(param, lr=lr)
112      loss_fn = nn.MSELoss()

```

Figure A1. The code for variable initialization.

(2) Optimization

- Line 119: "z_masked" is the trip assignment probability weight tensor (T_c) in Figure 5.
- Line 126–128: A normalization process in Figure 6.
- Line 130: "t_1" is the assigned trip tensor (T_g) in Figure 7.
- Line 131: "t_2" is the assigned sum trip tensor (T_h) in Figure 8.

```

116         for _ in range(n_iter):
117             optimizer.zero_grad()
118
119             z_masked = opt_target_tensor * prob_mask_tensor
120             z_masked_relu = F.relu(z_masked)
121
122             all_neg_row_mask = torch.all(z_masked <= 0, dim=1).reshape(zc, 1)
123             all_neg_row_mask = all_neg_row_mask.expand(-1, sc)
124             z_processed = torch.where(all_neg_row_mask, z_masked, z_masked_relu)
125
126             z_sum = torch.sum(z_processed, dim=1)
127             z_denom = z_sum.reshape(zc, 1).repeat(1, sc)
128             prob_tensor = torch.div(z_processed, z_denom)
129
130             t_1 = prob_tensor * volume_tensor
131             t_2 = torch.sum(t_1, dim=0)
132
133             loss = loss_fn(t_2, actual_demand_tensor)
134             loss_val = loss.detach().numpy()
135
136             print('iter count: {} / loss : {}'.format(*args: _ + 1, loss_val))
137
138             loss.backward()
139             optimizer.step()

```

Figure A2. The code for optimizing the trip assignment probability weight.

```

141         if _ == n_iter - 1:
142             optimized_probs = prob_tensor.tolist()
143             optimized_demand_list = t_2.detach().tolist()

```

Figure A3. The code for saving the optimized results after the last updating process.

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Article

The Environmental Benefits of an Automatic Idling Control System of Connected and Autonomous Vehicles (CAVs)

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Abstract: The transportation sector is regarded as the main culprit in greenhouse gas emission in the urban network, particularly idling vehicles waiting at signalized intersections. Although autonomous vehicles can be a promising technology to tackle vehicle idling, their environmental benefits receive little attention compared with their safety and mobility issues. This study investigated the environmental benefits of autonomous vehicles equipped with an automatic idling control function based on the queue discharge time and traffic signal information transmitted from the traffic signal controller via V2I communication using microscopic mobility and emission simulation models, VISSIM and MOVES, in Haeundae-gu in Busan, Korea. This study found that the function contributes to a significant reduction in CO₂ emissions by 23.6% for all-inclusive emission and 94.3% for idling emission, respectively. Moreover, total reduced idling time accounts for 47.6% of the total travel time and 94.3% of the total idling time, respectively. Consequently, the autonomous vehicles equipped with automatic vehicle idling control function under C-ITS can play an important role in reducing greenhouse gas emissions and fuel consumption as well in the urban network.

Keywords: cooperative intelligent transportation system; emissions; vehicle idling; traffic signal; VISSIM; MOVES

1. Introduction

1.1. Background

Figure 1 describes that, since 2010, the transportation sector accounts for about 14.3% of total greenhouse gas emissions (GHGs) (Figure 1a) and that approximately 95.2% or more of the transportation-related GHGs (Figure 1b) is attributable to the vehicles on the road among all transport systems in Korea [1]. Particularly, it is reported that a huge part of them originates from idling vehicles waiting at signalized intersections in the urban network [2,3]. To tackle this problem, recently manufactured vehicles can automatically control vehicle idling with a stop-and-go function when waiting for a desired traffic signal. Besides this, autonomous vehicles can be another promising technology to control vehicle idling; however, most studies regarding autonomous vehicles have been mainly focused on the safety and mobility and not on the environmental impact.

The safety and mobility performance of autonomous vehicles could be secured and reinforced with the aid of communication capability in the fashion of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications (i.e., cooperative intelligent transportation system, C-ITS), so it is necessary to investigate the environmental benefits of autonomous vehicles under C-ITS, particularly vehicle idling control at signalized intersections in urban areas.

1.2. Research Purpose

Recently, a new technology for transmitting traffic signal information from a traffic management center (TMC) or a traffic signal controller installed at the individual intersections of an approaching vehicle through wireless communication has been developed, and it is entering into practical uses.

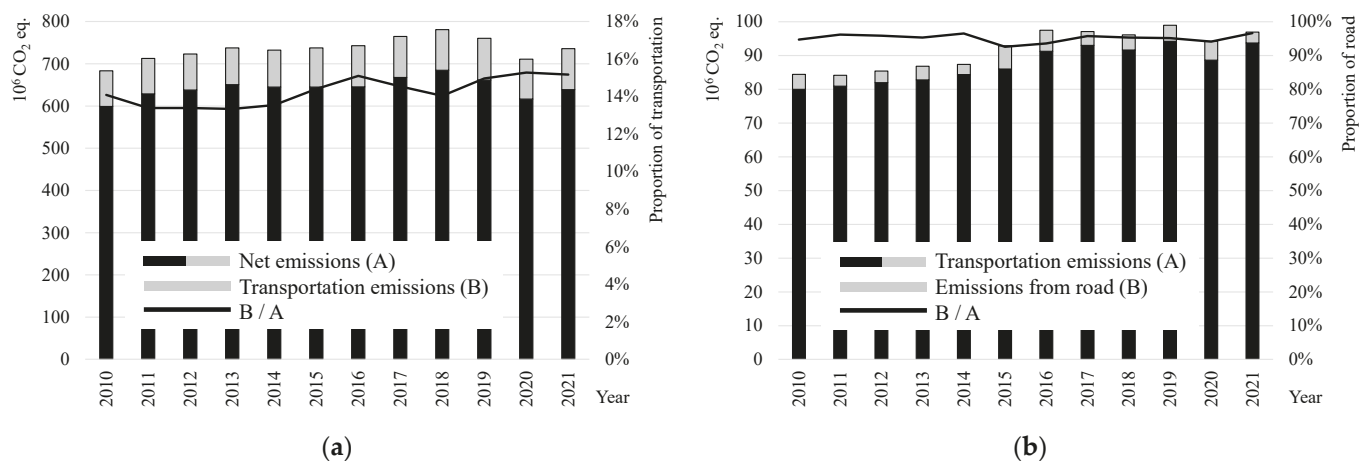


Figure 1. Status of greenhouse gas emissions of the transportation sector and roads in Korea.

The introduced mobility application using the traffic signal information transmitted to vehicles is simply intended to adjust their approaching speeds to minimize the chance for the vehicle to stop at the intersection, improve drivers' comfort, and reduce fuel consumption and GHG emission. This study highlights that such valuable information should be used for more diverse applications such as automatic vehicle idling control.

This study aims to evaluate the environmental benefits of autonomous vehicles internally enhanced by an automatic vehicle idling control function, capable of reflecting the queue length and traffic signal information shared through C-ITS, specifically V2I, by employing a microscopic mobility and emission simulators, VISSIM and VISSIM COM (i.e., component object model) and MOVES (i.e., motor vehicle emission simulator), respectively.

The remainder of this study is organized as follows: Section 2 provides an informative summary of related works. Section 3 describes the research methodology with the underlying concept and algorithm for the automatic vehicle idling control of autonomous vehicles under C-ITS. Section 4 presents the research methodology, conducted with VISSIM and VISSIM COM coupled with MOVES, and evaluates the proposed vehicle idling control function with a case study in Haeundae-gu in Busan, Korea. Lastly, Section 5 contains conclusions, research limitations, and future research issues.

2. Related Works

2.1. Identification of Traffic Signal Information

Prior to propagating traffic signal information through C-ITS such as V2I communication, a number of studies on the identification of traffic signal, localization, and state classification (i.e., traffic signal color) have mainly counted on the vision-based methods up to recently, conceding its problems due to occlusions, illumination, scale variations, and so on [4,5]. Nevertheless, most studies on it have made greater efforts to improve their detection performance, aiming for utilization in autonomous vehicle applications.

Jimenez-Palacios (1999), Omar et al. (2020), and Li et al. (2021) proposed and evaluated a vision-based traffic lights recognition algorithm under a variety of lighting conditions using a public data set on the actual city road at night with YOLOv3, YOLOv4, and convolutional neural network (CNN) models, concluding that it has a relatively high accuracy rate in complex scenarios and can promote the engineering application of autonomous vehicles with some limitations, such as the distance from vehicles to the traffic signal [4–6]. Vitas et al. (2020) employed the improved YOLOv4 algorithm and investigated its effectiveness in enhancing the detection and recognition precision of traffic signals, resulting in a precision that was 2.86% higher than the mean average precision of the original YOLOv4 algorithm and introducing it as a practical method for autonomous vehicle applications [7]. Also, Escalera et al. (2003) implemented the adaptive thresholding and deep learning

method to recognize the traffic signal based on images taken by a camera mounted on a vehicle, revealing an 89.60% true detection rate [8].

Despite these research efforts, there are still inherent limitations with the vision-based traffic signal recognition methods, which is that approaching vehicles must recognize the traffic signal and state without any latency due to traffic safety issues. Hence, a more robust and solid method (e.g., V2I communication) to recognize the traffic signal information compared with the vision-based one should be developed and implemented for the diverse autonomous vehicle applications.

2.2. Environmental Effect of Vehicle Idling

Pal et al. (2012), Bahndari et al. (2013), and Sharma et al. (2019) investigated the environmental impact of vehicular idling on emissions and found that significant emissions from idling vehicles account for the huge part of the total emissions from the transport sector, particularly at the signalized intersections during peak hour in urban areas [9–11]. Chaichan (2014) reported that CO₂ concentrations increased with idle time and engine speed from a diesel engine, and Kumar et al. (2015) specifically noted that the total emissions amounted to 2398.055 mg/m³ of hydrocarbons, 1087.068 mg/m³ of NO_x, and 10,612.612 mg/m³ of carbon monoxide daily during vehicle idling across 600 intersections in Delhi, India [12,13].

Engelmann et al. (2021) observed significant variations in emissions from passenger cars in special driving or non-driving situations like idling, which depended on vehicle types and the warm-up of their exhaust aftertreatment systems; Barlow et al. (2020) also showed that diesel heavy goods vehicles (HGVs) emitted the most pollutants per minute of idling, followed by SUVs, as obtained from the Department for Transport's Portable Emissions Measuring System (PEMS) database in London [3,14].

Accordingly, Martin et al. (2017) highlighted that it is generally better to turn off and restart the vehicle, even for short stops for emission reduction, and Omar et al. (2020) found that vehicle positioning in a queue and congestion levels significantly impact the decision to turn off the engine in India [5,15]. Wu et al. (2015) indicated that the idling stop policy has significant potential savings in CO₂ emissions from a case study in Taipei City [16].

2.3. Technology for Vehicle Idling Control

Kumar et al. (2013), Rahman et al. (2013), Shancita et al. (2014), and Yates et al. (2016) underscored the importance of adopting idle-reduction strategies to mitigate the adverse effects of vehicle idling on air quality at signalized intersections in urban areas and suggested multiple mitigation measures, such as auxiliary power units (APUs), direct-fired heaters, fuel cells, truck stop electrification, improving signal timing, promoting public transport, implementing land use and transport policies, encouraging non-motorized transport modes, and so forth [17–20]. This study mainly focused on stop-and-go technology and traffic signal operations aided with the sophisticated systems among the existing research efforts on alleviating the environmental effect of vehicle idling.

Stop-and-go technology allows vehicles to automatically turn off the internal combustion engine (ICE) during idling periods and restart it when the driver restarts, which is particularly beneficial in urban traffic conditions where vehicles frequently stop and start, leading to higher environmental pollution, thereby enabling significant improvements in reducing CO₂ emissions [21–24].

Cho et al. (2012) employed an ultrasonic sensor to estimate frontal traffic conditions and developed a neural network-based fuzzy logic algorithm to control engine idling for the idle stop-and-go system [25]. Zhu et al. (2017) analyzed vehicle specific power (VSP) to understand the impact of stop-and-go driving behaviors at intersections on emissions by employing a high-resolution driving simulator to analyze acceleration and deceleration behaviors [26]. Zhu et al. (2022) investigated the effects of stop-and-go systems on particulate emissions in gasoline direct injection vehicles under varying temperature conditions with testing vehicles equipped with stop-and-go systems [27]. Aarathy et al.

(2015), Lee et al. (2020), Chen et al. (2022), and Sim et al. (2022) introduced an enhanced control algorithm to stop-and-go technology by determining the optimal time to turn off the engine based on traffic light information disseminated through vehicle-to-infrastructure (V2I) communication, which is a significant step in integrating traffic signal information into idle stop-and-go systems [28–31].

Prati et al. (2018) showed that stop-and-go technology can reduce CO₂ emissions by more than 4–7% in urban traffic from a field test using three cars equipped with portable emission systems (PEMSs) to measure emissions in Napoli [22]. Fonseca et al. (2011) found that a vehicle equipped with a stop-and-go system reduced more than 20% of CO₂ emissions compared with one without the system in urban traffic conditions [32]. Also, Zhu et al. (2017) proved that the automatic stop-and-go function in hybrid electric vehicles (HEVs) can save over 16% of emissions [23].

Many researchers inspected the optimal time duration to control vehicle idling; that is, Chahal et al. (2018) revealed that idling for over 13 s leads to greater emissions than stopping and restarting the engine [33]. The U.S. Department of Energy (2015) highlighted that idling for more than 10 s produces more emissions than restarting the engine [34]. Sharma et al. (2017) indicated that it is more efficient to turn off the engine if idling is expected to last over 10 s [35]. Gaines et al. (2011) investigated the emissions associated with idling versus restarting the engine by comparing actual idling emissions, aiming to determine the impact of idling over various durations by the Argonne National Laboratory, finding that idling for more than 10 s emits more CO₂ than restarting the engine [36]. Alwis et al. (2017) recommended switching off vehicle engines if the waiting time is more than 15–20 s [37].

Besides the stop-and-go technology, numerous studies on the optimal operation of traffic signal and vehicle speed adjustment have been conducted. In detail, Bakibillah et al. (2020) explored the development of an eco-driving strategy that learns from driving data to generate optimal speed trajectories at signalized intersections by advising appropriate driving behaviors near intersections with the gaussian process regression (GPR) [38]. Zhao et al. (2019) studied vehicle emissions at unsaturated signalized intersections using a car-following model combined with a specific power emission model, finding that longer signal cycles, higher vehicle arrival rates, and increased traffic interference amplify emissions per vehicle [39]. Chen et al. (2007) developed a microscopic traffic–emission simulation platform to investigate the relationship between traffic operations and emissions and found that vehicle emissions are strongly influenced by their operating modes, especially during acceleration, and that optimized signal timing plans can significantly reduce emissions for all vehicle categories [40]. Zhao et al. (2021) presented a study on the influence of signal timing on CO₂ emissions in a mixed traffic environment of fuel and electric vehicles by developing a signal timing model aimed at minimizing CO₂ emissions under different traffic conditions, resulting in the observation that optimizing signal timing from the perspective of CO₂ emissions is effective in balancing emissions during acceleration, deceleration, and idling stages [41].

Li et al. (2018) proposed an optimal velocity control and separation strategy for connected and automated vehicles (CAVs) to minimize idling at red lights by accessing traffic light timing and adjusting their speed accordingly; the simulation results showed that implementing the strategy resulted in a 19.2% reduction in total travel time [42]. Jayawardana et al. (2022) proposed a reinforcement learning (RL) approach to develop eco-driving control strategies at signalized intersections to reduce CO₂ emissions with connected autonomous vehicles (CAVs) investigated with the SUMO microscopic traffic simulator, resulting in significant reductions in CO₂ emissions up to 25% [43]. Ubiergo (2014) explored the use of vehicle-to-infrastructure (V2I) communication to improve mobility and reduce environmental impacts by combining a car-following model and an emission model to simulate vehicle behavior and calculate emissions at signalized intersections, showing that around 8% of CO₂ emissions can be saved [44].

Out of the analysis of related works on the effect of autonomous vehicles on the reduction of CO₂ emission, little research has been conducted on the environmental benefits of automatic idling control function in autonomous vehicles with C-ITS in the urban network. Furthermore, unless the time it takes for an individual vehicle in the queue to start moving can be taken into account, the traffic signal information shared through V2I communication cannot be integrated into the proposed function in determining whether or not to control vehicle idling and in estimating the CO₂ emission. Therefore, this study is distinguished from other studies in the respect that it considered the time to move in the queue based on the arrival time of shockwave from the stop line to vehicle position in the queue and compared it with the shared traffic signal information.

3. Research Methodology

While vehicles traverse the urban traffic network, which is composed of multiple signalized intersections, drivers could manage vehicle idling themselves by turning off the engine while waiting for the traffic signal associated with turning direction. However, drivers do not have any ways to know how long their waiting time is until they pass the intersection, so a sophisticated technology needs to be applied to autonomously control vehicle idling without depending on human instincts.

As seen in Section 2. Related Works, research efforts have not been made on the environmental benefits of autonomous vehicles under C-ITS, whose function is enhanced with automatic vehicle idling control at signalized intersection in the urban network, according to the best of our knowledge. Accordingly, this study creates a pivotal idling control method and evaluates its environmental benefits with microscopic simulation models, VISSIM, VISSIM COM, and MOVES.

This study suggests a novel methodology of estimating CO₂ emissions from vehicles waiting in the queue at signalized intersections in Figure 2. Specifically, this study needs to observe the spatial and temporal trajectories of all vehicles around signalized intersections to find idling situations, interactively implement control of vehicle idling, and accordingly estimate the CO₂ emission, so the microscopic simulation models (i.e., mobility and emission) supported by the user interface are an important research means.

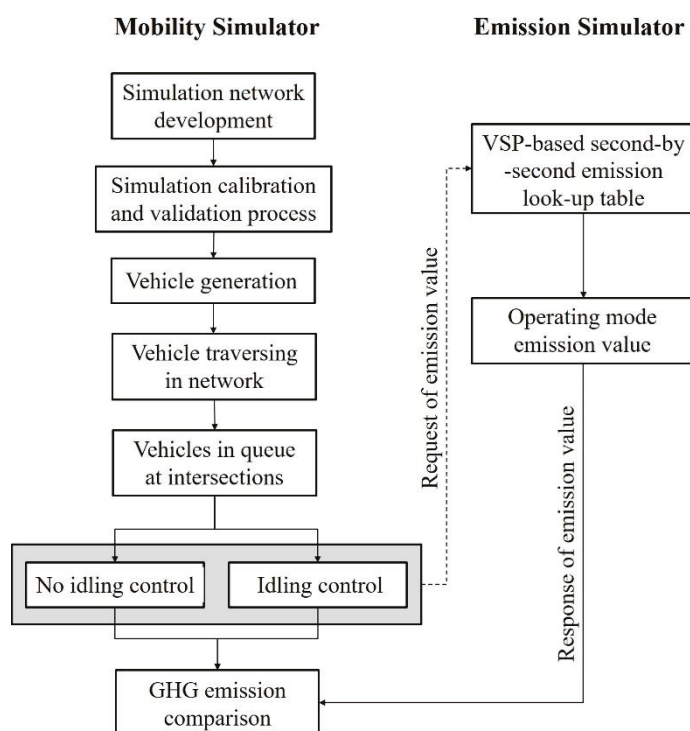


Figure 2. Research framework with analytical modules.

The microscopic mobility simulator, VISSIM, is typically used to investigate the impact of traffic infrastructure or operation alternatives on traffic flow or safety because it is faster, safer, and more cost-effective than a field experiment and implementation [45–47]. It used to be complemented with a user interface (i.e., VISSIM COM), capable of not only reading the data of the internal objects such as vehicles, links, evaluations, etc., but also modifying their attributes and properties like vehicle routing, speed, signal timing, etc., at a discrete time step during the running of a simulation [48,49]. In addition, MOVES (motor vehicle emission simulator) is a representative microscopic emission simulator developed by the U.S. Environmental Protection Agency (U.S. EPA) and refers to the vehicle trajectories and vehicle specific power (VSP).

3.1. Mobility Simulator for Idling Control Process

The basic concept and algorithm of automatic vehicle idling control are provided in Figure 3. There are two fundamental requirements for the algorithm: that is, the autonomous vehicle should be physically equipped with a communication device and the reference time should be set to be compared with the waiting time to execute automatic vehicle idling control. The reference time is supposed to be defined according to the various vehicle characteristics such as vehicle type, vehicle year, fuel type, etc., but this study adopted a specific value (i.e., 10 s) referenced from the existing works.

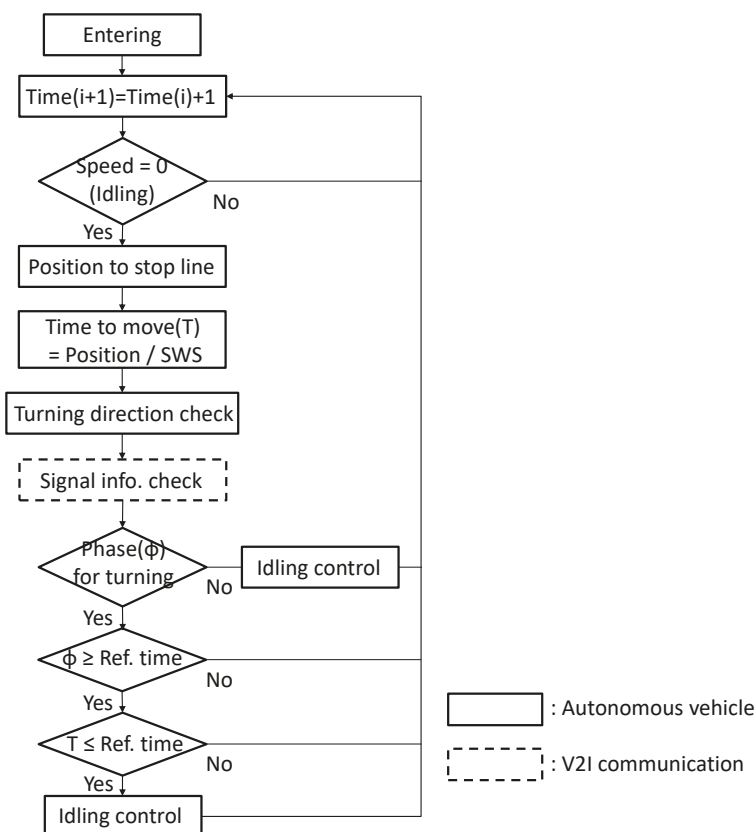


Figure 3. Automatic vehicle idling control method.

Specifically, the mobility simulator consists of five steps from vehicle generation to vehicle idling identification and control. Most steps (i.e., solid box in Figure 3) can be realized by the autonomous vehicles themselves, such as speed, position, turning direction, vehicle idling control, etc., except one step (i.e., dashed box in Figure 3), which is sharing traffic signal information via V2I communication. Each step is explained as follows:

Step 1: Vehicle generation

Vehicles are generated on the entering links at pre-determined headways depending on traffic demand.

Step 2: Identification of vehicle idling situations

The speed of individual vehicles is monitored at every simulation time and when their speed is 0 kph, which is when they stop before a stop line or join a queue and the idling condition occurs. Then, this study computes the time that the shockwave reaches stopped vehicles from the stop line at the intersection of interest, referring to the time for vehicles to be able to start to move.

Step 3: Transmission of signal information through V2I communication

Every time vehicle idling situation is identified, the traffic signal information such as cycle length, current and consecutive phases, phase sequence, etc., is checked to determine if the automatic vehicle idling control function should be activated or not.

Step 4: Determination of vehicle idling control

At first, if the transmitted signal phase is not compatible with the turning direction of idling vehicles, the vehicle idling should be controlled. On the other hand, in case the signal phase matches the turning direction of idling vehicles and the phase is same as the reference time (i.e., Ref. time in Figure 3) or more, if the shockwave arrival time to the idling vehicles (i.e., time to start to move) is same as the reference time or less, the vehicle idling is controlled as well.

Step 5: Estimating GHG emissions reciprocally linked to emission simulator

At every simulation time, all individual vehicles resort to the emission simulator to calculate the CO₂ emissions corresponding to operation modes such as braking, idling, and running. Later, aggregated CO₂ emissions associated with scenarios with or without an automatic vehicle idling control function are compared to see the environmental benefits of the proposed function.

There are two types of scenarios depending on the automatic vehicle idling control of an autonomous vehicle under C-ITS. One is no idling control (i.e., Figure 4a), and the other is vehicle idling control considering the queue length, time to start, reference time, and traffic signal information transmitted through V2I communication (i.e., Figure 4b).

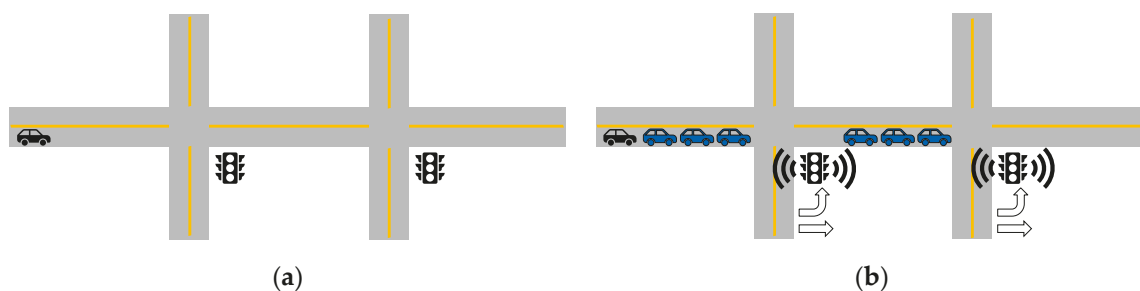


Figure 4. Scenario illustration with or without vehicle idling control function. Note: the arrow means signal phase.

More specifically for Figure 4b, VISSIM observes all trajectories of individual vehicles at every simulation time and compares the waiting time and signal phase corresponding to the designated turning direction when stopping at the intersection until the simulation is terminated. When the waiting time is over the reference time defined in this study, the automatic idling control function is implemented, assuming that the reference time is 10 s. For example, if the waiting time informed by the traffic signal controller through V2I communication is 15 s, the vehicle automatically controls the idling by turning off the engine and restarts afterwards, consequently resulting in a reduction of CO₂ emissions corresponding to 5 s.

3.2. Emission Simulator for GHG Emission Estimation

The U.S. EPA has developed and upgraded an emission simulator named the motor vehicle emission simulator (MOVES) for estimating the amount of CO, NO_x, and CO₂ emitted by vehicles at different levels from on-road and non-road sources. MOVES depends on the operation modes defined by vehicle speed and vehicle specific power (VSP) as explanatory variables that were noted as highly correlated with the emissions of interest [50]. The concept of VSP is the instantaneous power demand of the vehicle divided by its mass, which is used in the evaluation of vehicle emissions. As can be seen in Equation (1), it is the value obtained by dividing the sum of the loads resulting from aerodynamic drag, acceleration, rolling resistance, and hill-climbing by the mass of the vehicle [4,51].

$$\text{Vehicle specific power (VSP)} = (Av + Bv^2 + Cv^3 + mv(a + g\sin\theta)) / m_{\text{fixed}} \quad (1)$$

where:

VSP : Vehicle specific power (kW/ton);

A : Rolling resistance (kW·s/m);

B : Rotating resistance (kW·s²/m²);

C : Drag resistance (kW·s³/m³);

m : Source mass (ton);

v : Speed (m/s);

a : Acceleration (m/s²);

θ : Road grade;

g : Acceleration of gravity (9.8m/s²);

m_{fixed} : Fixed mass factor (ton) [52,53].

Table 1 shows the weighted average of CO₂ emissions of all vehicles for 23 operating modes in MOVES such as braking, idling, coasting, cruising, and accelerating by referring to the emission rate of CO₂ associated with VSP, vehicle speed, vehicle type, and fuel type.

Table 1. CO₂ emission rates for multiple operating modes in MOVES.

								Unit: Kg/h
Op. Mode	Op. Mode Description	Passenger Car		Transit Bus		Passenger Truck	Long-Haul Vehicle	Diesel
		Gasoline	Diesel	Diesel	CNG	Diesel	Diesel	
0	Braking	3.03	3.03	15.15	8.32	4.37	15.47	
1	Idling	2.81	2.81	7.46	6.58	3.37	7.62	
11	VSP < 0	4.41	4.41	10.02	8.85	5.45	10.23	
12	0 ≤ VSP < 3	6.09	6.09	29.14	21.02	6.82	29.76	
13	3 ≤ VSP < 6	8.47	8.47	53.38	61.00	9.81	54.50	
14	6 ≤ VSP < 9	10.70	10.70	77.89	101.67	12.43	79.53	
15	9 ≤ VSP < 12	12.76	12.76	98.51	142.34	14.99	100.58	
16	12 ≤ VSP	15.41	15.41	135.50	203.34	18.72	138.35	
21	VSP < 0	6.00	6.00	8.08	11.77	7.30	8.25	
22	0 ≤ VSP < 3	6.83	6.83	37.46	24.84	7.83	38.25	
23	3 ≤ VSP < 6	8.32	8.32	62.12	65.28	9.67	63.43	
24	6 ≤ VSP < 9	10.68	10.68	89.92	77.35	12.52	91.81	
25	9 ≤ VSP < 12	14.25	14.25	115.62	108.29	16.08	118.05	
27	12 ≤ VSP < 18	18.78	18.78	159.71	154.71	22.14	163.07	
28	18 ≤ VSP < 24	25.31	25.31	223.59	216.59	29.57	228.30	
29	24 ≤ VSP < 30	34.68	34.68	287.47	278.47	40.54	293.52	
30	30 ≤ VSP	43.55	43.55	351.35	340.35	47.76	358.76	

Table 1. Cont.

Op. Mode	Op. Mode Description							Unit: Kg/h
		Passenger Car		Transit Bus		Passenger Truck	Long-Haul Vehicle	
		Gasoline	Diesel	Diesel	CNG	Diesel	Diesel	
33	$VSP < 6$	8.55	8.55	33.32	40.12	10.54		34.03
35	$6 \leq VSP < 12$	13.71	13.71	101.90	82.54	16.13		104.05
37	$12 \leq VSP < 18$	17.86	17.86	159.49	137.56	21.32		162.85
38	$18 \leq VSP < 24$	23.29	23.29	223.29	192.59	27.70		227.99
39	$24 \leq VSP < 30$	31.02	31.02	287.09	247.61	36.30		293.13
40	$30 \leq VSP$	39.55	39.55	350.89	302.64	48.04		358.28

4. Evaluation of Automatic Idling Control of CAVs

This study investigated the environmental benefits of the automatic vehicle idling control function in Haeundae-gu in Busan, Korea, within the established research framework. Because Haeundae-gu is a globally highly popular tourist town that has grown rapidly over the past few decades, it is an appropriate study site due to the sufficient traffic demand for this study.

4.1. Case Study with Haeundae-Gu in Busan, Korea

Figure 5 shows the study area, Haeundae-gu, in Busan, Korea. The basic input data required to build the VISSIM network such as the geometry, traffic flow (i.e., traffic volume and turning ratio), and traffic signal information (i.e., cycle length, phase, phase sequence, etc.) has been collected from an up-to-date aerial photo, traffic impact assessment reports, and the regional Road Traffic Authority with field survey complementation. After one hour of warm-up time, during which the network was populated with a sufficient number of vehicles, the vehicles entering the network for the next one hour were used for the analysis.

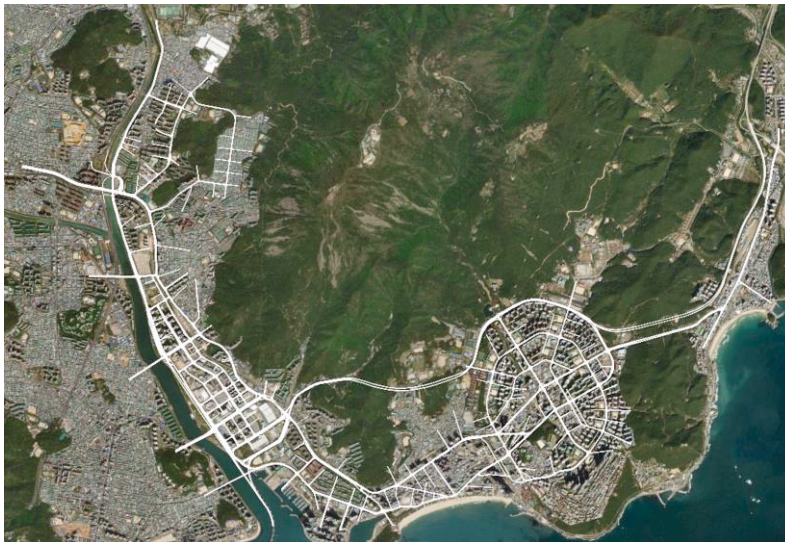


Figure 5. VISSIM network (10 km × 10 km) of Haeundae-gu in Busan, Korea.

As for MOVES, the *VSP* operates in numerous operating modes at various speeds and accelerations collected from the microscopic simulation model, VISSIM. This study considers the passenger cars and gasoline as the vehicle type and fuel type in Table 1. Also, Table 2 indicates the default values corresponding to individual variables in Equation (1), excluding geographical factor (i.e., network slope) [53].

Table 2. MOVES default database in Equation (1).

Item	Value
Rolling resistance (A)	0.156461 (kW·s/m)
Rotating resistance (B)	0.00200193 (kW·s ² /m ²)
Drag resistance (C)	0.000492646 (kW·s ³ /m ³)
Source mass (m)	1.4788 (ton)
Fixed mass factor (m_{fixed})	1.4788 (ton)

This study has calibrated the Haeundae-gu network with the three most significant queue length-related parameters, such as emergency stopping distance, lane change distance, and average standstill distance, out of 50 internal parameters based on the afternoon non-peak traffic demand using a Monte Carlo experiment. The simulation network was calibrated with three parameters adjusted to 7.2 m, 30.3 m, and 2.0 m, respectively. For validation purposes, the morning non-peak traffic demand has been input to the calibrated model, and it estimated the queue length within a reasonably acceptable range on the main artery. Therefore, the simulation outputs derived from this network are reliable enough to evaluate the environmental effect of the automatic vehicle idling control function [49].

4.2. Results and Analysis

This study evaluated the temporal and environmental benefits of autonomous vehicles under C-ITS when automatically controlling idling in the case that the informed waiting time is longer than the reference time in the Haeundae-gu network.

Table 3 shows that the total number of vehicles analyzed in this study is 15,888 vehicles, and 99.5% of them (i.e., 15,813 vehicles) were forced to experience idling at least once until leaving the network, resulting in 1602 idling hours out of total travel time, 3173 h, which is approximately 50.5%. The average travel time per vehicle is 719 s/veh, which is the sum of average moving time (354 s/veh) and average idling time (365 s/veh). The total saved idling time by applying the automatic vehicle idling control function proposed in this study is 1511 h, which accounts for 47.6% of the total travel time and 94.3% of the total idling time, respectively. The average saved idling time is 334 s/veh, which is the same percentage as the saved travel time.

Table 3. Temporal and environmental effects of automatic vehicle idling control function.

	Time			Emission		
	Total	Average	Rate	Total	Average	Rate
Vehicles	3173 h	719 s/veh		64,641,228 kg/h	4069 kg/h	
Idling	1602 h	365 s/veh	50.5%	16,152,220 kg/h	1017 kg/h	25.0%
Saved idling	1511 h (94.3%)	344 s/veh	47.6%	15,230,566 kg/h	959 kg/h (94.3%)	23.6%

Table 3 also reveals that the total CO₂ emissions from all vehicles is 64,641,228 kg/h at an average of 4069 kg/h. The amount of CO₂ emissions from idling vehicles takes up 25.0% of the total CO₂ emissions, which is 1017 kg/h per vehicle on average. The saved CO₂ emissions due to the proposed function in this study corresponds to 23.6% of the total CO₂ emissions and 94.3% of the total idling CO₂ emissions, respectively. Therefore, the proposed function enables idling time and CO₂ emitted during idling to be significantly reduced by over 94% without relying on human judgement.

In addition to the total and average travel time and CO₂ emissions in terms of vehicle unit, it is noteworthy to analyze them at the individual idling level. Table 4 shows that the total number of idling experienced by 15,813 vehicles is 113,986 times, which is 7.2 times per vehicle on average. Their average time and emission per idling are 50.6 s and 142 kg/h, respectively. Consequently, approximately 134 kg/h CO₂ emissions out of 142 kg/h, accounting for 94.3% of the total, were saved by the automatic vehicle idling control function,

which was executed based on the queue discharge time, reference time, and traffic signal information transmitted from the traffic signal controller through V2I communication.

Table 4. Effects of the automatic vehicle idling control function at the individual idling level.

Item	Value
Total idling count	113,986 times
Average idling count	7.2 times/vehicle
Average idling time	50.6 s/idling
Average idling emission	142 kg/h/idling
Average controlled idling emission	134 kg/h/idling

5. Conclusions, Discussion, and Future Research Issues

The transportation sector is regarded as a main culprit in greenhouse gas emission in the urban network, particularly idling vehicles waiting at signalized intersections. There have been many efforts to alleviate these adverse effects by utilizing more advanced information and communication technologies and enforcing emission regulations as well. Even though autonomous vehicles can be a promising technology to tackle vehicle idling, their environmental benefits obtain no attention compared with the safety and mobility issues.

This study underlined that the CO₂ emitted by idling vehicles at signalized intersections accounts for a significant proportion of the citywide emissions, suggesting that controlling vehicle idling is an inevitable way to reduce CO₂ emissions. This study introduces an automatic vehicle idling control function that enables vehicles to autonomously decide vehicle idling control in the queue at signalized intersections and investigate its environmental benefits.

This study attempts to introduce the basic algorithm of the automatic idling control function and investigate the environmental benefits of autonomous vehicles equipped with it based on the traffic signal information transmitted from the traffic signal controller under C-ITS by employing the microscopic mobility and emission simulator, VISSIM, VISSIM COM, and MOVES, in Haeundae-gu in Busan, Korea, as a case study. The most discernable point of this study from the existing works is to simultaneously take into account the queue length, reference time, and transmitted traffic signal information prior to determination of the vehicle idling control.

According to the simulation outputs, the total saved idling time thanks to the automatic idling control function accounts for 47.6% of the total travel time and 94.3% of the total idling time, respectively. Also, it could reduce 23.6% and 94.3% of CO₂ emissions out of the total and idling amounts, respectively.

In conclusion, the autonomous vehicles equipped with an automatic vehicle idling control function under C-ITS can play an important role in reducing the CO₂ emissions in the urban traffic network. Particularly, this study contributes to suggesting a novel methodology to compute the queue discharge time, utilized to determine whether to control vehicle idling or not, and utilizing on data about vehicle position in the queue, shockwave speed, reference time, and traffic signal information shared by V2I communication.

In addition, although electric vehicles and low-emission vehicles are rapidly being distributed, they have not yet had a meaningful impact on the overall reduction of CO₂ emissions in urban areas to date. Therefore, the function proposed in this study can play a sufficient role in reducing CO₂ emissions in the process of expanding the market penetration rate of these vehicles. Therefore, this study strongly supports a logical basis on the assertive deployment of the automatic vehicle idling control function in major cities, especially those suffering from CO₂ emissions.

Even though there is a drawback to the stop-and-go function, which is a representative technology of vehicle idling control introduced in Section 2, that is, it cannot reflect the queue discharge time and reference time and unconditionally controls vehicle idling whenever the vehicle stops, it is expected to significantly reduce CO₂ emissions. Intuitively, the automatic vehicle idling control function proposed in this study outperforms the stop-

and-go function in reducing CO₂ emission, but this study has a limitation in that it did not make a quantitative comparison between them.

Because the related technology and equipment to implement the proposed function are already off-the-shelf, it is expected to see it in reality in the near future. Prior to the actual implementation, the following issues should be addressed to improve the research performance in future research. The reference time to be compared with the queue discharge time and traffic signal information is assumed to be 10 s but should be more realistic, reflecting the vehicle type, vehicle year, fuel, etc. All vehicles are assumed to be powered by gasoline, but vehicle types should be diversified due to the fast propagation of more eco-friendly vehicles such as electric vehicles, hydrogen vehicles, etc., which means that the CO₂ emission value should be more diverse to be referenced. Lastly, the shockwave speed used to estimate the queue discharge time should be investigated in the field.

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Article

Evaluating the Impact of V2V Warning Information on Driving Behavior Modification Using Empirical Connected Vehicle Data

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Abstract: A connected vehicle (CV) enables vehicles to communicate not only with other vehicles but also the road infrastructure based on wireless communication technologies. A road system with CVs, which is often referred to as a cooperative intelligent transportation system (C-ITS), provides drivers with road and traffic condition information using an in-vehicle warning system. Road environments with CVs induce drivers to reduce their speed while increasing the spacing or changing lanes to avoid potential risks downstream. Such avoidance maneuvers can be considered to improve driving behavior from a traffic safety point of view. This study seeks to quantitatively evaluate the effect of in-vehicle warning information using per-vehicle data (PVD) collected from freeway C-ITSs. The PVD are reproduced to extract the speed–spacing relationship and are evaluated to determine whether the warning information induces drivers to drive in a conservative way. This study reveals that the in-vehicle warning prompts drivers to increase the spacing while decreasing their speed in the majority of samples. The rate of conservative driving behavior tends to increase during the initial operation period, but no significant changes were observed after this period; that is, the reliability of in-vehicle warning information is not constant in the CV environment.

Keywords: connected vehicle; in-vehicle warning system; vehicle interaction; driving behavior; PVD

1. Introduction

The term connected vehicle (CV) denotes a technology and system that utilizes wireless communication technology to provide information about traffic conditions downstream. This communication occurs between vehicles as well as between vehicles and infrastructure. The driver receiving the information is expected to quickly and safely respond to unexpected situations to prevent accidents from risk factors [1,2]. Since the early 2000s, various studies using real-time in-vehicle data have been conducted in the United States and Europe as communication technologies and services advance [3–6]. In South Korea, the first pilot study of the cooperative intelligent transportation system (C-ITS) started in 2014 in Sejong and gradually expanded to other cities, including Seoul, Jeju, and Gwangju. In each study, the C-ITS infrastructures, including in-vehicle warning systems, roadside units (RSU), and other wireless communication units, were installed, tested, and operated. Apart from the study in urban areas, the Korea Expressway Corporation (KEC) installed C-ITSs in some sections of expressways in the metropolitan area in 2018. This installation encompassed the development and implementation of over 700 in-vehicle warning systems, a digital tachograph (DTG), and an advanced driving assistance system (ADAS). From the system, one can easily obtain various in-vehicle data, including speed, acceleration rate, latitude, longitude, time to collision (TTC), and spacing (often referred to as PVD).

In the C-ITS environment, we anticipate that drivers who receive vehicle-to-everything (V2X)-based warning information will likely adjust their behavior by either reducing their speed, increasing spacing, or changing lanes to avoid potentially hazardous traffic conditions downstream. Thus, assessing the quantitative impact of the warning information provided on driver behavior would play a crucial role for traffic operators.

This study suggests a method to quantitatively evaluate the effect of in-vehicle warning information using per-vehicle data (PVD) collected from freeway C-ITSs. Based on findings from a previous study [7], aggressive drivers (“Aggressive driver” means a driver who maintain shorter spacing at a given speed than ordinary drivers) typically maintained speeds ranging from 75 kph to 140 kph while keeping a spacing of 32.4 m (i.e., standard deviation: 27.4 m), whereas conservative drivers (“Conservative driver” means a driver who maintain longer spacing at a given speed than ordinary drivers) speeds were distributed between 74 kph and 105 kph with a spacing of 62.2 m (i.e., standard deviation: 32.9 m). Leveraging insights from this earlier research, this study aims to quantitatively evaluate the impact of warning information from the C-ITS. To achieve this, two experiments were designed within the same C-ITS environment: one experiment where the in-vehicle warning information is provided to drivers and the other where it is not. We examined the PVD collected at second intervals from the two experiments to investigate the relative changes in speed and spacing within the speed–spacing plane and see if driving behavior tends to become more conservative when the warning information is actually provided versus when it is not. Furthermore, this study quantitatively assessed the number of vehicles responding to the warning information and a comparative analysis was conducted between the two experiments.

The remainder of this paper is organized as follows. Section 2 presents previous studies related to the evaluation of in-vehicle warning information. Section 3 presents the methodology to evaluate the in-vehicle warning information. Section 4 introduces the analysis area and empirical data used in this study. Section 5 shows the results of the evaluation and finally this paper closes in Section 6 with the conclusions of the study.

2. Literature Review

After reviewing the literature that evaluated the effect of V2V-based in-vehicle warning information, we can categorize the research into three groups based on the type of data.

The first group of studies used simulated data from microscopic simulation, where in-vehicle warning information was evaluated based on average speed, acceleration, volume of traffic, etc. For example, some studies examined simulated data to optimize mobility, safety, and the environmental benefits in a CV environment [8,9]. Another study simulated automated driving vehicles in CV environments. The researchers calculated the traffic volume, travel times, and speeds to evaluate the CVs based on the in-vehicle information [10,11]. Guglielmi et al. (2017) evaluated the CV environments with heavy vehicles based on intersection movement assistance (IMA), forward collision warning (FCW), and blind spot warning/lane change warning (BSW/LCW) via VISSIM simulation [12]. Rahman et al. (2019) evaluated automated braking and lane-keeping assistance scenarios using time exposed time to collision (TET), time integrated time to collision (TIT), time exposed rear-end crash risk index (TERCRI), lane-changing conflicts (LCC), number of critical jerks (NCJ), and the number of conflicts that are reproduced by simulations [13]. These simulation-based studies concluded that CV environments can simultaneously provide positive effects on mobility and safety. Traffic simulation has been utilized to evaluate the effectiveness of warning information not only for driving safety, but also traffic flow performance [14–16]. Sharma et al. (2021) showed that in mixed traffic conditions, CVs improve the efficiency and safety of traffic flow [17]. Hu et al. (2021) analyzed the performance of mobility according to the market penetration rate (MPR) of CVs. The results showed that as the MPR increases in mixed traffic, the average travel time of all traffic decreases and the average speed increases [18].

The second group of studies included those using driving simulators, where in-vehicle warning information was provided using various types of display methods. Li et al. (2021) analyzed the impact of the CV environment on the tunnel entrance zone. They calculated the speed, standard deviation of the speed, and acceleration and evaluated drivers' speed control in the warning zone [19]. Adomah et al. (2022) combined a driving simulator and VISSIM to evaluate the impact of weather conditions (i.e., foggy conditions) [20]. They used TTC, TET, TIT, and a speed-related index as the measure of effectiveness (MOE). Ali et al. (2020) evaluated CV environments using a driver simulator based on spacing and TTC [21]. Yue et al. (2018) simulated the relationship between various types of traffic accidents and TTC in CV environments [22]. Chang et al. (2019) evaluated the safety effectiveness of providing warning information. The analysis used speed standard deviation, TET, and TIT to evaluate the longitudinal safety effect of warning information in the event of fog. The results showed that fog warning systems are beneficial in reducing speed and improving driver behavior [23]. Bakhshi et al. (2021) evaluated the effectiveness of warning information for curved road sections with slippery road conditions for truck drivers in a driving simulation environment. The results showed that warning information decreased off-road crashes by utilizing a kinematic-based surrogate measure of safety (K-SMs) [24]. Duan et al. (2023) analyzed the effectiveness of an audible warning system based on a driving simulator environment to improve bottlenecks in highway construction areas. The analysis showed that warning information can effectively reduce the risk of bottlenecks, but the effectiveness decreases with the delay in providing warning information [25]. In addition, several studies have evaluated the effectiveness of variable speed limit systems (VSLs) in CV environments. The results show that the average speed and volatility of speed are reduced in severe weather conditions such as fog, increasing safety [26,27].

The third group of studies included studies that employed PVD. These studies compared various MOEs between situations with in-vehicle information and situations without in-vehicle information. Zhang et al. (2022) evaluated truck drivers' driving behavior using GPS data and an in-vehicle driver monitoring system [28]. Hsu et al. (2022) evaluated the impact of a motorcycle safety warning system (MSWS) using RFID data [29]. MohamMad et al. (2021) examined PVD collected from the safety pilot model deployment (SPMD) program to analyze vehicle maneuvers, such as differences in speed and lateral/longitudinal differences in acceleration in CV environments [30]. Jang et al. (2020) evaluated the impact of in-vehicle warning information based on TTC, TET, standard deviation in acceleration, jerk, and rate exceeding the speed limit, which were reproduced from the PVD [31]. Xie et al. (2019) compared time to collision with disturbance (TTCD) with TTC, which were calculated from the PVD in CV environments to determine which surrogate safety measure (SSM) was better for explaining rear-collision crash potentials [32]. Arvin et al. (2019) analyzed CV-based in-vehicle data to evaluate intersection crash risk using the semiparametric geographically weighted Poisson regression (S-GWPR) model and random parameter (RP) Poisson model [33].

The proposed study herein differs from previous ones in several respects. Most previous studies used either simulated data with warning information or investigated PVD to compare situations with and without in-vehicle warning information. On the other hand, the research seeks to evaluate the effect of improving driving behavior before and after warning information is provided using PVD. Unlike previous studies, we employed the speed–spacing relationship to evaluate in-vehicle warning information. The speed–spacing relationship is one of the fundamental relationships that enables the visualization of traffic state progression. One can differentiate aggressive or conservative drivers from ordinary drivers. However, there were limitations to constructing a speed–spacing relationship even using PVD, due to the difficulty of extracting two consecutive vehicle trajectories. Given that the CV systems employed in this study are equipped with ADASs, we could obtain spacing information to establish the speed–spacing relationship.

3. Methodology

To empirically measure the effectiveness of in-vehicle warning information, we undertook a microscopic analysis utilizing PVD collected at second intervals. Leveraging the big data allowed the identification of individual vehicle dynamics, enabling an investigation into the relative changes in speed and spacing before and after the provision of warning information within the speed–spacing plane.

Conventionally, the relationship between speed and vehicle distance is illustrated in Figure 1a [34]. In fact, the relationship can be derived from the fundamental relationship in Figure 1b frequently employed in macroscopic traffic flow analysis [35]. For instance, traffic state A in Figure 1b is characterized by d_A , q_A , and V_A (the slope of a straight line from origin to state A as per the fundamental equation). Given that spacing is the reciprocal of density, point A' in Figure 1a corresponds to state A in Figure 1b.

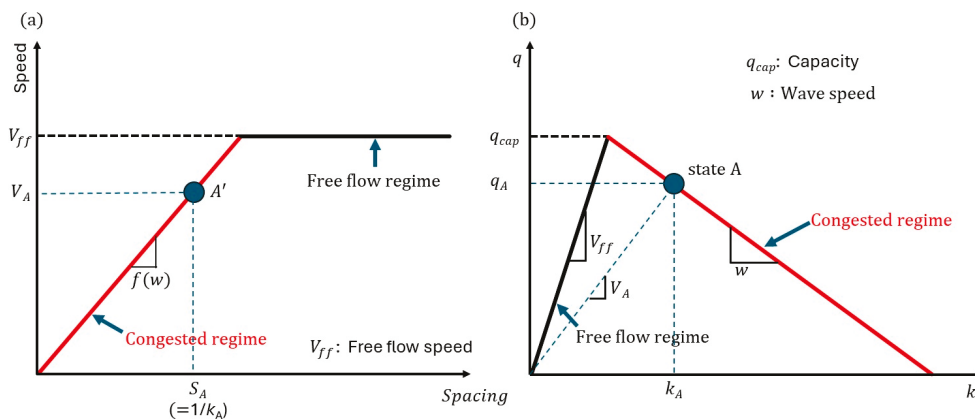


Figure 1. (a) Conventional speed–spacing relationship and (b) fundamental relationship between flow (q) and density (k).

In both relationships, delineated by black and red solid lines in Figure 1, there are two distinct regimes: free flow and congestion. As depicted in Figure 1a, the relationship between spacing and speed is directly proportional in the congested regime. Conversely, density is inversely proportional to flow in fundamental relationships. However, density and flow are aggregated measurements in traffic flow theory, and it is not possible to reproduce them directly from the PVD. On the other hand, as both spacing and speed are extractable from the data, our focus lies in examining the speed–spacing relationship to accomplish the objective in this study.

The speed–spacing relationship provides insight into how ordinary drivers establish spacing corresponding to a given speed, and conversely, how they determine speed based on spacing. Suppose that a target vehicle is at point A in Figure 2a and its preceding vehicle decelerates in a traffic jam. If the driver of the target vehicle is an ordinary driver, the driver slows down while decreasing its spacing and that driver theoretically follows the trajectory in speed–spacing plane moving from point A to point B in Figure 2a. However, if the driver is a conservative driver, it tends to maintain additional spacing while decelerating harder than the ordinary driver. As a result, the trajectory of the driver's speed–spacing relationship moves from point A to point C. In contrast, an aggressive driver is anticipated to maintain a relatively short spacing at a given speed and its trajectory moves from point A to point D in Figure 2a. That is, the internal area of a given speed–spacing relationship signifies the speed–spacing behavior of conservative drivers, whereas the external area represents that of aggressive drivers.

The objective of the in-vehicle warning information provided by the C-ITS is to prevent accidents by inducing drivers to take proactive actions against potential hazards downstream. In other words, the warning information is a service that advises the average driver to be more conservative in response to the situation ahead. Such conservative driving behavior can be distinguished from the speed–spacing trajectory of ordinary

drivers. Figure 2b shows the hypothetical trajectories on the speed–spacing plane between an ordinary driver who has not been alerted and a conservative driver who has.

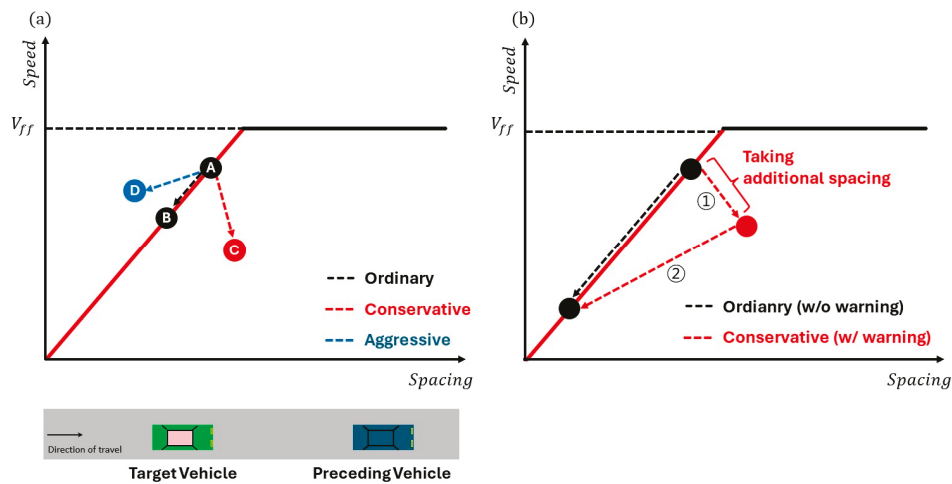


Figure 2. (a) Speed–spacing trajectories from aggressive, conservative, and ordinary drivers, (b) comparison of speed–spacing trajectories between an ordinary and a conservative driver.

If the driver responds to the in-vehicle warning, it is expected to slow down and create additional spacing as the conservative driver shown in Figure 2b. Therefore, the average speed decreases, while the spacing increases right after the warning. Conversely, for an ordinary driver who does not receive warning information, the speed–spacing dynamics continue to adhere to the usual pattern, resulting in spacing decreasing concurrently with deceleration, as per the black dotted line in Figure 2b. Even for aggressive drivers, there are two possible scenarios: either maintaining a constant speed with a tendency to decrease spacing or increasing speed while decreasing spacing. Either way, it is distinguished from the conservative driver’s trajectory, as spacing decreases. Hence, this study aims to investigate the relative differences in speed to identify conservative driving behavior when drivers receive the in-vehicle warning in the following way.

First, two experiments were conducted within the same C-ITS environment. In the first experiment, the in-vehicle warning information is actually provided to the driver and the log is recorded in the PVD. In the second experiment, the driver does not receive the warning information, but a log of pertinent timestamps is recorded. Thus, the experimenter can see from the data when the warning information is provided but the driver cannot. Second, we extracted speed and spacing measurements immediately before and after the in-vehicle warning log in each PVD dataset collected from the two experiments. Third, for each experiment, we compared the distribution of speed and spacing before and after the provision of the in-vehicle warning information. Furthermore, upon careful examination of the differences between the two experiments, we ascertained whether driving behavior tends to become more conservative when the warning information is actually provided versus when it is not. Fourth, following the calculation of an index to quantitatively assess the number of vehicles responding to the warning information (see Equation (1)), a comparative analysis was conducted between the two experiments.

$$\text{BMI (Behavior Monitoring Indicator)} = \frac{\text{Number of effective vehicles}}{\text{Total number of vehicles}} \times 100 \quad (1)$$

where the number of effective vehicles is those vehicles where speed decreases while spacing increases.

4. Analysis Area and Data

The PVD employed in this study were collected from 400 buses, 250 trucks, and 50 SUVs on freeways. KEC installed C-ITS infrastructures on the road and in-vehicle units

were installed in these 700 vehicles. The data were collected from three freeway sections, as illustrated in Figure 3. The total section length is 85.4 km, and the longest section is a part of the Gyeongbu Line that connects the capital of South Korea and Busan. The PVD were collected over 16 months in 2019 and 2020. Over the two years, the two experiments were performed, the first of which was from July 2019 to July 2020; vehicles equipped with C-ITS in-vehicle units received in-vehicle warning information (we call this period the “with” period in this study). However, from August 2020 to October 2020, the drivers did not receive the warning information because the in-vehicle unit was turned off over this period (we call this the “without” period in this study). However, there was a log in the data at the time when the warning information should have been provided. This data over the “without” period was used as a control group against the data during the “with” period to analyze the drivers’ driving behavior when no warning information was provided.

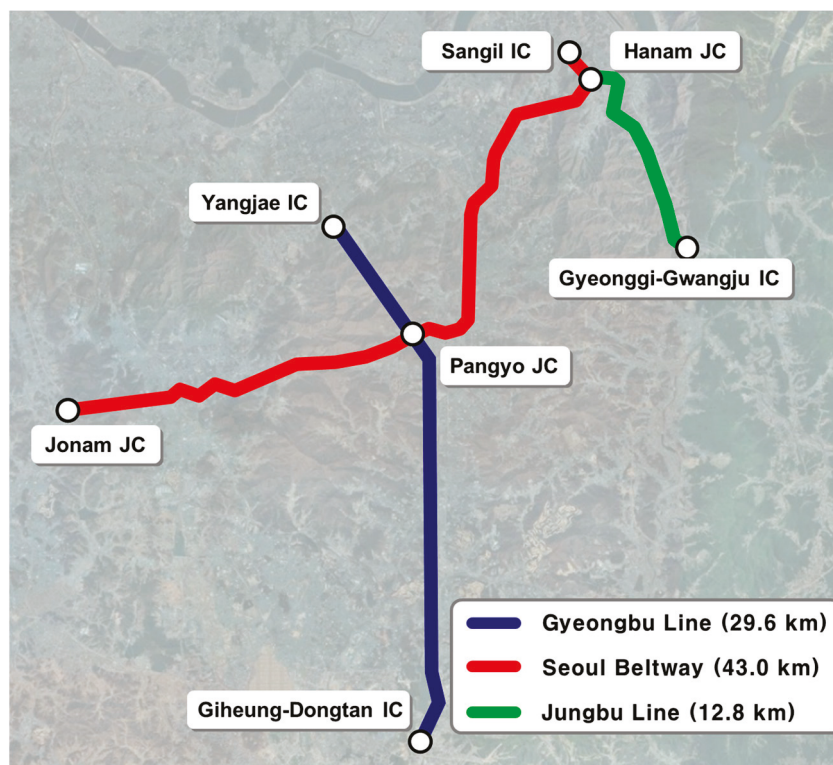


Figure 3. Analysis area.

Table 1 shows vehicle records included in the PVD. The PVD originate from two sub-systems, DTG, including general vehicle travel records (e.g., speed, acceleration, location, etc.), and ADAS, with records of FCWS (forward collision warning system), LDWS (lane departure warning system), TTC, and spacing. In total, 108 types of vehicle records are logged every second in the PVD. Of those records, this study analyzed timestamp, speed, spacing, and in-vehicle warning logs.

In this study, the effect of FCWS to prevent direct or secondary accidents caused by other vehicle breakdowns or accidents downstream was evaluated in terms of driving behavior. The FCWS was activated whenever the forward collision risk increases due to the slowing or sudden stop of the preceding vehicle downstream, which results in short spacing in contrast to relative speed.

To analyze driving behavior following the provision of warning information, this study took a 30 s record before and after FCWS was provided (refer to Figure 4). The reason why the time unit chosen was 30 s was to obtain a sufficient sample of the two variables (speed and vehicle spacing) and at the same time, it was short enough to fully analyze the impact of providing warning information. Since in-vehicle records are logged every

second, in theory, two groups of 30 s data are analyzed. However, some samples were obtained where a few records were missed due to certain technical issues. Thus, this study considered a sample that had at least 15 s consecutive records both before and after the in-vehicle warning to be valid.

Table 1. Type of records in PVD.

PVD	DTG	Vehicle Info.	• Speed, acceleration, brake (operation state and strength), gearbox, direction, angular velocity; • Longitude, latitude, altitude, vehicle type, vehicle classification; • External light, warning light, wiper status, external temperature, etc.; • Dangerous driving behavior code ¹, mileage.
		Service Info.	• Service number, message ID, event, display status, service activation time, etc.
	ADAS	• FCWS occurrence information; • LDWS occurrence information; • Spacing, TTC.	

¹ In Korea, the government defined 11 dangerous driving behaviors in early 2000, and DTG data has been utilized to categorize them. The “dangerous driving behavior code” in Table 1 means the categorized result from DTG.

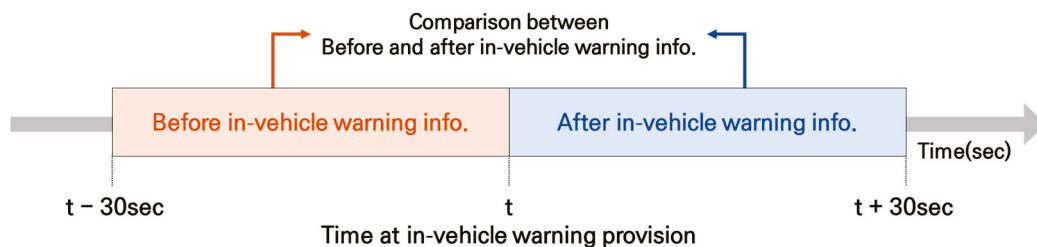


Figure 4. Analysis sample extraction.

Table 2 summarizes the total number of valid samples extracted in the analysis by each analysis period.

Table 2. Data collection summary.

Experiments	Data Collection Period	Number of Samples
“With”	17 July 2019~31 July 2020 (381 days)	1055
“Without”	1 August 2020~31 October 2020 (92 days)	198

5. Results

5.1. Speed–Spacing Relationship

First of all, this study scrutinized speed and spacing measurements over time in speed–space plane by sample. Figure 5 shows typical examples of speed–spacing trajectories from “without” and “with” periods, which were extracted from some of the samples mentioned in Table 2. In each figure, a star represents the speed and spacing at the time of the in-vehicle warning. An in-vehicle warning is activated based on relative speed and spacing between vehicles. Thus, the warnings in Figure 5 do not occur at the same spacing. Blue dots are speed and spacing measurements before the warning and red dots after. The solid black line is a theoretical speed–spacing relationship for convenience. Figure 5a shows the time series changes of speed and spacing from one of the samples collected over the “without” period. On the other hand, Figure 5b represents the case extracted from the “with” period.

In Figure 5a, speed and spacing are generally located along the theoretical speed–spacing relationship. In addition, one can easily recognize that speed decreases as spacing decreases after the in-vehicle warning. Thus, this case would represent a case from an “ordinary driver” as mentioned in Section 3. In Figure 5b, on the other hand, most of speed and spacing are located inside the theoretical relationship. In fact, it appears that some of them are much further to the right in the theoretical relationship right after the time of the warning. It is suspected that the driver reacted to the warning and took additional spacing

at a given speed. Therefore, this can be classified as a case of “conservative driver” as mentioned in Section 3. Focusing on average speed and spacing before and after warning, both speed and spacing decrease after the warning in Figure 5a. However, the average speed decreases, and the spacing increases in Figure 5b.

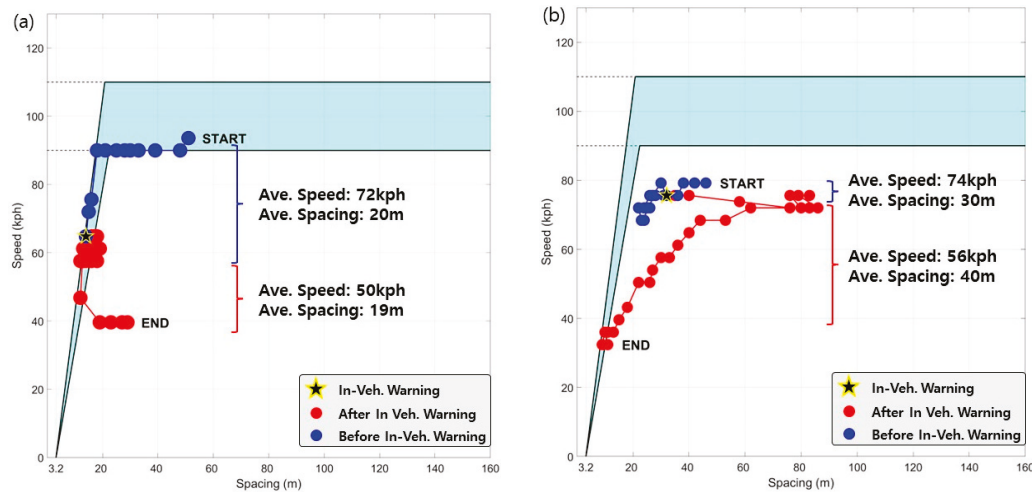


Figure 5. Example of determining whether driving behavior is improved: (a) ordinary driver; (b) conservative driver (72 kph/50 kph/20 m/19 m vs. 74 kph/56 kph/30 m/40 m).

5.2. Relative Difference in Speed and Spacing between “without” and “with” Periods

To evaluate the effectiveness of the in-vehicle warning information, this study investigates the distributions of speed and spacing between the “without” and “with” periods. Figure 6 and Table 3 summarize the distributions and basic statistics of speed from the “without” and “with” periods, respectively.

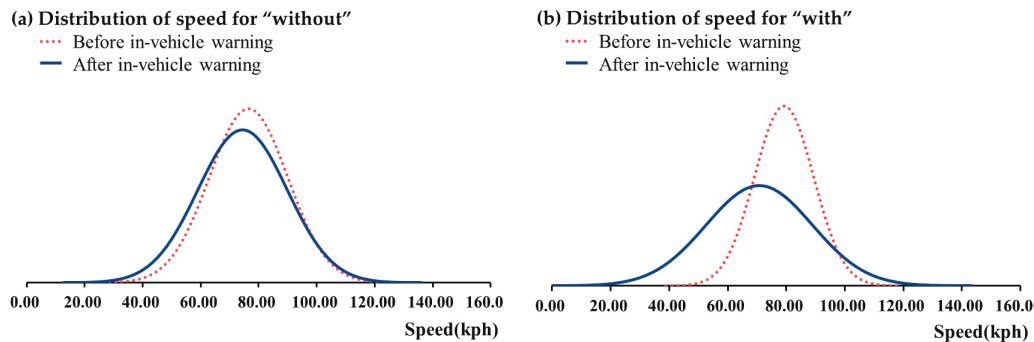


Figure 6. Speed distribution of (a) “without” and (b) “with”.

Table 3. Statistics of “without” and “with” for speed.

Statistics for Speed	Without		With	
	Before	After	Before	After
Number of records	5048	5139	31,013	26,161
Mean (kph)	76.47	74.46	79.23	70.75
Maximum (kph)	104.4	104.4	115.97	103.97
Minimum (kph)	0	0	5.98	0
Standard deviation (kph)	13.54	15.43	10.11	18.18
Variance (kph ²)	183.34	237.96	102.25	330.63
Median (kph)	79.98	77.98	79.99	75.02

As shown in Figure 6 and Table 3, the average speed after the in-vehicle warning is lower than before in both periods. Such differences are expected according to Figure 5. Interestingly, we observed that the standard deviation of speed after the warning was larger than that before in both cases but the differences in “with” was much higher than in “without”. It is suspected to be the result of driver deceleration to obtain additional spacing when the warning information is actually provided, which can also be confirmed in Figure 5.

In addition, this study conducted t-tests of speed distribution, as illustrated in Figure 6, to confirm the statistical significance. Table 4 shows the one-tailed two sample t-test result in speed for “without” and “with” periods, which was conducted with a significance level of $\alpha = 0.05$. The results in Table 4 reveal that a significant difference in speed between before and after the in-vehicle warning indicated that average speed before the warning was faster than after in both periods.

Table 4. T-test result in speed.

$H_0 : \text{Speed}_{\text{before}} = \text{Speed}_{\text{after}}$ $H_A : \text{Speed}_{\text{before}} < \text{Speed}_{\text{after}}$						
Speed	Mean		Standard Deviation		t	p-Value (* $p < 0.05$)
	Before	After	Before	After		
“without”	76.47	74.46	13.54	15.43	−6.9966	0.000 *
“with”	79.23	70.75	10.11	18.18	−70.2528	0.000 *

This study repeats the investigation in Figure 6, Tables 3 and 4 for spacing and the results are summarized in Figure 7, Tables 5 and 6.

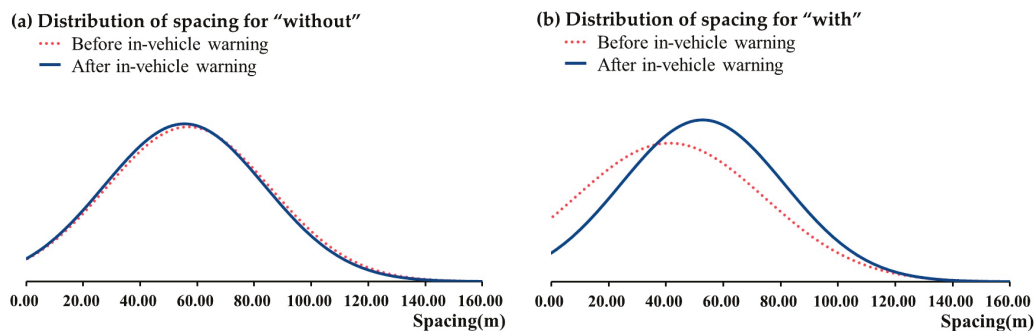


Figure 7. Spacing distribution of (a) “without” and (b) “with”.

Table 5. Statistics of “without” and “with” for spacing.

Statistics for Spacing	Without		With	
	Before	After	Before	After
Number of records	5048	5139	31,013	26,161
Mean (m)	56.81	55.52	41.36	52.84
Maximum (m)	138.00	137.00	138	143
Minimum (m)	3.00	3.00	3.00	2.00
Standard deviation (m)	28.77	28.24	33.13	28.39
Variance (m ²)	827.72	797.70	1097.64	805.73
Median (m)	56.00	56.00	40.00	52.00

As shown in Figure 7 and Table 5 for “without”, the average spacing after the warning was similar to before the warning. In Table 5 for “with”, on the other hand, the difference between the two seems clear: the average spacing after the warning was lower than before. The contrast between the “without” and “with” periods in spacing supports the premise

that the in-vehicle warning induces drivers to take additional spacing at a given speed. Table 6 summarizes the one-tailed two sample t-test result in spacing for both periods.

According to the p -value during the “without” period, we cannot reject the null hypothesis that spacing before the in-vehicle warning is the same as after while we accept the alternative hypothesis during the “with” period.

Summarizing the investigation in speed and spacing between the “with” and “without” periods, we saw that average speed after the in-vehicle warning was lower than before during both periods. However, average spacing after the warning was greater than before only during the “with” period. The findings support our suspicion that when drivers receive actual in-vehicle warning in the C-ITS environment, they are more likely to decelerate while taking additional spacing to prepare for situations downstream.

Table 6. T-test result in spacing.

$H_0: \text{Spacing}_{\text{before}} = \text{Spacing}_{\text{after}}$						
$H_A: \text{Spacing}_{\text{before}} < \text{Spacing}_{\text{after}}$						
Spacing	Mean		Standard Deviation		t	p-Value (* $p < 0.05$)
	Before	After	Before	After		
“without”	56.81	55.52	28.77	28.24	2.2779	0.9886
“with”	41.36	52.84	33.13	28.39	−44.0336	0.000 *

5.3. Comparison between “with” and “without” Periods in BMI (Behavior Monitoring Indicator)

This study also compared the “with” period with the “without” period based on the BMI calculated from Equation (1) to see if the driving behavioral difference due to the in-vehicle warning information is consistent over time. Figure 8 shows monthly box plots of BMI between July 2019 and October 2020 where both “without” and “with” periods are included. In each box plot, the top and bottom edges of a box show the first and third quartiles, and the horizontal line within the box shows the median value of the observations. A monthly average BMI is highlighted as a triangle shape, and the average BMI by period is represented as a dotted line.

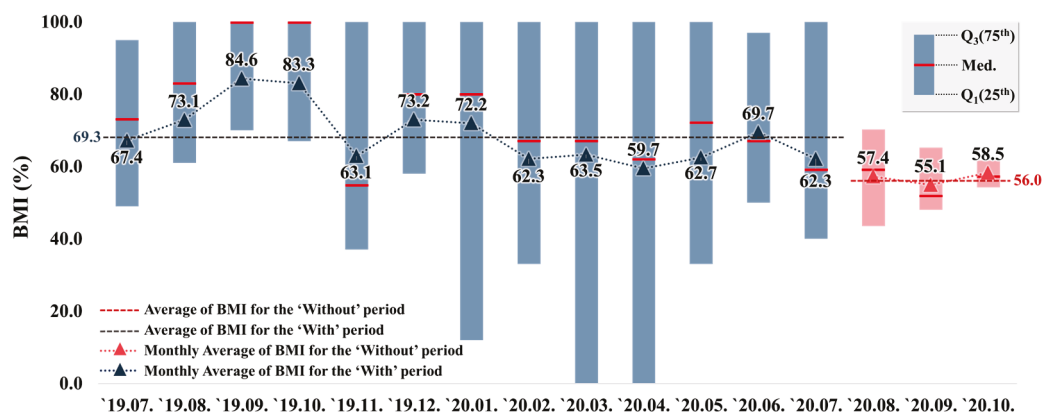


Figure 8. Timeseries of monthly BMI over 13 months.

In Figure 8, we can see that the median BMI was between 55% and 59% during the “without” period and between 62% and 85% during the “with” period. Without exception, all median BMI during the “with” period was higher than “without”. It appears that the variation in the height of the boxplot is larger in the “with” period. The difference in average BMI values between the two periods is about 13%. Figure 8 shows that more drivers responded to the warning when it was actually provided. Focusing on the trend of the monthly BMI over the “with” periods, the BMI tended to increase from July 2019 to September 2019, which was the initial period of providing FCWS warnings. Since that time,

the median BMI tended to decrease a little and then it stabilized at the average value, which was 69.3%. We suspect that some drivers selectively react to the in-vehicle warning after going through an adaptation phase. Perhaps the relatively high variation in BMI during the “with” period may also be explained by that reason.

6. Discussion and Conclusions

In the C-ITS environment, various in-vehicle warning information is implemented. Thus, it is essential to evaluate the warning services using appropriate quantitative indicators and to monitor whether the effect continues during the operation period. The evaluation process is also important because the results of the evaluation can be applied to calibrate the service parameters (e.g., activation conditions and exposure duration).

This study aims to quantitatively assess the impact of in-vehicle warning information using PVD collected from freeway C-ITSs. Leveraging the background of traffic flow theory and individual vehicle data collected in every second, we evaluated whether the warning information induces drivers to drive in a conservative way. For the evaluation, this study employed PVD collected from 700 vehicles on freeways over two different time periods: one period when the in-vehicle warning information was provided to drivers and the other when it was not.

After identifying the driving characteristics of conservative drivers in a speed–spacing plane, we compared various statistics related to speed and spacing between the two data collection periods. Our analysis revealed several significant findings regarding the effectiveness of in-vehicle warning information as follows.

- During the “with” period, drivers tend to decelerate and increase spacing when they receive an in-vehicle warning.
- Compared with the “without” period, we found empirical evidence that the in-vehicle warning information was effective in encouraging drivers to drive more conservatively.
- Since the “with” period was followed by the “without” period, some drivers selectively react to the in-vehicle warning after going through an adaptation phase (i.e., “with” period).
- Drivers’ reliability and compliance rate to the warning information could be time sensitive.

These findings provide an insight that it is imperative for the C-ITS operators to devise an MOE to evaluate the reliability of warning information and continually monitor these measures.

Despite the C-ITS operation period in this study extending over a year, it was difficult to obtain a sufficient number of valid samples. Especially, we collected the “without” data for 3 months and a relatively smaller number of samples were collected as compared with the “with” period. Expanding the data collection would enhance the comprehensiveness of this study. Of the many different types of warning information, this study only considers the FCWS warning. In future research, we intend to investigate whether other warning information has a different impact on the driver in terms of conservative driving behaviors. We emphasize that the speed–spacing relationship was applied to evaluate the effectiveness of the in-vehicle warning information. However, lateral movement, including lane-changing maneuvers, represents another potential driving behavior to be expected after receiving an in-vehicle warning. Analyzing lateral movement can be accomplished using the PVD by collecting additional in-vehicle records such as steering angle, angular velocity, and lane information.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviation

Abbreviation	Meaning
ADAS	advanced driving assistance system
BSW	blind spot warning
C-ITS	cooperative intelligent transportation system
CV	connected vehicle
DTG	digital tachograph
FCW	forward collision warning
FCWS	forward collision-warning system
IMA	intersection movement assistance
KEC	Korea Expressway Corporation
K-SMos	kinematic-based surrogate measure of safety
LCC	lane changing conflicts
LCW	lane change warning
LDWS	lane departure warning system
MOE	measure of effectiveness
MPR	market penetration rate
MSWS	motorcycle safety warning system
NCJ	number of critical jerk
PVD	per-vehicle data
RP	random parameter
RSU	roadside units
S-GWPR	semiparametric geographically weighted Poisson regression
SPMD	safety pilot model deployment
SSM	surrogate safety measure
TERCRI	time exposed rear-end crash risk index
TET	time exposed time to collision
TIT	time integrated time to collision
TTC	time to collision
TTCD	time to collision with disturbance
VSLs	variable speed limit systems

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Article

A Novel Spatial–Temporal Deep Learning Method for Metro Flow Prediction Considering External Factors and Periodicity

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Abstract: Predicting metro traffic flow is crucial for efficient urban planning and transit management. It enables cities to optimize resource allocation, reduce congestion, and enhance the overall commuter experience in rapidly urbanizing environments. Nevertheless, metro flow prediction is challenging due to the intricate spatial–temporal relationships inherent in the data and the varying influence of external factors. To model spatial–temporal correlations considering external factors, a novel spatial–temporal deep learning framework is proposed in this study. Firstly, mutual information is utilized to select the highly corrected stations of the examined station. Compared with the traditional correlation calculation methods, mutual information is particularly advantageous for analyzing nonlinear metro flow data. Secondly, metro flow data reflecting the historical trends from different time granularities are incorporated. Additionally, the external factor data that influence the metro flow are also considered. Finally, these multiple sources and dimensions of data are combined and fed into the deep neural network to capture the complex correlations of multi-dimensional data. Sufficient experiments are designed and conducted on the real dataset collected from Xi'an subway to verify the effectiveness of the proposed model. Experimental results are comprehensively analyzed according to the POI information around the subway station.

Keywords: metro flow prediction; mutual information; spatiotemporal correlations; external factors; transformer

1. Introduction

Urban rail transit is an important means of transportation in modern times. Due to the high cost of opening a new line [1], analysis of passenger flow is helpful to make full use of existing urban rail transit and to improve route planning, so as to improve its efficiency. Therefore, it is particularly important to analyze its passenger flow and predict it.

The main factors affecting the passenger demand include space, time, and semantic factors [2]. From the perspective of space, urban areas can be divided into residential areas, commercial areas, industrial areas, scenic areas, and other functional areas. In different urban functional areas, the distribution of subway stations and the demand for taking subways are different. Passenger demand between areas with similar urban functions is related [3]. In addition, passenger demand between adjacent stations is correlated. If the passenger demand of the first few stations is large, there is a high probability of high passenger demand at the next station [1]. From the perspective of time, subway passenger demand between different stations may change over time. Aside from time and space factors, whether residents choose to take the subway is also subject to a variety of semantic factors, including meteorological factors, traffic control for holidays and special activities, and other factors [4], such as location conditions and textual semantic information [5,6]. Therefore, the difficulty and key point of accurately predicting subway passenger demand

is to fuse semantic-rich nonlinear features and dynamically model the spatial–temporal correlation of data.

There are three main types of methods to predict metro flow: statistical methods, traditional machine learning methods, and deep learning methods. To predict metro flow, traditional methods like the simple moving average (MA) [7], autoregressive moving average (ARMA) [7,8], autoregressive integrated moving average (ARIMA), and their variants [7–9] are used. For example, Tang et al. used the ARIMA method in terms of varying features, forecasting steps, and forecasting horizons [9]. Nevertheless, metro flow data is usually nonlinear. This means that the linear assumption of these models limits their prediction accuracy.

To understand nonlinear dependencies in metro flow data, researchers have studied machine learning approaches like multilinear regression (MLR) [10], support vector regression (SVR) [9], logistic regression (LR) [11], support vector machines (SVMs) [12,13], decision trees (DTs) [14], the hidden Markov model (HMM) [15], and back propagation neural networks [16]. These methods overcome the limitations of the linear assumption of data. Nevertheless, the traditional machine learning methods often rely on feature extraction and selection, and they can only capture shallow nonlinear dependencies. Predicting traffic accurately is very difficult because we cannot capture detailed patterns in big datasets. This limits the use of accurate metro flow prediction.

Deep learning is a powerful machine learning technique. It has great potential for predicting metro flow [17]. Deep learning can automatically model complex relationships between stations and time intervals. For instance, Xiong et al. proposed a real-time metro flow prediction model using a convolutional neural network (CNN) to predict an urban rail transit passenger flow time series and spatial–temporal series [18]. Recurrent neural networks (RNNs) have emerged as the preferred neural network for temporal dependencies [19]. Nevertheless, traditional RNNs have the problem of gradient disappearance and gradient explosion in long-term prediction. LSTM and GRU networks are special versions of RNNs that solve the gradient problem effectively [20]. GRUs can capture long-term dependencies in sequential data and train the model faster [21]. Shi et al. used a fully connected neural network with short-term memory to predict metro flow [21]. The network was trained using historical metro flow data and meteorological data. Furthermore, there are advanced deep learning approaches like attention mechanism-based methods and semi-supervised deep learning methods [22–24]. Xie et al. innovatively built a spatial–temporal dynamic graph relationship learning model [25], and Zhang et al. introduced a spatial–temporal graph GAN for accurate short-term passenger flow forecasting [26].

However, these studies lack sufficient consideration at the semantic level of the demand for subway travel. The spatial correlation modeling did not consider the impact of metro flow patterns and similar regional functions of adjacent stations ahead of the examined station. Furthermore, the long-term dependency features of the incorporated data were not taken into account when modeling time correlation.

In summary, the key to accurately predicting metro flow lies in modeling the spatial–temporal and semantic information of the metro flow data. Therefore, this paper proposes a novel deep learning method to model the spatiotemporal correlations of the incorporated data considering semantic information. The contributions of this study are as follows: (1) This paper models the spatial correlation of metro flow data considering the flow of related stations ahead of the examined station. Firstly, from a location perspective, there may be a correlation between the metro flow of related stations ahead of the examined station. Thus, this paper selects the metro flow data of strongly correlated stations using mutual information as the incorporated data. Compared to Pearson’s coefficient, mutual information methods are more suitable for nonlinear flow data. Secondly, from a semantic perspective, stations with similar urban functions (point of interest) may have similar metro flows. Thus, this paper explains the experimental results from the perspective of urban functions. (2) Besides the urban function factor, there are other external factors that may affect the metro flow of stations, such as meteorological factors. Thus, this paper

incorporates external data. (3) According to the previous two steps, the incorporated data includes the metro flow data of the examined station, the metro data of the selected stations, and various external data. To model the temporal correlation of the incorporated data, the transformer neural network is adopted to capture the time dependence between multidimensional data. The self-attention mechanism in the network can perform parallel computation and overcome information attenuation in long-term sequence prediction. In addition, the self-attention mechanism can enable deep neural networks to focus on features that are important for improving prediction accuracy when training the network. Compared with neural networks without self-attention mechanisms, the predicted results are more explanatory. (4) Finally, sufficient experiments are conducted on real metro flow data set collected from Xi'an subway to verify the effectiveness of the proposed method. Moreover, this study analyzes the prediction results, visualizes the feature weights learned from the network at different times, analyzes the important features and moments captured by the network, and evaluates the prediction results.

2. Related Work

2.1. Factors' Impact on Metro Flow

Metropolitan traffic flow is a complex and dynamic phenomenon influenced by various intrinsic and extrinsic factors, including spatial characteristics, temporal dependencies, and external factors from multi-source data. From the view of spatial modelling, subway systems, as integral components of urban transportation networks, exhibit a dynamic spatial structure wherein the flow of passengers is intricately connected. The downstream flow of metro stations is influenced by the upstream flow. Yuhang Xu et al. proposed a feature fusion network (AFFN) to fuse spatial dependencies from multiple knowledge-based graphs and even hidden correlations between stations [27].

From the perspective of temporal dependencies, historical passenger flow has a certain impact on the future passenger flow, and human flows in a city have shown periodic patterns over days, weeks, or months. Metro passenger data is generally associated with temporal characteristics that are repetitive at fixed time intervals. For example, the metro passenger flow at a certain time interval may be similar to that of the same time interval on the previous day, which suggests that 24 h should be taken as the cycle period [19]. Hongwei Jia et al. proposed a network which uses three independent channels with the same structure to model recent, daily periodic, and weekly periodic complicated spatiotemporal correlations, respectively. This model captured not only the steady trend, but also the sudden changes in passenger flow [28]. Peikun Li et al. proposed a framework of short-term passenger flow to explore the factors that influence prediction accuracy based on time granularity and station class [29].

External factors may influence passenger flow, such as weather conditions, air quality, the day of the week, holidays, and events. Arief Koesdwiady et al. adopted a DBN to predict traffic flows and investigated the correlation between weather parameters and traffic flow [30]. Jinlei Zhang et al. proposed an architecture to forecast short-term passenger flow in an urban rail transit on a network scale. It was the first time that air-quality indicators had been taken into account, and their influences on prediction precision were quantified [31]. Junbo Zhang et al. proposed a deep learning approach to forecast the entry and exit flow of crowds in each region of a city. This approach was combined with external factors, such as weather [32]. Enhui Chen et al. proposed a generic framework to analyze short-term passenger flow, considering the dynamic volatility and nonlinearity of passenger flow during special events [33].

2.2. Metro Flow Prediction Models

Methods for predicting metro flow have usually been classified into traditional statistical approaches and machine learning techniques. The traditional statistical method ARIMA comprises a linear combination of time-lagged variables and error terms. It has found extensive application in predicting traffic-related data including, but not limited to,

metro flow, traffic flow, travel time, speed, and occupancy [34–36]. For instance, Yan et al. used ARIMA and focused on determining the most appropriate parameters of ARIMA to predict short-term metro flow [37]. The traditional statistical approaches demonstrate strong and consistent performance in modeling time series that exhibit linearity and stationarity. However, metro flow data often exhibits nonlinearity, thereby limiting the predictive accuracy of models based on linear assumptions.

To capture nonlinear dependencies within metro flow data, researchers have explored a range of machine learning approaches, including multilinear regression, support vector machines, random forest regression, hidden Markov models, backpropagation neural networks, hybrid methods, and so on. For instance, Liu et al. proposed a least-square support vector approach to handle the complex fluctuations in holidays and predicted passenger flow for a metro system [12]. Yao et al. proposed an innovative approach for predicting metro flow, employing a random forest regression model and leveraging multi-source data [38]. Nevertheless, these conventional machine learning methods are constrained in their ability to capture only shallow nonlinear dependencies, neglecting the long-term time series patterns and deeper nonlinear dependencies inherent in the data.

Recently, deep learning has evolved into an advanced machine learning technique, holding considerable promise for predicting metro flow. Deep learning methods possess the ability to automatically model intricate spatial and temporal dependencies within data. Moreover, the reliance on manual feature engineering can be mitigated by employing deep neural networks. For instance, deep neural networks are designed to intricately and abstractly extract nonlinear features embedded in their inputs [39]. Shen et al. used a convolutional neural network (CNN) model for metro passenger flow prediction employing spatial–temporal data fusion. The dynamics of spatial–temporal passenger flow were transformed into a two-dimensional time–space matrix that characterized the temporal and spatial relationships of passenger flow. Then, the optimal hyperparameter combinations for the CNN were determined by the grid search algorithm [40]. Recurrent neural networks (RNNs) are able to model temporal dependencies. However, they face challenges such as gradient vanishing and explosion during long-term prediction. Long short-term memory (LSTM) networks and gated recurrent units (GRUs), as specialized RNN variants, effectively address the severe gradient problem. They excel in capturing long-term dependencies in sequential data, with the added advantage of faster model training for GRUs. Sun et al. proposed a novel ensemble learning model assembling LSTM, support vector regression (SVR), and a sparrow search algorithm to deal with long term metro passenger flow prediction [41]. Moreover, several advanced deep learning approaches have been applied to metro flow prediction, such as attention mechanism-based approaches, graph neural network-based approaches, and some hybrid deep learning approaches. For example, Zhang et al. proposed a novel deep learning method combining a graph convolutional network (GCN) and a three-dimensional convolutional neural network (3D-CNN) enhanced by the incorporation of a residual module and an attention mechanism [42]. Due to their self-attention mechanism, transformer-based deep learning architectures are applied for traffic prediction widely, and are capable of sequential data modeling. Thus, a transformer-based deep learning framework is designed, incorporating various types of influencing factor data, for this study.

3. Methods

3.1. Problem Statements and Framework

The objective of predicting the passenger flow at a specific subway station is to utilize historical data to accurately predict the numbers of inbound and outbound passengers for forthcoming single or multiple time intervals. Let $S_i = (S_1, S_2, \dots, S_n)$ represent a station with a total of n stations. For time t , the data of entry or exit given the target site over the past h time intervals is denoted as $X = (X_{t-h+1}, X_{t-h+2}, \dots, X_t)$, where $X \in R^h$ and X_t represent the entry (or exit) data of station S_i during the t^{th} time interval. X_t contains $X_t^{S_i}$, X_t^i , X_T , and $X_t^{F_i}$, which represent related station flow data, station flow data, periodic flow

data, and external factor data, respectively. The predicted flow of the future t time intervals is denoted as $X' = (X_{t+1}, X_{t+2}, \dots, X_{t+t'})$, where $X \in R^{t'}$ and t are positive integers.

To address the problem of metro flow prediction, this study proposes a spatiotemporal framework based on a transformer framework considering external factors and time periodicity, which is shown in Figure 1. Specifically, the input of the framework includes the recent historical metro flow data of the examined and related stations, temperature, precipitation data, and the historical metro flow for different time periods. From the spatial perspective, the mutual information is utilized to select the strongly correlated upstream stations of the examined relation. The metro flow from the selected stations is incorporated into the neural network. From the temporal perspective, the current metro flow is influenced by the historical metro flow from recent time intervals and the historical metro flow data from the previous days and weeks at the same interval. Thus, the metro flow from recent historical intervals and different time periods is considered to be incorporated. From the semantic perspective, the metro flow is also influenced by external factors, such as temperature, and precipitation. Those data are represented as a multidimensional feature matrix and input into the transformer network. Then, the metro flow of the future intervals is predicted.

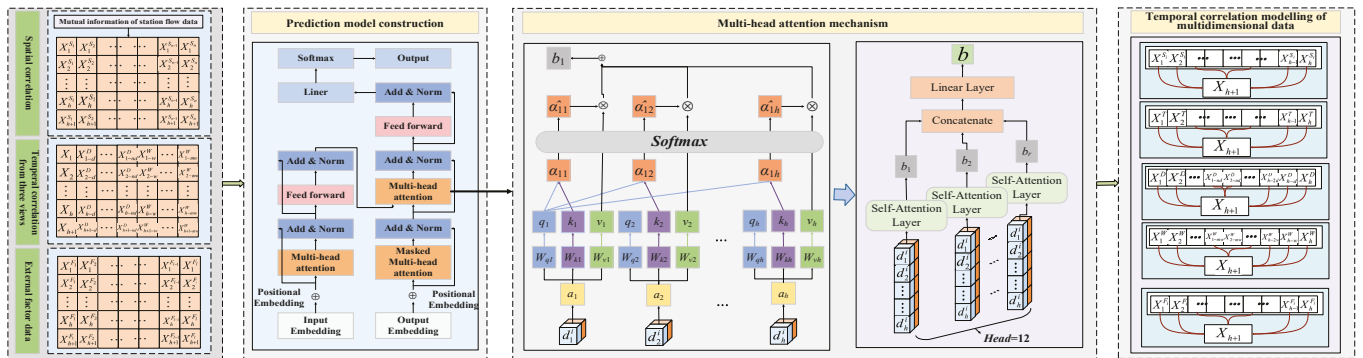


Figure 1. The research framework of this study.

3.2. Spatial Correlation Based on Station

Stations exhibiting similar patterns of flow fluctuations are regarded as correlated. Consequently, in this study, the metro flow of correlated stations is incorporated to construct predictive models. However, stations with such correlations are not always geographically adjacent. Additionally, the metro flow at a specific station is typically influenced by the flow patterns at stations that are similarly correlated. Thus, the mutual information is utilized in this study to select the stations that have an important impact on the current station using historical metro flow data. Mutual information is very capable of capturing the nonlinearity of flow data. Unlike traditional correlation coefficients, such as the Pearson correlation coefficient, which predominantly focuses on linear relationships, mutual information has the ability to effectively measure both linear and nonlinear correlations. Considering that the traffic of the examined station is affected by the traffic of the upstream stations, only the upstream stations that have a significant impact on the examined station are considered.

The vectors $X^i = (x_1^i, x_2^i, \dots, x_h^i)$ and $X^s = (x_1^s, x_2^s, \dots, x_h^s)$ represent the entry and exit station sequences of site i and site s , respectively. Where $i, s \in (1, 2, \dots, n)$, h represents the number of input data and x_h^i represents the entry and exit flow at station i in the h^{th} time interval. The series statistics represent the number of entry and exit stations of a station over a fixed length of time and arrange them in chronological order. The information entropy, $H(X^i)$, of the entry and exit stations, X^i , of the station, i , is expressed as

$$H(X^i) = \sum_{c_i \in X^i} p(c_i) \lg p(c_i) \quad (1)$$

Here, c_i is the number of entry and exit stations at a certain time in the sequence of station entry and exit stations in X^i , while $p(c_i)$ is the probability of $x_t^i = c_i$.

The mutual information, $I^{is}(X^i; X^s)$, of X^i and X^s is calculated to represent the correlation between site i and site s .

$$I^{is}(X^i; X^s) = H(X^i) - H(X^i|X^s) \quad (2)$$

$$I^{is}(X^i; X^s) = \sum_{c_i \in X^i} \sum_{c_s \in X^s} p(c_i, c_s) \lg \frac{p(c_i, c_s)}{p(c_i)p(c_s)} \quad (3)$$

Here, $H(X^i|X^s)$ is X^i conditional entropy of given X^s , which represents the uncertainty of the entry and exit station quantity X^i of station i when the value of the entry and exit station quantity X^s of station s is given; $p(c_i, c_s)$ is a joint probability function of $x_t^i = c_i$ and $x_t^s = c_s$. The mutual information measures the degree of interdependence between two variables, indicating the reduced uncertainty of one variable by knowing another variable by computing the mutual information to obtain the two upstream sites most relevant to the current site.

3.3. Temporal Correlation Based on Three Views of Historical Metro Flow

Many previous studies only use historical metro flow data at several previous time intervals. Two sequences of data come from the same number of historical time intervals, which may also differ due to factors such as peak intervals, holidays, etc. Thus, temporal features such as previous time and the day of the week require consideration when constructing a prediction model. Previous time intervals represent the correlations between metro flow at a current time interval and historical time intervals. Day of the week represent the historical trend of metro flow change because the data comes from the same time interval of the same day during previous weeks. Time series-related flow features are represented as $X_T = \{X_t^T, X_t^D, X_t^W\}$, where t represents the t^{th} time interval. X_t^T represents the metro flow at the t^{th} time interval, $X_t^D = (X_{t-d}^D, X_{t-2d}^D, \dots, X_{t-nd}^D)$ represents the metro flow at the same time interval of previous days, and n is the number of days. $X_t^W = (X_{t-w}^W, X_{t-2w}^W, \dots, X_{t-mw}^W)$ represents the metro flow at the same time interval of previous weeks and m is the number of weeks. As the framework figure shows, there are three views of historical flow data that are considered. Except for the recent historical flow data, the flow data with historical trends is incorporated into the deep neural network.

3.4. Incorporation of External Influencing Factor Data

From the semantic perspective, this study incorporates external factor data into the predictive model, which is represented as $X_t^{F_l} = (X_t^{F_1}, X_t^{F_2}, \dots, X_t^{F_l})$, where l is the number of external factors. In this paper, the external factor data includes temperature and precipitation. The underlying reason is the substantial impact that weather conditions have on individuals' choices of transportation modes when traveling. For instance, higher temperatures or heavy rainfall can lead to changes in the usual patterns of subway usage, such as increased ridership during rainy days, as people avoid walking or cycling. By including these external factors in the predictive model, the accuracy and reliability of the prediction model is enhanced.

3.5. Prediction Model Construction Based on the Transformer Framework

Multidimensional feature data contains rich spatiotemporal information. The data are fed into the deep neural network for complex temporal correlation of multi-dimensional data. The data includes the historical metro flow from highly correlated stations, historical metro flow of examined stations from two temporal perspectives, and external factor data.

After calculating the mutual information, the selected flow data of the two sites most related to the examined site, the historical flow data of the examined site, the periodic flow data, and the external factor data are combined to obtain the model input data $D^i = (d_1^i, \dots, d_h^i)$, where $D^i \in R^{h \times l}$. The l includes the most related station's S^1 and S^2 ,

the historical flow data of the current site, the periodic flow data, the temperature, and the precipitation, and the periodic flow data contains X_t^T , X_t^D , and X_t^W .

The combined multi-dimensional data are then input into the transformer network. The network adopts an encoder–decoder structure, and the encoder consists of a multi-head self-attention layer and a feed-forward layer. A normalization layer is used after each layer to increase the speed of network training. The encoder is trained to generate a hidden layer vector and pass it to the decoder. The decoder consists of two multi-head self-attention layers and a feed-forward layer, each sub-layer is followed by a normalization layer, and the first multi-head self-attention layer uses a mask mechanism.

The core of encoding–decoding is the multi-head attention mechanism, which preliminarily encodes D^i to obtain matrix $A = (a_1, \dots, a_h)$, where a_t is the vector obtained by d_t^i after encoding and $t \in (1, 2, \dots, h)$. The initialized feature matrices W_Q , W_K , and W_V are used to linearly transform A to obtain the query vector, $Q = (q_1, \dots, q_h)$, the key vector, $K = (k_1, \dots, k_h)$, and the value vector, $V = (v_1, \dots, v_h)$, i.e.,

$$Q = W_Q A, K = W_K A, V = W_V A \quad (4)$$

In the self-attention mechanism, the scaled dot product is usually used as the attention scoring function. Firstly, the attention score is obtained through the dot product of query vector Q and key vector K , then it passes the softmax and product value vector, V , to obtain the whole weight and output vector. Its equation is represented as:

$$Z(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

Then, the multiple groups of W_Q , W_K , and W_V are multiplied with the encoded input vectors to obtain multiple groups of Q , K , and V . The multiple group matrix $b_1, \dots, b_r$ obtained from groups W_Q , W_K , and W_V are stitched together to obtain the final output, b . The transformer network trains with the multi-head attention mechanism as its core, and the potential temporal correlation in the data can be effectively captured.

4. Dataset, Experimental Settings, and Evaluation

4.1. Dataset Description

To verify the effectiveness of the method proposed in this study, the entry and exit metro flows with fifteen-minute granularity from Xi'an subway stations between October 2018 and March 2019 were collected. Table 1 shows the station names and numbers used in this study.

In addition, temperature and precipitation data of Xi'an city with the same time granularity were also collected for experiments. Moreover, POI data were collected according to the latitude and longitude range of the subway station and utilized to explain the experimental results in this study. A POI refers to a distinct geographic location that provides a particular service to individuals, such as a shopping center, industrial facility, or residential area. In total, there were 241,869 POIs collected near each subway station within an 800 m radius of line 1 to line 4. In this study, Zhonglou station and Hangtiancheng station were selected as the research objects.

4.2. Experimental Settings

Experiments were conducted using Python 3.7 and PyTorch 1.7.1 on a desktop computer with an Intel i9-13900KF 3.0 GHz CPU (Intel, Santa Clara, CA, USA), which has a performance of 153,377 MOps/s and 64 GB RAM. It used 80% of the data in the dataset for training and another 20% for test data. LSTM and GRU have a two-layer network with 128 neurons each. The deep encoder network was set up to 12 heads. The learning rate was set to 0.001, the training iteration was set to 100 times, and the batch size was set to 64.

The typical approaches used for time series data prediction were adopted as the baseline methods, including LSTM, GRU, and the transformer framework.

Table 1. Subway station descriptions.

Station Number	Station Name
S1	Beikezhan Station
S2	Beiyuan Station
S3	Yundonggongyuan Station
S4	Xingzhengzhongxin Station
S5	Fengchengwulu Station
S6	Shitushuguan Station
S7	Daminggongxi Station
S8	Longshouyuan Station
S9	Anyuanmen Station
S10	Beidajie Station
S11	Zhonglou Station
S12	Yongningmen Station
S13	Nanshaomen Station
S14	Tiyuchang Station
S15	Xiaozhai Station
S16	Weiyijie Station
S17	Huizhanzhongxin Station
S18	Sanyao Station
S19	Fengqiyuan Station
S20	Hangtiancheng Station
S21	Weiqunan Station

4.3. Evaluation

To verify the prediction performance of the proposed method, the RMSE, MAE, and MAPE were adopted as the evaluation indicators. The equations are as follows:

$$RMSE = \sqrt{\frac{1}{C} \sum_{i=1}^C (y_i - y'_i)^2} \quad (6)$$

$$MAE = \frac{1}{C} \sum_{i=1}^C \|y_i - y'_i\| \quad (7)$$

$$MAPE = \frac{1}{C} \sum_{i=1}^C \left\| \frac{y_i - y'_i}{y_i} \right\| \quad (8)$$

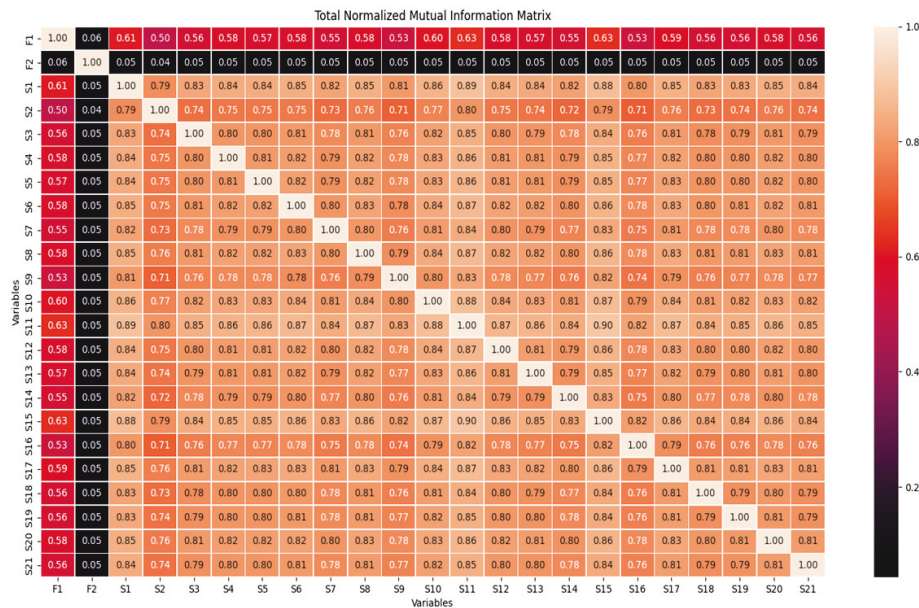
Here, y'_i and y_i denote the predicted value and observed true value, respectively, and C is the number of all samples.

5. Experimental Results

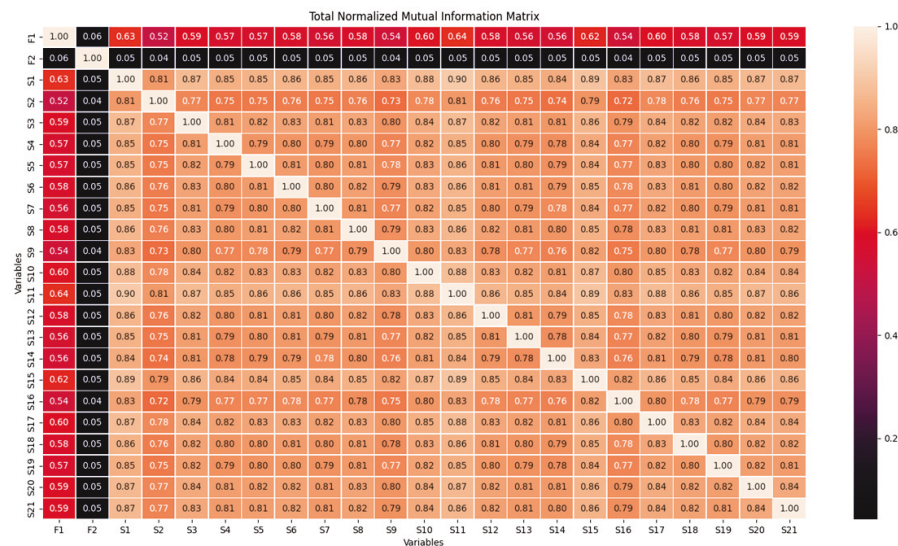
5.1. Results of Spatial Modelling

The object of spatial modelling is to incorporate the flow data of highly correlated stations into the model to improve the prediction accuracy. MI was used to measure the spatial correlation of stations using the flow data. The results of MI among all stations are shown in Figure 2. According to the results, the station XiaoZhai was selected as the

correlated station of the predicted station, Zhonglou. The MI value was 0.9, which is higher than other stations.



(a)



(b)

Figure 2. Total normalized mutual information matrix. (a) Mutual information calculated by entry flow. (b) Mutual information calculated by exit flow.

5.2. Results of Time Interval Determination

When predicting metro flow, data with different historical time intervals can lead to different results. Shorter time intervals might not provide enough input data for the model to capture time-related patterns, while longer intervals could incorporate irrelevant inputs. Thus, to determine the optimal number of historical time intervals for superior predictive performance, this study incorporates historical data with different time intervals into the model to forecast entry and exit flows for the next time interval. The entry and exit metro flow prediction results of different historical time intervals for the two selected stations are illustrated in Table 2.

Table 2. The entry and exit flow prediction results of different historical time intervals.

Time Interval	Evaluating Indicators											
	Zhonglou Station (Entry)			Zhonglou Station (Exit)			Hangtiancheng Station (Entry)			Hangtiancheng Station (Exit)		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
24	75.25	49.32	13.69%	91.08	61.42	22.71%	56.31	36.30	25.37%	61.15	40.46	39.58%
28	78.20	51.76	13.67%	91.99	59.51	23.55%	56.10	34.75	16.37%	60.59	41.24	44.43%
32	74.90	48.54	20.52%	88.77	57.41	20.76%	56.12	34.04	16.54%	58.67	39.05	42.97%
36	78.73	50.21	17.14%	88.67	60.03	14.85%	56.15	34.82	18.25%	59.82	39.55	35.64%
40	74.51	48.82	17.14%	90.41	63.14	35.93%	55.98	37.83	31.40%	54.39	37.23	31.49%
44	73.10	49.22	19.02%	88.45	60.95	20.05%	54.29	33.46	20.82%	54.62	36.97	36.77%
48	71.27	46.85	10.35%	85.78	59.50	26.49%	53.46	33.51	19.12%	52.80	35.19	18.78%
52	69.27	45.34	16.02%	87.24	59.57	15.40%	53.83	32.35	17.89%	54.01	36.04	30.34%
56	70.55	47.89	19.14%	86.28	55.52	13.97%	55.01	33.05	17.83%	53.69	36.27	27.52%
60	67.63	45.30	14.75%	93.86	60.84	18.00%	54.74	33.40	19.63%	53.60	36.65	35.14%

The results indicate that the optimal historical time intervals for predicting entry and exit flow at Zhonglou Station are 48 and 56, respectively. Similarly, the optimal historical time intervals for predicting entry and exit flow at Hangtiancheng Station are 52 and 58, respectively. Taking Zhonglou Station's entry flow prediction as an example, when the input time interval was set to 48, the RMSE, MAE, and MAPE were 71.27, 46.85, and 10.35%, respectively. Notably, the MAPE exhibited the most significant decrease compared to other time intervals. The model demonstrated the best predictive performance under these specific input time intervals. Therefore, this time interval configuration was adopted for subsequent experiments.

5.3. The Predicted Results of the Selected Stations

Table 3 presents the specific numerical values of three evaluation indicators for entry and exit metro flow predictions at Zhonglou Station and Hangtiancheng Station using different methods. In comparison to baseline methods (LSTM, GRU, transformer), the proposed method based on the transformer (MFP-EP) framework outperformed the baseline methods. The self-attention mechanism effectively captured the underlying long-term dependencies among features. Based on the results, incorporating various related data can improve the prediction accuracy. The model considers the influence of the upstream flow, the correlated stations, the recent historical metro flow, the historical temporal trend, and the external factors.

Moreover, when incorporating all factors comprehensively, the predictive accuracy was higher compared to considering individual factors separately. For instance, taking Zhonglou Station's entry flow as an example, the overall predictive performance of MFP-EP + F1 + F2 + 2S + 4C was the best among the methods considered. Its RMSE, MAE, and MAPE values were 68.60, 45.86, and 10.04%, respectively. Compared to the transformer method, these values decreased by 13.58%, 18.56%, and 64.50%, respectively. Additionally, when compared to LSTM, these values decreased by 18.18%, 20.37%, and 67.08%, respectively.

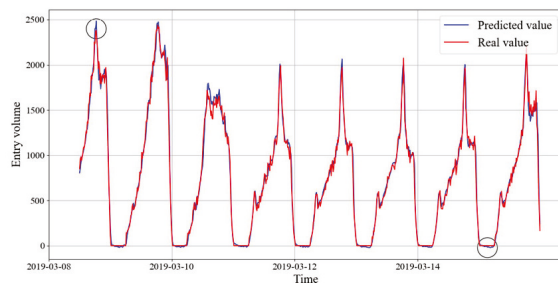
5.4. Analysis of Prediction Results

Figure 3 illustrates the distribution of predicted values versus actual values when the model comprehensively considered factors such as temperature, precipitation, and the actual metro flow of the two stations that were most correlated to the target station based on the transformer method. According to the figure, it is evident that the distribution of predicted values closely aligns with the actual values, with most predictions closely

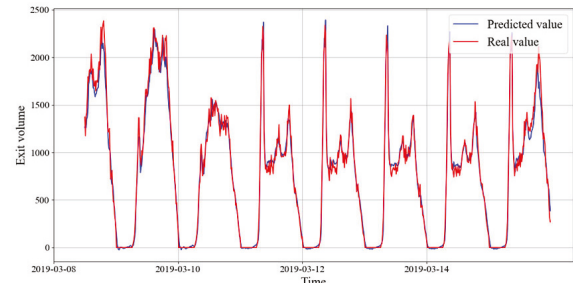
matching the real data. The model successfully captured the peak and off-peak patterns of entry and exit flow. In Figure 3a, the peaks and troughs are marked with hollow circles. The peak occurred during the evening rush hours, specifically between 17:00 and 19:00, while the trough corresponds to the early morning hours when the subway services are temporarily halted.

Table 3. Prediction results for the selected stations.

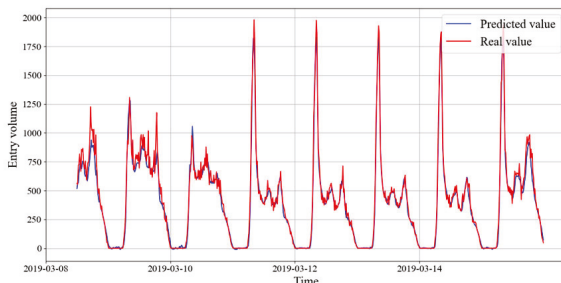
Experimental Methods	Zhonglou Station (Entry)			Zhonglou Station (Exit)			Hangtiancheng Station (Entry)			Hangtiancheng Station (Exit)		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
LSTM	83.84	57.59	30.50%	96.72	66.94	22.52%	56.57	35.83	28.06%	60.39	38.68	36.50%
GRU	82.66	55.00	31.24%	96.66	67.35	22.99%	55.84	34.21	27.52%	58.91	40.38	38.74%
Transformer	79.38	56.31	28.28%	96.90	65.49	19.56%	55.21	34.50	24.24%	59.15	40.80	33.25%
MFP-EP + F1	72.57	48.06	15.24%	92.25	64.96	43.82%	55.73	34.61	18.04%	54.78	38.91	41.23%
MFP-EP + F2	72.86	48.22	16.44%	97.29	63.18	15.53%	53.88	35.21	21.55%	55.57	37.82	31.28%
MFP-EP + F1 + F2	70.43	47.68	19.33%	90.77	61.15	23.06%	55.12	35.14	27.73%	54.53	38.01	38.24%
MFP-EP + 1S	72.58	49.55	20.13%	93.61	60.93	23.32%	54.85	33.39	21.71%	54.35	37.01	25.89%
MFP-EP + 2S	70.06	48.08	10.80%	83.56	55.73	18.71%	53.31	36.47	21.83%	55.06	37.42	35.20%
MFP-EP + F1 + F2 + 2S	71.27	46.85	10.35%	86.28	55.52	13.97%	53.83	32.35	17.89%	52.80	35.19	18.78%
MFP-EP + F1 + F2 + 2S + 4C	68.60	45.86	10.04%	80.26	51.52	13.35%	52.42	30.24	16.83%	51.39	33.83	17.84%



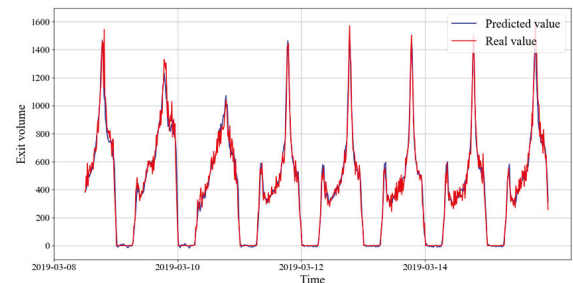
(a)



(b)



(c)



(d)

Figure 3. Entry and exit volume of Zhonglou Station and Hangtiancheng Station. (a) Entry volume prediction results for Zhonglou Station. (b) Exit volume prediction results for Zhonglou Station. (c) Entry volume prediction results for Hangtiancheng Station. (d) Exit volume prediction results for Hangtiancheng Station.

Furthermore, the experimental results indicate that the peak entry and exit flows at Zhonglou Station are generally higher than those at Hangtiancheng Station. Both stations exhibited certain patterns, with variations in entry and exit flow between weekdays and weekends. Specifically, the peak entry and exit flows at Zhonglou Station typically ranged between 2000 and 2500, whereas at Hangtiancheng Station, the peak flow usually ranged between 1400 and 2000. This study then explained the flow changes from the perspective of urban functional zones. POI data within an 800 m radius around Zhonglou Station and Hangtiancheng Station were collected, as shown in Table 4. The data in the table refers to the number of POIs of a specific type within 800 m of the site. For example, 884 refers to the number of food and beverage services within 800 m of Zhonglou Station. The results indicate significantly higher numbers for sports and leisure services, accommodation services, public facilities, and scenic spots around Zhonglou Station (256, 900, 91, 35, respectively) compared to Hangtiancheng Station (53, 166, 10, 7, respectively). This suggests that Zhonglou Station serves as a commercial and tourist hub with a relatively high population density. Additionally, the number of companies, government institutions, and social organizations around Zhonglou Station is notably higher than around Hangtiancheng Station, indicating a larger daily population flow.

Moreover, 10 March 2019 was a Sunday, a typical rest day for most people. As expected, the entry and exit flows at the target stations significantly decreased on this day. In contrast, from 11 March to 15 March, which fall within the workweek, the entry and exit flows exhibit similar patterns. Additionally, the residential areas around Hangtiancheng Station are noticeably more abundant than around Zhonglou Station. This indicates that Hangtiancheng Station is located in a residential area, resulting in lower entry and exit counts on weekends compared to weekdays. In contrast, Zhonglou Station, as a tourist destination, experiences higher entry and exit counts on weekends compared to weekdays.

Finally, a few predicted values deviated from the actual values, which could be attributed to prediction errors caused by uncertain events. This observation aligns with the real urban traffic conditions, where traffic congestion during peak hours and unexpected traffic incidents can irregularly impact travel demand data, thus reducing the model's predictive accuracy.

Table 4. POI data within an 800 m radius around Zhonglou Station and Hangtiancheng Station.

POI	Zhonglou Station	Hangtiancheng Station
Food and beverage services	884	792
Shopping services	838	882
Life services	888	811
Sports and leisure services	256	53
Health care services	160	188
Accommodation services	900	166
Scenic spots	35	7
Government agencies and social organizations	216	115
Science and education cultural services	149	114
Transportation facilities services	263	69
Financial and insurance services	81	39
Incorporated businesses	302	81
Public facilities	91	10
Industrial parks	0	2
Residential areas	71	105

5.5. Analysis of Time Interval Correlation by Attention Mechanism

In comparison to other time intervals, the network focuses more on learning the entry flow of nearby time intervals within the same day. Taking the prediction of entry flow at Zhonglou Station as an example, Figure 4 illustrates the attention weight distribution obtained from an attention layer with a time interval of 48 steps. The horizontal axis represents the time steps, with each tick indicating one time interval, and the color intensity indicates the corresponding attention weight. For instance, consider Figure 4a, where the prediction time is 8:45~9:00. Time steps 2, 46, 47, and 48, corresponding to the time intervals 9:00~9:15, 20:00~20:15, 20:15~20:30, and 20:30~20:45, respectively, have relatively higher attention weights. These time intervals represent specific periods on the same day, as well as on previous days and weeks. Furthermore, Zhonglou Station is located near popular tourist attractions, and the entry flow during these time intervals remains high throughout the day, as the predicted time interval also falls within the peak period.

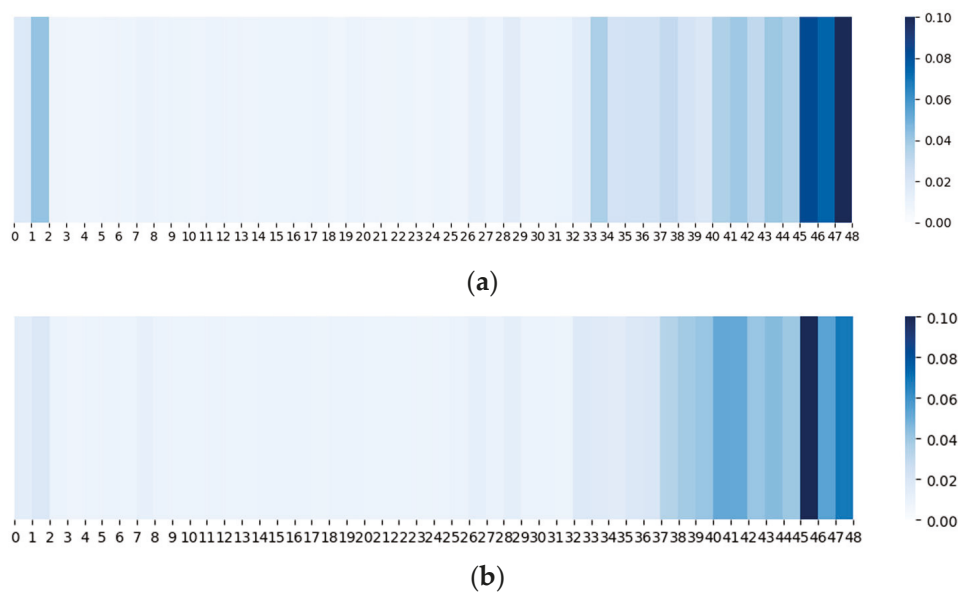


Figure 4. Attention matrices generated by the transformer framework. (a) Time interval: 8:45–9:00. (b) Time interval: 6:45–9:00.

5.6. Analysis of Multi-Step Prediction Results for Entry and Exit Flow

The predictive performance of the model was also validated for multi-step metro flow prediction. Figure 5 illustrates the multi-step prediction results for the next eight steps (2 h). Compared with the baseline method, the proposed method is more accurate over a longer prediction period. Specifically, compared with the LSTM model, the mean values of $MFP-EP + F1 + F2 + S1 + S2$ for RMSE, MAE, and MAPE were reduced by 15%, 24.63%, and 34.02%, respectively, when the predicted step size is 2, and the proposed method was reduced by 6.5%, 7.26%, and 34.70%, respectively, compared with the mean of the baseline method when the predicted step size was 8.

The prediction error increased with the prediction step size. There are two main reasons for this. Firstly, compared with single-step prediction, the error accumulates in the process of multi-step prediction. The larger the number of prediction steps, the greater the accumulated error. Secondly, with the increase in time steps, the traffic environment gradually becomes complex, and the nonlinearity and fluctuation of the flow data in and out of the station gradually increase.

Compared with deep learning methods such as LSTM, the performance advantage of the proposed method in multi-step prediction is more obvious. This is not only due to the fact that the self-attention mechanism of the transformer model can capture more information in the time series prediction, but also because the model considers the temperature, the

precipitation, the flow of the correlated stations, and the flow of different time granularities. The error accumulation rate of the method in multi-step prediction is much lower than that of methods such as LSTM.

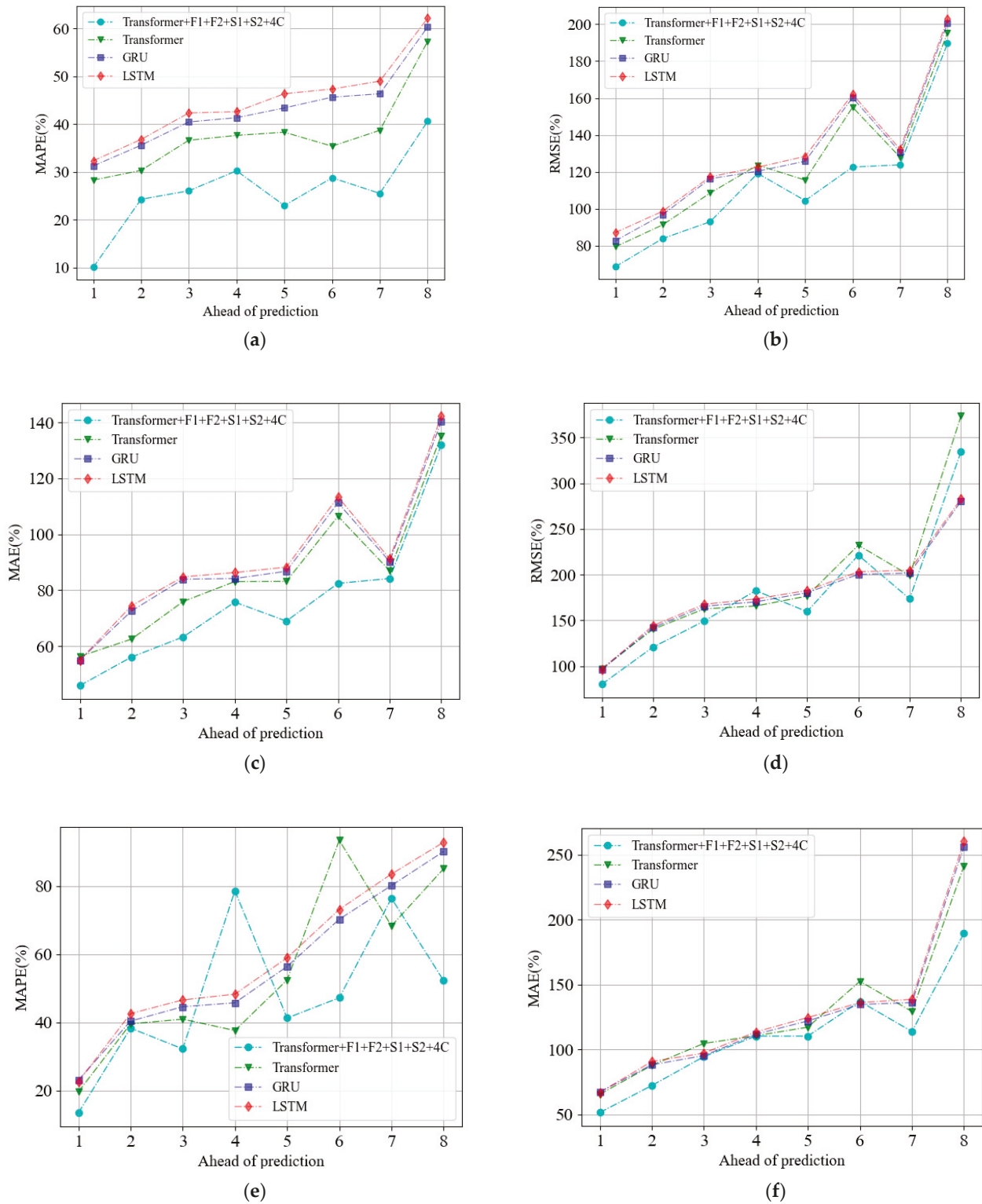


Figure 5. Cont.

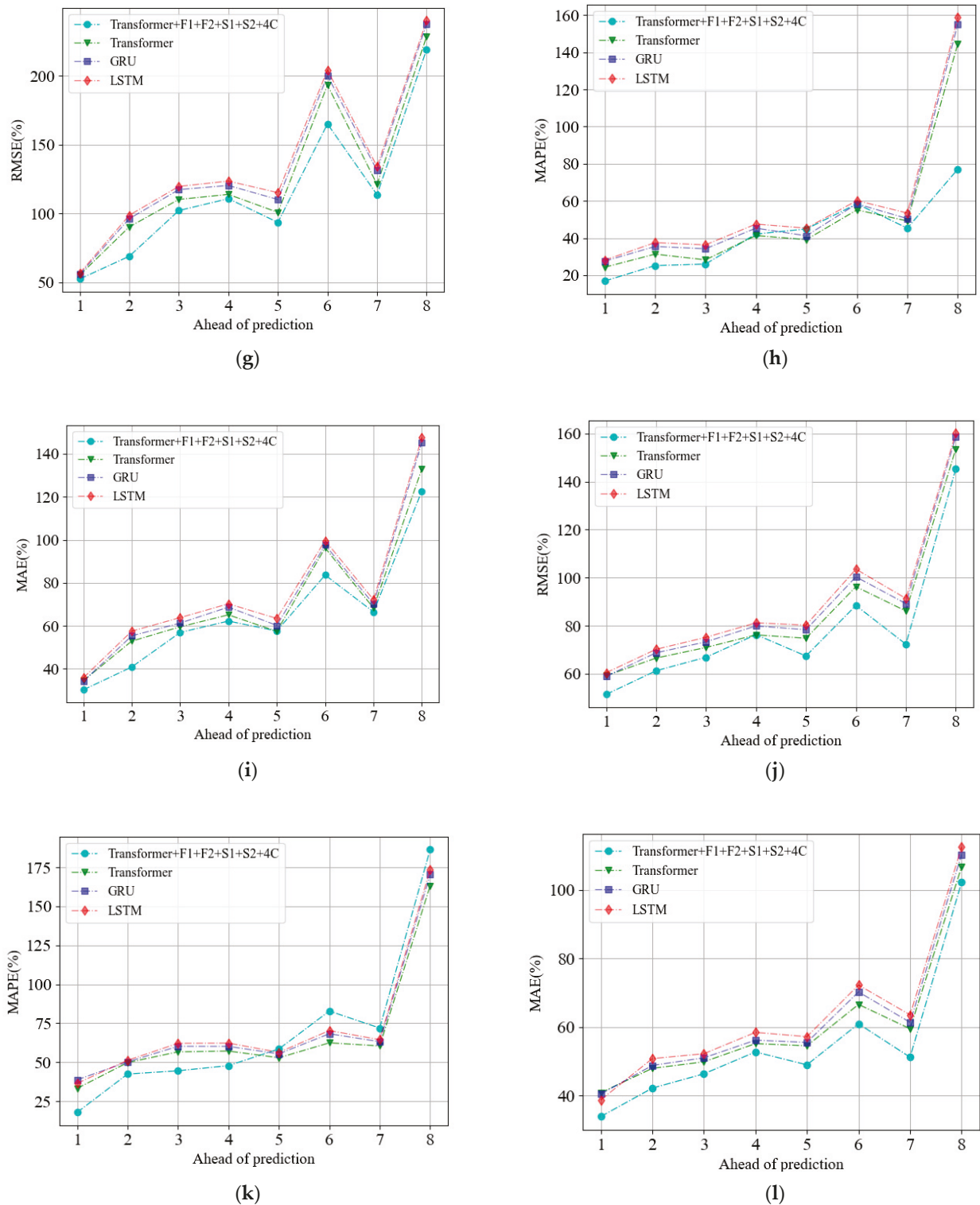


Figure 5. Results of multi-step metro flow prediction using different methods. (a) MAPE of entry of Zhonglou station. (b) RMSE of entry of Zhonglou station. (c) MAE of entry of Zhonglou station. (d) RMSE of exit of Zhonglou station. (e) MAPE of exit of Zhonglou station. (f) MAE of exit of Zhonglou station. (g) RMSE of entry of Hangtiansheng station. (h) MAPE of entry of Hangtiansheng station. (i) MAE of entry of Hangtiansheng station. (j) RMSE of exit of Hangtiansheng station. (k) MAPE of exit of Hangtiansheng station. (l) MAE of exit of Hangtiansheng station.

6. Conclusions and Future Works

In conclusion, this study emphasizes the importance of integrating spatiotemporal and semantic aspects in metro flow prediction. To accurately predict metro flow, a novel deep learning model is proposed considering the spatial correlations, the temporal correlations from different time granularity, and the external weather factors. To model the spatial correlations, mutual information is leveraged to explore the nonlinear flow patterns between stations and determine the highly correlated stations. Then, the metro flow of recent historical time intervals, the metro flow at the same time intervals of previous days and weeks, and the temperature and precipitation data are combined and incorporated as the input data. Then, the multi-source and multi-dimensional data are fed into the transformer neural network. The self-attention mechanism of the network allows for effective handling of multidimensional data and enhances the accuracy of long-term predictions by focusing on key features. Extensive experiments with real data from the Xi'an subway validate our method's efficacy, providing insights into significant features and moments that impact metro flow. Additionally, with POI information around the selected stations, our study delves into the fluctuations in metro flow. This analysis has the potential to offer valuable insights and practical recommendations for management authorities. The proposed method and comprehensive analysis highlight the significant potential of our approach in enhancing the accuracy and applicability of metro flow predictions in urban settings.

In the future, we will explore how to incorporate the distribution of POI features into the prediction model, investigating the influence of POI size and the distribution of geographical location on entry and exit traffic flow. Additionally, we will collect data on sudden events to study their impact on passenger flow and develop prediction models accordingly.

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Conflicts of Interest: The authors declare no conflict of interest.

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Article

A Multi-Agent Driving-Simulation Approach for Characterizing Hazardous Vehicle Interactions between Autonomous Vehicles and Manual Vehicles

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Abstract: The advent of autonomous vehicles (AVs) in the traffic stream is expected to innovatively prevent crashes resulting from human errors in manually driven vehicles (MVs). However, substantial safety benefits due to AVs are not achievable quickly because the mixed-traffic conditions in which AVs and MVs coexist in the current road infrastructure will continue for a considerably long period of time. The purpose of this study is to develop a methodology to evaluate the driving safety of mixed car-following situations between AVs and MVs on freeways based on a multi-agent driving-simulation (MADS) technique. Evaluation results were used to answer the question ‘What road condition would make the mixed car-following situations hazardous?’ Three safety indicators, including the acceleration noise, the standard deviation of the lane position, and the headway, were used to characterize the maneuvering behavior of the mixed car-following pairs in terms of driving safety. It was found that the inter-vehicle safety of mixed pairs was poor when they drove on a road section with a horizontal curve length of 1000 m and downhill slope of 1% or 3%. A set of road sections were identified, using the proposed evaluation method, as hazardous conditions for mixed car-following pairs consisting of AVs and MVs. The outcome of this study will be useful for supporting the establishment of safer road environments and developing novel V2X-based trafficsafetyinformation content that enables the enhancement of mixed-traffic safety.

Keywords: mixed traffic; car-following situation; multi-agent driving simulation; driving behavior; road alignment

1. Introduction

According to the crash statistics reported by the Korea Expressway Corporation, rear-end crashes accounted for approximately 76% of the total number of crashes that occurred on Korean freeways from 2013 to 2019 [1]. The advent of autonomous vehicles (AVs) is expected to innovatively reduce such rear-end crashes resulting from human-driver errors because AVs make evasive maneuvers more rapidly than MVs [2,3]. However, it is difficult to observe substantial safety benefits obtainable with AVs in the short-term because the mixed-traffic conditions in which AVs and manually driven vehicles (MV) coexist in the current road infrastructure will continue for a considerably long period of time. Therefore, the first step toward the enhancement of traffic safety on freeways is to understand the interactions between AVs and MVs under these circumstances. More specifically, the mixed

car-following behavior between an AV and MV is of keen interest for evaluating the risk of rear-end crashes. The change in road alignments, including horizontal and vertical curves, is a significant factor affecting driving behavior [4,5]. Vehicles traveling in a section where the road-alignment changes are required to adjust the acceleration and operate the steering wheel. In this case, the driver's improper decision making could lead to hazardous situations, leading to a greater crash potential. AVs driven by machines in support of sensor-based awareness of the surrounding environment will have significantly different driving behaviors from MVs driven by humans with various uncertainties. It is, therefore, important to understand the characteristics of a mixed car-following pair, which consists of an MV following an AV or an AV following an MV. An emerging question is 'What road conditions would make the mixed car-following situations hazardous?' This question motivates our study. The existing road conditions are devised to ensure the safety of the MV. However, vehicle interactions between AVs and MVs need to be evaluated to identify which geometric conditions are vulnerable in terms of mixed traffic safety. A hypothesis established in this study is that the different interactions observed for each driving pair of AVs and MVs would lead to different road conditions that are vulnerable to safety.

This study proposes a methodology to evaluate the driving safety of mixed car-following situations between AVs and MVs on freeways, which is fundamental to fully exploiting the benefit of crash prevention using AVs. The proposed methodology can be applied to identify hazardous road-alignment conditions for mixed car-following pairs. A multi-agent driving-simulation (MADS) technique, which is able to synchronize the space and time domains on the road by connecting two driving simulators, is conducted to evaluate driving safety. MADS experiments allow for effectively observing the interactions that occur when the subject vehicle follows the preceding vehicle. This study defined a driving simulator as an agent. The SCANerTM STUDIO program is used to simulate the road network and the maneuvering of the AV. Driving information for each vehicle is collected with driving experiments on AV pairs, mixed pairs, and MV pairs. A total of three safety indicators, including acceleration noise (AN), standard deviation of lane position (Std.LP), and average headways (Avg.HW), are used to identify the vehicle interaction of mixed car-following situations in terms of traffic safety. The evaluation results allow for identifying road-alignment conditions where mixed car-following pairs would experience relatively more hazardous situations.

2. Literature Review

This study aims to analyze the interaction between vehicles concerning the change in road alignments in mixed traffic conditions and to develop a driving-safety-evaluation method. From these perspectives, existing studies addressing mixed traffic and driving safety by road alignments are reviewed to draw research opportunities.

2.1. Interaction between AVs and MVs in Mixed Traffic Flow Crash Potential Index

Various studies have been conducted on evaluating safety using the market penetration rate (MPR) of AVs in mixed-traffic flow. The conflict rate decreased in the car-following situation when the MPR of AVs increased [6]. Yao et al. (2020) derived the analysis result that the standard deviation of speed was smaller when vehicles of the same type were driven than mixed traffic flow composed of different types of vehicles [7]. Guériau et al. (2020) found that the congestion level on freeways increased at 2.5% and 7% of AVs, whereas the congestion decreased when AVs occupied 20% of the traffic stream [8]. Mousavi et al. (2021) evaluated the impact of AVs' MPRs on the number of traffic conflicts [9]. As the mixing rate of AVs increases, the number of rear-end conflicts decreases by 84–100%, and the number of lane-change conflicts decreases by 42–100%. Hou (2023) established a framework, which is composed of a traffic simulation and crash models, to assess the safety of mixed-traffic flow [10]. The increase in AVs' MPRs leads to improved multi-vehicle safety and single-vehicle safety. Mahdinia et al. (2021) conducted an experiment to evaluate the car-following behavior of an MV following an AV in terms of traffic safety [11]. Driving

safety is improved by decreasing the variation in speed and acceleration in addition to the increase in time-to-collision (TTC). Park et al. (2004) found that mixed traffic triggers unstable traffic flows and increases the frequency of conflict [12]. Gouy et al. (2014) revealed that an increase in the standard deviation of speed results in a decrease in safety based on an analysis of MV safety in mixed traffic [13].

2.2. Driving Safety by Road Alignments

A literature review of the existing studies on the effects of road-alignment changes on driving behavior and safety was conducted. Findley et al. (2012) presented that the horizontal curve is a critical element leading to hazardous situations because it would increase the driver's workload [14]. Jung et al. (2021a) evaluated road alignments in terms of lateral driving safety based on heuristic and statistical analysis techniques [15]. It was identified that an increase in the length of the horizontal curve reduces the lateral driving safety of the vehicle. The driver's ability to control the vehicle is reduced in the section where the horizontal curve radius is small and the longitudinal slope is downhill [5]. Jeong et al. (2017a) presented a curve radius that affects the lane departure and the average driving speed [4]. As the curve radius decreased, the frequency of crashes tended to increase [16]. Choudhari et al. (2020) analyzed the risk level regarding road-alignment parameters of two-lane horizontal curves. The risk sharply increase as the radius reduces below 100 m [17]. The lane-departure rate was the highest in the case of an uphill section with a curve radius of less than 3000 m. Gooch et al. (2016) found that the crash frequency decreases as the curve radius increases based on the relationship between the curve radius and crash frequency [18].

2.3. Research Opportunities

It was found that the safety of mixed traffic flow changed according to the market share of AVs in the traffic stream. In addition, the road-alignment condition is a significant factor associated with driving safety. Therefore, it is necessary to evaluate driving safety in the mixed traffic flow at the initial stage of the introduction of AVs. It should also be noted that vehicle interactions need to be investigated in different road-alignment conditions in terms of driving safety to derive effective countermeasures. Although previous studies to address mixed traffic flow have been widely conducted, less effort has been made to evaluate the vehicle interactions of AVs and MVs from the viewpoint of driving safety. Unlike existing studies, this study attempted to evaluate driving safety for different road-alignment conditions in the car-following situations of AVs and MVs, which is useful for drawing valuable insights for AV-related simulations, road design, and mixed traffic flow management.

3. Methodology

The proposed analysis framework is presented in Figure 1. This study consists of two stages. Stage 1 includes a method on how to simulate the maneuvering of AV in the driving simulation environment. An AV-driving control logic is implemented using the SCANeR™ STUDIO program based on a thorough review of the characteristics of AV maneuvering that can be identified using the literature. Simulated road networks based on various alignment conditions and scenarios with different car-following pairs are created in the first stage. The proposed evaluation method including driving safety indicators and a comparison approach is presented in the second stage. Safety indicators are derived from the data derived from driving simulation experiments using outlier detection and correction. Regarding the safety evaluation, the rate of change of the safety indicator found using the target analysis road section compared to the baseline, which is a tangent and flat section, is used as the evaluation index in this study. It is then determined that the driving safety of mixed car-following pairs with a large change rate of the evaluation index would be reduced.

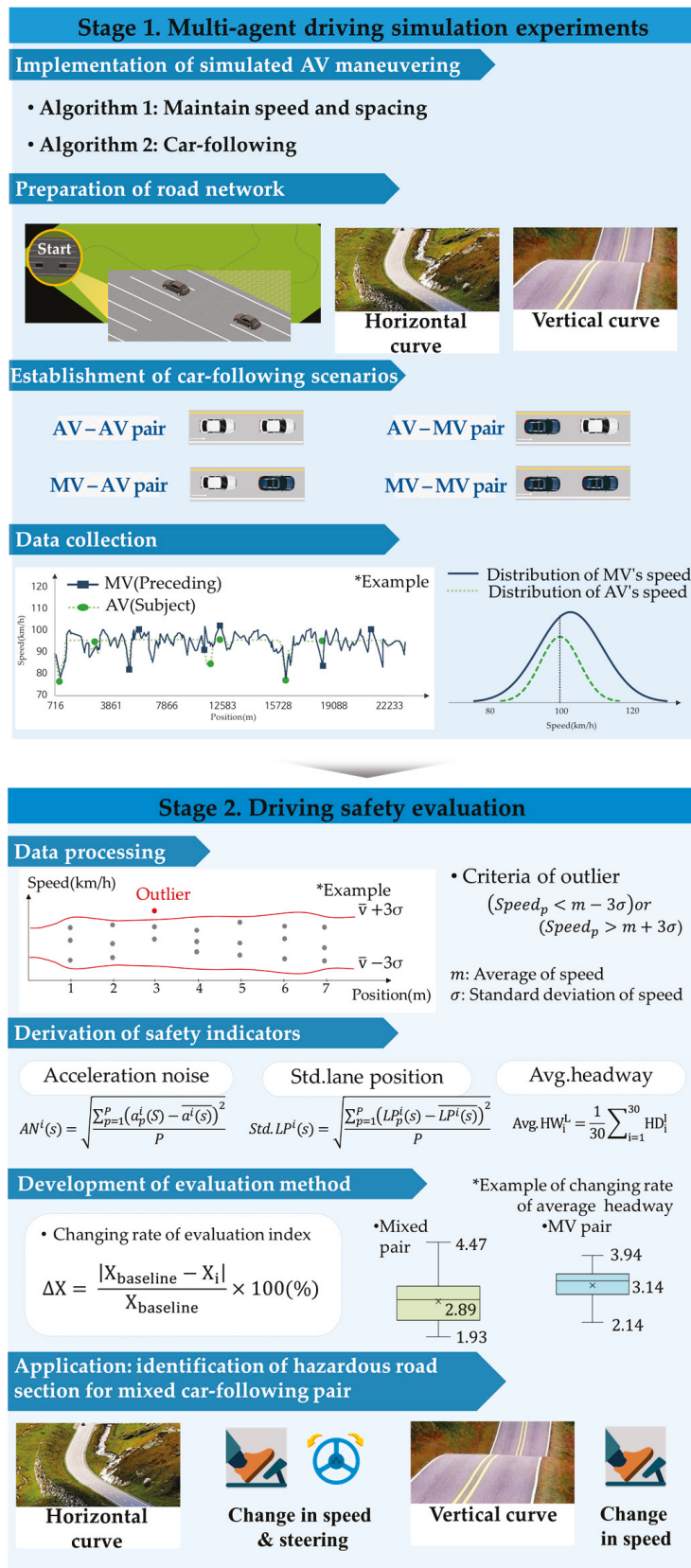
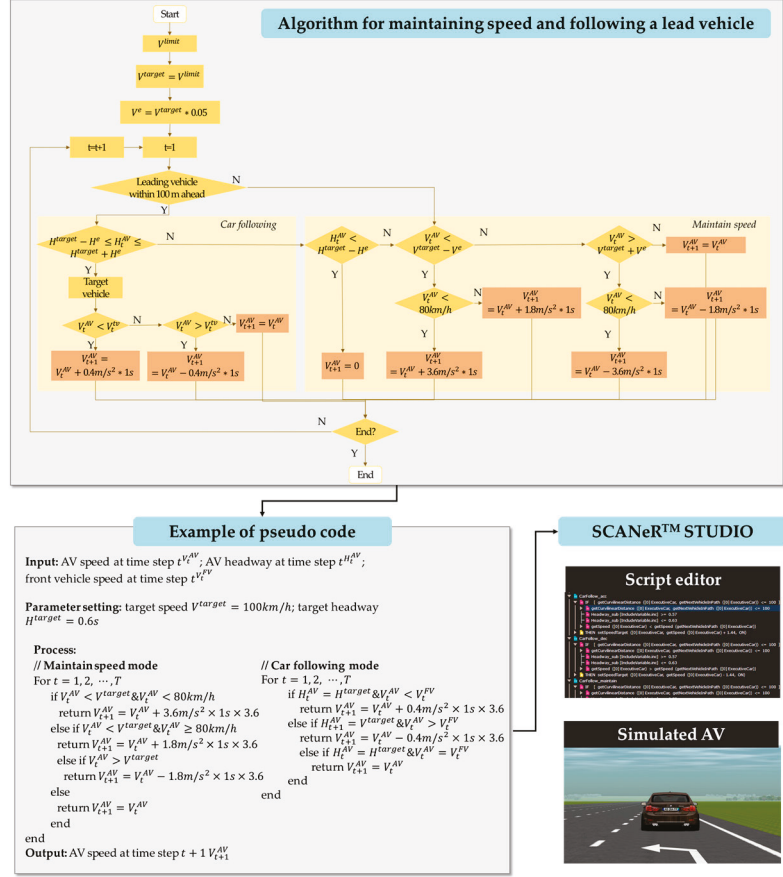


Figure 1. Overall framework.

To ensure the reality of the simulated AV-driving behavior we were required to



The standard deviation of acceleration, standard deviation of lane position, and standard deviation of spacing were used to evaluate the difference in driving behavior between an AV and MV. The feasibility of the simulated AV behavior was evaluated by applying the three indicators mentioned above to the data collected from driving simulations in a previous study conducted by the authors of this study [27]. The value of evaluation indicators found using the AV data was smaller than that of the MV. In addition, all indicators had statistically significant differences ($p < 0.05$) at the 95% confidence level. These results support the validity of the proposed AV simulation method. Figure 3 presents algorithmic descriptions of maintain speed and car following. Figure 4 presents algorithmic descriptions of lane changing. Figure 5 presents algorithmic descriptions of avoidance obstacles. Figure 6 presents algorithmic descriptions of merge.

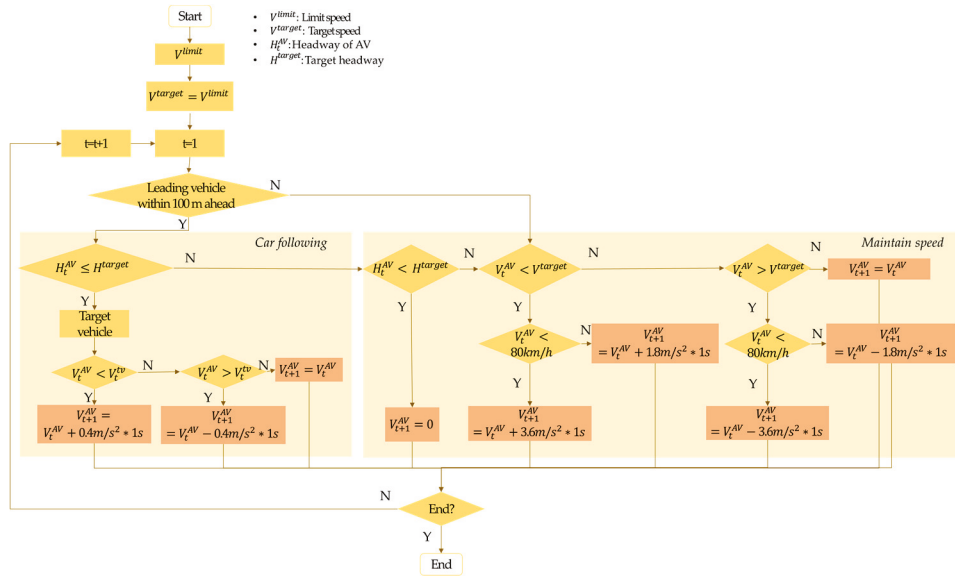


Figure 3. Algorithmic description of maintain speed and car following [27].

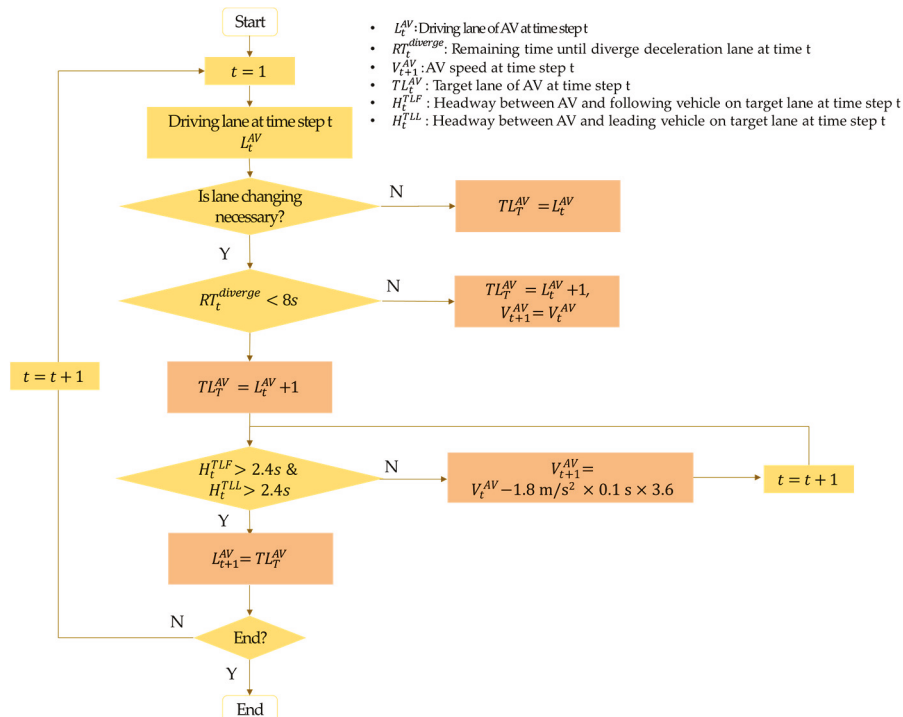


Figure 4. Algorithmic description of lane changing [27].

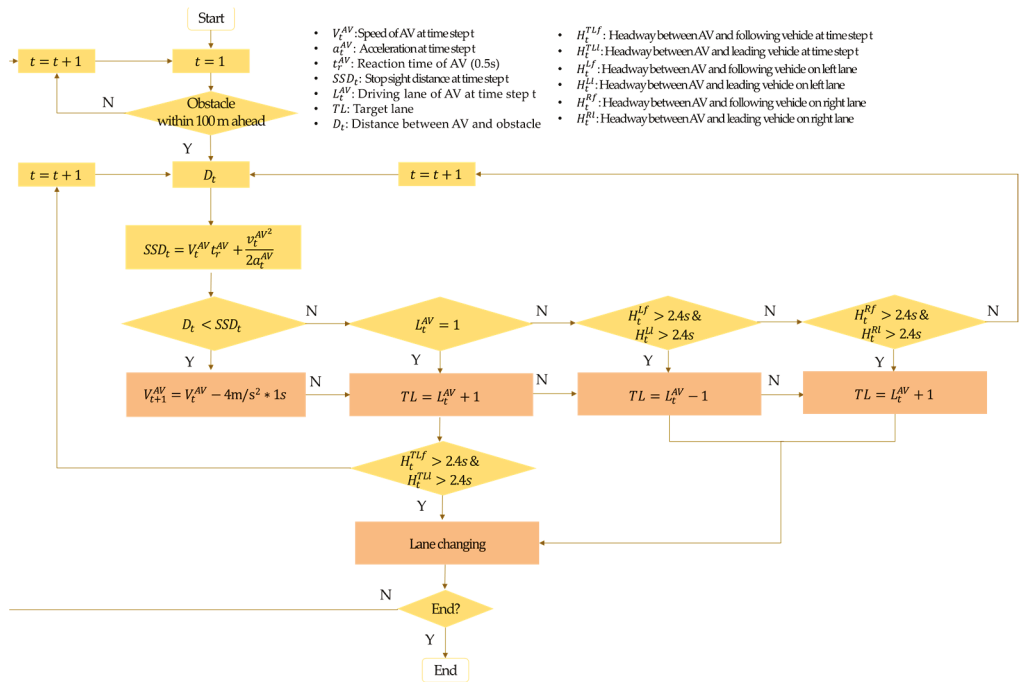


Figure 5. Algorithmic description of obstacle avoidance [27].

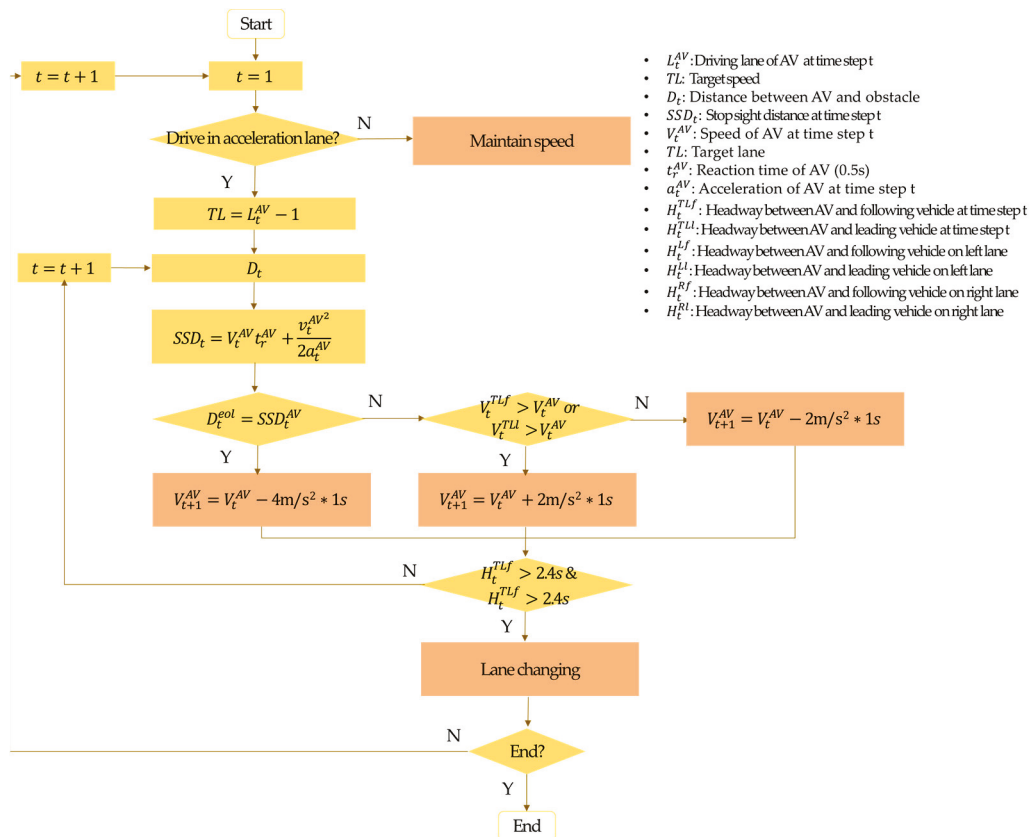


Figure 6. Algorithmic description of merge [27].

3.2. Driving Simulation

It is necessary to establish a road network in which the vehicle can drive to perform a driving simulation. Road geometric characteristic information currently used in Korea's freeway crash database was used to select the representative road-alignment conditions

for simulation experiments [1]. The criteria for categorizing the horizontal curve length and longitudinal slope of the freeway accident data are shown in Table 1. The horizontal curves in the freeway accident data are categorized based on 500 m and 1000 m. Uphill and downhill are categorized by 1% and 3%, respectively. A total of 24 road sections, including various alignment conditions, were prepared. The radius of the horizontal curve was set equally to 710 m in consideration of the minimum required design standard [28]. In addition, a flat tangent section was placed between each analysis section to minimize the influence of the adjacent road-alignment characteristics and to independently evaluate the driving safety in each section. The length of the tangent section was 250 m, which corresponded to the minimum stopping distance [28]. The total length of the network was 22.3 km, which consisted of a horizontal curve, vertical curve, combined alignment, and tangent section.

Table 1. Road-alignment conditions by section.

Section ID	Road Conditions			Section ID	Road Conditions		
	Curve	Slope	Length		Curve	Slope	Length
1	Left	-	500 m	13	Left	1% uphill	1000 m
2	Left	-	1000 m	14	Left	3% uphill	1000 m
3	Right	-	500 m	15	Right	1% downhill	1000 m
4	Right	-	1000 m	16	Right	3% downhill	1000 m
5	-	1% uphill	120 m	17	Right	1% uphill	500 m
6	-	3% uphill	360 m	18	Right	3% uphill	500 m
7	-	1% downhill	55 m	19	Left	1% downhill	500 m
8	-	3% downhill	165 m	20	Left	3% downhill	500 m
9	Left	1% uphill	500 m	21	Right	1% uphill	1000 m
10	Left	3% uphill	500 m	22	Right	3% uphill	1000 m
11	Right	1% downhill	500 m	23	Left	1% downhill	1000 m
12	Right	3% downhill	500 m	24	Left	3% downhill	1000 m

The driving scenarios consist of three different car-following pairs. The scenarios include AV pairs, MV pairs, and mixed pairs. An AV pair is a case in which both the preceding vehicle and the following vehicle are AVs. An MV pair refers to a scenario where both the preceding vehicle and the following vehicle are MVs. Meanwhile, the mixed pair, which is the main concern of this study, is composed of $AV_L - MV_F$ pairs and $MV_L - AV_F$ pairs depending on the combination of AVs and MVs. The MV follows the AV in the $AV_L - MV_F$ pair, but the AV follows the MV in the $MV_L - AV_F$ pair.

An experimental environment was constructed in which a multi-agent driving simulator was interlocked to enable simultaneous travel in the same space after the two driving simulators were synchronized using the network. Figure 7 illustrates the concept of the multi-agent driving simulation. Each simulator is connected via the TCP/IP communication protocol. Simulators send driving status data including the positions, speeds, accelerations, brake powers, and angular velocities. SCANerTM STUDIO is used to construct a simulation environment by designing 3D virtual reality for road alignments and scenarios. This study conducts a car-following situation between preceding and subject vehicles using MADS. In the simulated environment, two drivers drive at the same time. The driving simulation environment is designed to drive two vehicles on a three-lane freeway. Drivers can increase the vehicle speed up to 100 km/h. During the driving simulation experiment, the drivers do not overtake the preceding vehicle. Additionally, both the preceding vehicle and subject vehicle drivers are instructed to keep driving in the second lane without lane changes. Drivers can determine their driving behavior in accordance with the surrounding vehicles or road alignments. Vehicle trajectory data are found using each simulator through which the preceding and subject vehicles have traveled the network. The driving behavior of individual vehicles and vehicle interactions are analyzed using the discovered trajectory data.

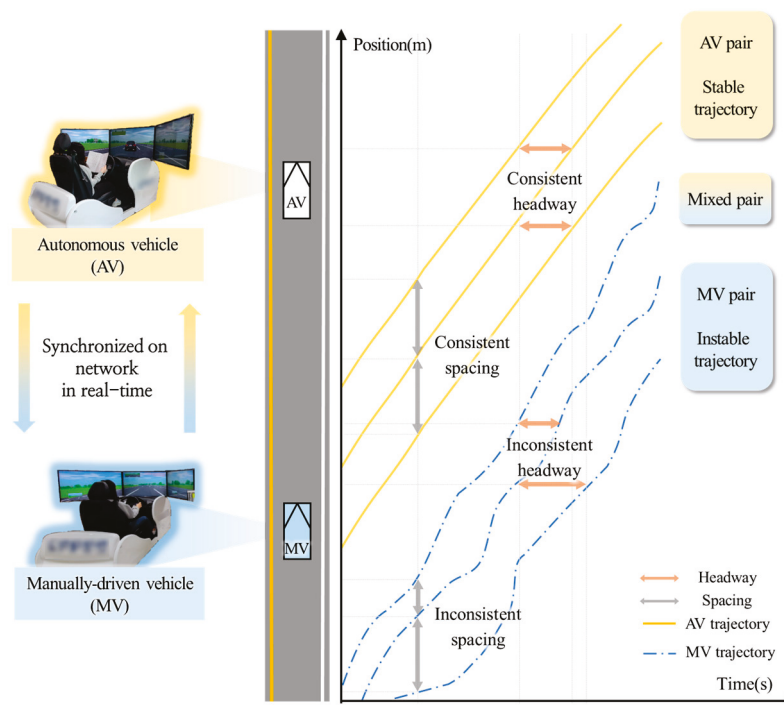


Figure 7. Conceptual illustration of MADS experiments.

The trajectory data include vehicle positions over time, which can be used to further derive both longitudinal driving behavior and lateral driving behavior. Longitudinal driving behavior is represented using the speed and acceleration of the vehicles. Lateral driving behavior information is represented using the lane position and lateral acceleration of the vehicles. Data were collected at 10 Hz. To identify the change in driving behavior with road-alignment conditions, data collected at 0.1 s intervals in the time domain need to be converted into the space domain in 1 m increments. Because outliers of trajectory data may affect the analysis results, proper preprocessing is needed to filter out outliers. In this study, the criterion for determining outliers was defined as a range that deviated from 99.7% of the data distribution.

3.3. Data Analysis

It is desirable to conduct a comparative evaluation rather than giving absolute meaning to the experimental results because the driving simulation does not perfectly reflect reality. For this purpose, this study defined a flat tangent road section without horizontal and vertical curves as the baseline condition to be compared. The rate of change of the safety indicator found from the target analysis road section compared to the baseline, which is shown as Equation (1), is used as the evaluation index. It is then determined that the driving safety of mixed car-following pairs with a large change rate of the evaluation index would be reduced. Selected safety indicators include the acceleration noise, the standard deviation of lane positions (Std.LP), and the average headway to evaluate the longitudinal driving safety, lateral driving safety, and inter-vehicle safety, respectively.

$$\Delta x = \frac{|x_{baseline} - x_s|}{x_{baseline}} \times 100\% \quad (1)$$

where Δx is defined as the rate of the safety indicator compared to the baseline, $x_{baseline}$ is the evaluation index of the baseline, x_s is the safety indicator found from section s , and s is the number of sections (1, 2, ..., S).

Acceleration noise has been effectively used to evaluate the longitudinal driving safety of vehicles. The standard deviation of acceleration refers to the degree of variance of speed change [29]. A higher acceleration noise value negatively affects traffic safety. Increased

acceleration noise indicates that there is decreased driving safety. The acceleration noise can be found using Equation (2).

$$AN^i(s) = \sqrt{\frac{\sum_{p=1}^P (a_p^i(s) - \overline{a^i(s)})^2}{P}} \quad (2)$$

$$\overline{AN(s)} = \frac{\sum_{i=1}^I AN^i(s)}{I}$$

where $AN^i(s)$ is defined as the acceleration noise at section s for driver i , $\overline{AN(s)}$ represents the average acceleration noise at section s , a_p^i represents acceleration at position p for driver i , $\overline{a}$ represents the average acceleration noise, and i represents driver ID (1, 2, ..., I).

Lateral driving safety represents the safety of the vehicle in a direction perpendicular to the driving direction. Lateral driving safety can be evaluated by identifying whether the vehicle travels well along the centerline of the lane when driving in a curved road section. The lane position is defined as the distance from the center of the lane to the center of the vehicle in this study. The value of the lane position is 0 when the center of the lane coincides with the center of the vehicle. The lane position is collected as a (−) value when the vehicle is driving on the left side of the lane center. The lane position is collected as a (+) value when the vehicle is driving on the right side of the lane center. The absolute value of the lane position is used for the driving safety evaluation. The Std.LP is the deviation of the lane position from the center of the lane. The higher the Std.LP, the higher the variance of the vehicle position. This indicator has been widely used for lateral safety evaluation [30,31]. The Std.LP can be found using Equation (3). When the rate of change of the Std.LP in the analysis section compared to the baseline is positive, it means that the driving safety deteriorates compared to the baseline.

$$Std.LP^i(s) = \sqrt{\frac{\sum_{p=1}^P (LP_p^i(s) - \overline{LP^i(s)})^2}{P}} \quad (3)$$

where $Std.LP^i(s)$ is defined as the standard deviation of the lane position at section s for driver i , LP_p^i represents the lane position at position p for driver i , and $\overline{LP}$ represents the average lane position.

Headway represents the time from the point where the front bumper of the preceding vehicles has passed to the vehicle head of the subject vehicle in the car-following situation. Headway is used as an index for the analysis of the interaction between vehicles [32]. Acceleration and deceleration affect the headways, while each vehicle drives the road network. When the headways increase, the likelihood of collision between vehicles decreases [33,34]. The average headway represents an indicator to evaluate the safety of the interaction between preceding and subject vehicles. The average headway, which is found using Equation (4), decreases when the rate of the average headway on the analysis sections compared to the baseline is negative. A higher headway indicates a decrease in driving safety.

$$Avg.HW^i(s) = \frac{\sum_{i=1}^I HW^i(s)}{I} \quad (4)$$

$$HW^i(s) = \frac{\sum_{p=1}^P HW_p}{P}$$

where $HW^i(s)$ is defined as the headway at section s for driver i and $Avg.HW^i(s)$ represents the average headway at section s for driver i .

4. Results

4.1. Analysis of Speed Profiles by Vehicle Pair

Descriptive statistics of driving speed are presented with examples of speed profiles for each car-following pair, as shown in Figure 8. In the AV pair, the average speed and the standard deviation of speed were observed to be approximately 95 km/h and 0.11–0.38 km/h, respectively. Additionally, the results of the speed ranges of 0.43 and

1.13 km/h of AV_L and AV_F showed that the driving behaviors of the two vehicles are quite similar. The mechanical and deterministic movement, which resulted from the maneuvering control logic, of the preceding AV_L also had an effect on the movement of the following AV_F . In the case where an MV follows an AV, which is the first scenario of the mixed pair ($AV_L - MV_F$), the difference in the standard deviation of the speed between MV_F and AV_L was significantly large; although, the average driving speeds were similar, indicating that the driving behavior was meaningfully different. In addition, the speed range of AV_L was 0.42 km/h, whereas the speed range of MV_F was 40.00 km/h. Another interesting finding was observed with the second scenario of the mixed pair ($MV_L - AV_F$). The standard deviation of speed for the AV_F following MV_L was observed to be 19.80 km/h, which indicates that the standard deviation of speed was larger than that of the AV pair. The stochastic movement resulting from the human driver also had an effect on the movement of the following AV. Therefore, it can be said that there is a significant difference in driving behavior between AV and MV that follow the preceding AV_L . In the MV pair, the average driving speed was 100 km/h, which is the highest speed among all vehicle pairs. As expected, the largest speed variation was found in the MV pair. Because MVs are driven according to the human driver's awareness and decisions, they are likely to make more frequent changes in driving speed with greater acceleration rates. When a vehicle pair consists of the same vehicle type, stable interaction between vehicles is found due to similar driving behavior [29]. The difference in the standard deviation of speed is 0.27 km/h in the $AV_L - AV_F$ pair and 0.18 km/h in the $MV_L - MV_F$ pair. On the other hand, in the case of mixed pairs, the standard deviations of speed were 6.55 km/h and 1.04 km/h for $AV_L - MV_F$ and $MV_L - AV_F$, respectively.

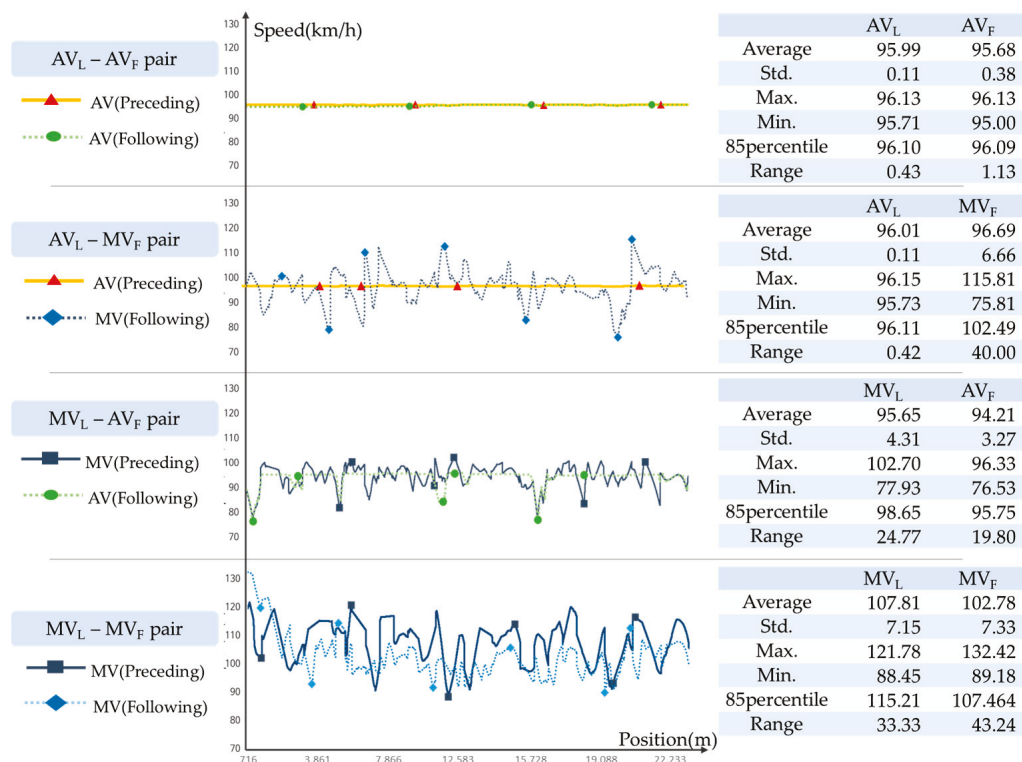
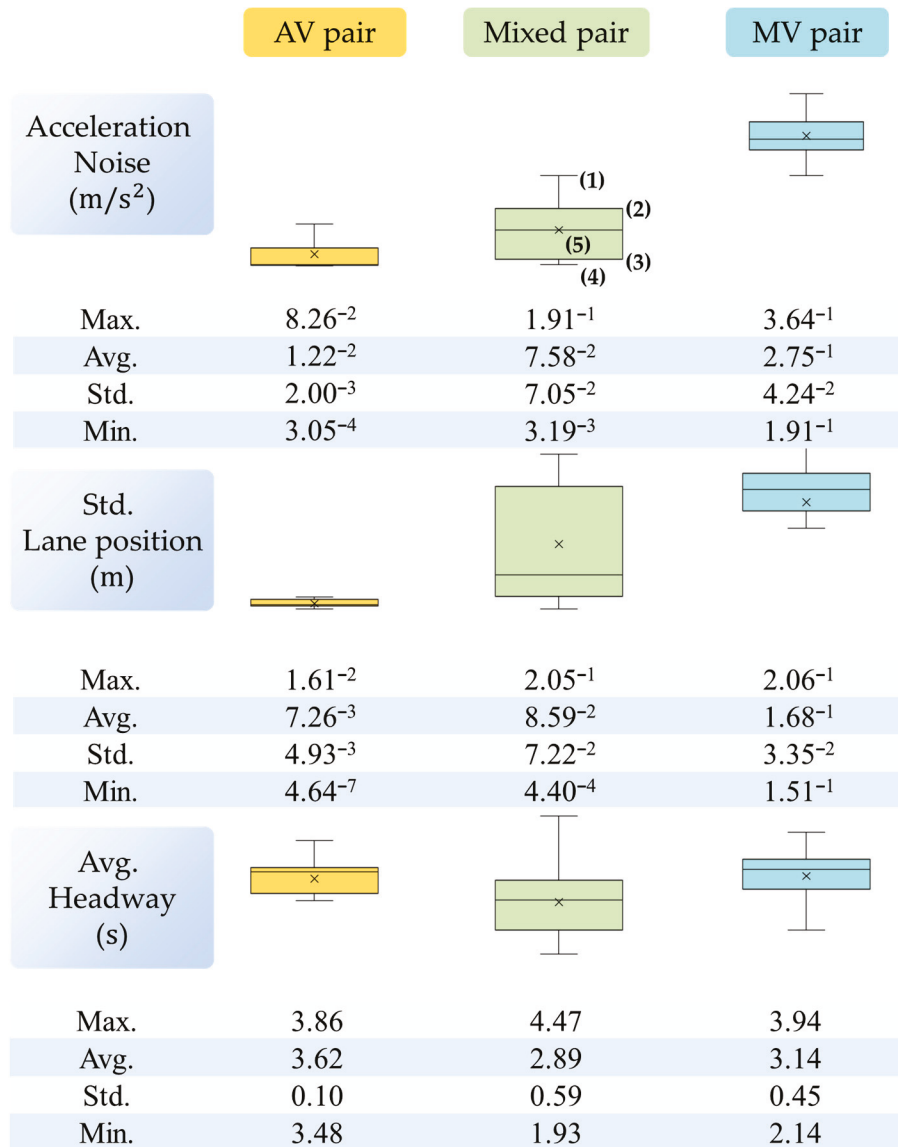


Figure 8. Example of a speed profile.

4.2. Driving Safety Evaluation

The evaluation results are summarized in Figure 9. Since the AV drives in accordance with maneuvering control algorithms, the acceleration noise of the AV pair (1.22^{-3} m/s^2) was smaller than that of the mixed pair (7.58^{-3} m/s^2), and it was 98.8% smaller than that of the MV pair (2.75^{-1} m/s^2). The Std.LP in the AV pair (7.26^{-3} m) decreased by 92.5% compared to the mixed pair and by 96.2% compared to the MV pair. As a result of

comparing the average headway, the average headway of the AV pair was 3.62 s, which represents the highest headway among other vehicle pairs, maintaining the widest spacing between preceding and following vehicles. The standard deviation of the headway of AV pairs is 0.10 s, which is the smallest among all vehicle pairs.



Note: (1) Maximum, (2) 3rd quartile, (3) 1st quartile, (4) Minimum, (5) Average

Figure 9. Comparison of safety indicators by vehicle pair.

Analyses of variation (ANOVA) are performed for each safety indicator separately. The statistical analysis results are presented in Table 2. Significance probabilities of acceleration noise and Std.LP are 0.00 for all car-following pairs. Significance probabilities of Avg.HW are less than 0.05 for all car-following pairs. The safety indicators, in accordance with the 24 sections, have significant differences from the other pairs at the 95% significance level. The result of the ANOVA test implies that the proposed indicators are capable of discriminately explaining the difference in driving safety among scenarios.

Table 2. Results of ANOVA with safety indicators.

	AV Pair			Mixed Pair			MV Pair		
	N	F	<i>p</i> -Value	N	F	<i>p</i> -Value	N	F	<i>p</i> -Value
AN	30	3839.59	0.00	30	4.25	0.00	30	9.94	0.00
Std.LP	30	278,083.99	0.00	30	3.39	0.00	30	14.18	0.00
Avg.HW	30	324,079.95	0.00	30	3.90	0.00	30	1.83	0.01

A comparison of the evaluation index by road section is presented in Table 3. The acceleration noises in the baseline case are 0.01^{-2} m/s² for the AV pair, 0.05 m/s² for the mixed pair, and 0.1 m/s² for the MV pair. In the AV pair, the acceleration noise in Section 5–8, 10, 12, and 18 increased the most to 0.01. In the mixed pair, the acceleration noise increased by 225% compared to the baseline in Sections 14, 22, and 24. The highest acceleration noise was observed in Section 24 in the MV pair. The lateral driving safety characterized using the Std.LP was the worst for all pairs in Section 11. Section 11 has alignment characteristics of a right-curve length of 500 m and a downhill slope of 1%. In the case of driving to the right, the sight distance of the drive was shorter in the case of the right curve than in the case of the left curve [19], so the lateral driving safety of Section 11 was the worst in all vehicle pairs. With regard to the headway, the headway of the AV pair in Section 1 was 2.67 s, which was reduced by 55% compared to the baseline. The average headway of the mixed pair was 2.23 s, which was a 44% decrease in Section 16 and 24 compared to the baseline. A 45% reduction in the average headway was observed in Section 15 with the MV pair. Furthermore, the hazardous road conditions were found to be different for the AV pair, mixed pair, and MV pair. The longitudinal safety was poor in Section 24 for the MV pair and in Sections 24 and 14 for the Mixed pair. The hazardous road section for the AV pair is entirely different from that of the MV pair and mixed pair. With regard to the inter-vehicle interaction indicators, the hazardous road sections were different for the AV pair, mixed pair, and MV pair. These results prove that the hypothesis established in this study is valid.

Table 3. Comparison of evaluation index by road sections.

Section ID	AV Pair			Mixed Pair			MV Pair		
	AN (Δ AN)	Std.LP (Δ Std.LP)	Avg.HW (Δ Avg.HW)	AN (Δ AN)	Std.LP (Δ Std.LP)	Avg.HW (Δ Avg.HW)	AN (Δ AN)	Std.LP (Δ Std.LP)	Avg.HW (Δ Avg.HW)
0	0.01^{-2}	0.04^{-5}	5.90	0.05	0.02	3.97	0.10	0.05	3.86
1	0.05^{-2} (400)	0.11^{-1} (2,749,900)	2.67 * (−55)	0.11 (175)	0.09 (350)	3.94 (−1)	0.20 (89)	0.17 (240)	3.10 (−20)
2	0.04^{-2} (300)	0.08^{-1} (1,999,900)	2.97 (−50)	0.08 (100)	0.09 (350)	3.68 (−7)	0.17 (61)	0.16 (220)	3.44 (−11)
3	0.05^{-2} (400)	0.05^{-1} (1,249,900)	3.32 (−44)	0.08 (100)	0.09 (350)	3.73 (−6)	0.14 (32)	0.17 (240)	3.81 (−1)
4	0.04^{-2} (300)	0.03^{-1} (749,900)	3.62 (−39)	0.07 (75)	0.08 (300)	3.38 (−15)	0.16 (51)	0.16 (220)	3.80 (−1)
5	0.01 * (9900)	0.05^{-5} (25)	3.84 (−35)	0.06 (50)	0.05 (150)	3.21 (−19)	0.14 (32)	0.09 (80)	3.55 (−8)
6	0.01 * (9900)	0.01^{-4} (150)	3.98 (−33)	0.10 (150)	0.08 (300)	3.27 (−18)	0.22 (108)	0.17 (240)	3.38 (−12)
7	0.01 * (9900)	0.01^{-4} (150)	4.08 (−31)	0.05 (25)	0.03 (50)	3.02 (−24)	0.11 (4)	0.06 (20)	3.34 (−13)

Table 3. Cont.

Section ID	AV Pair			Mixed Pair			MV Pair		
	AN (Δ AN)	Std.LP (Δ Std.LP)	Avg.HW (Δ Avg.HW)	AN (Δ AN)	Std.LP (Δ Std.LP)	Avg.HW (Δ Avg.HW)	AN (Δ AN)	Std.LP (Δ Std.LP)	Avg.HW (Δ Avg.HW)
8	0.01 * (9900)	0.01 ⁻⁴ (150)	4.16 (−29)	0.10 (150)	0.07 (250)	2.81 (−29)	0.18 (70)	0.12 (140)	3.51 (−9)
9	0.02 ⁻¹ (1900)	0.11 ⁻¹ (2,749,900)	4.28 (−27)	0.08 (100)	0.09 (350)	2.92 (−26)	0.17 (61)	0.17 (240)	3.40 (−12)
10	0.01 * (9900)	0.12 ⁻¹ (2,999,900)	4.45 (−25)	0.10 (150)	0.09 (350)	2.82 (−29)	0.24 (127)	0.16 (220)	3.29 (−15)
11	0.02 ⁻² (100)	0.14 ⁻¹ * (3,499,900)	4.69 (−21)	0.07 (75)	0.11 * (450)	2.53 (−36)	0.15 (42)	0.21 * (320)	2.99 (−22)
12	0.01 * (9900)	0.05 ⁻¹ (1,249,900)	4.87 (−17)	0.10 (150)	0.09 (350)	2.71 (−32)	0.20 (89)	0.20 (300)	2.84 (−26)
13	0.01 ⁻¹ (900)	0.08 ⁻¹ (1,999,900)	5.05 (−14)	0.09 (125)	0.09 (350)	2.87 (−28)	0.28 (165)	0.18 (260)	3.27 (−15)
14	0.03 ⁻¹ (2900)	0.09 ⁻¹ (2,249,900)	5.17 (−12)	0.13 * (225)	0.09 (350)	3.23 (−19)	0.24 (127)	0.16 (220)	2.26 (−41)
15	0.01 ⁻¹ (900)	0.04 ⁻¹ (999,900)	5.24 (−11)	0.08 (100)	0.09 (350)	2.59 (−35)	0.15 (42)	0.18 (260)	2.18 * (−45)
16	0.03 ⁻¹ (2900)	0.04 ⁻¹ (999,900)	5.24 (−11)	0.10 (150)	0.10 (400)	2.23 * (−44)	0.26 (146)	0.19 (280)	2.21 (−43)
17	0.02 ⁻¹ (1900)	0.05 ⁻¹ (1,249,900)	5.23 (−11)	0.08 (100)	0.09 (350)	2.76 (−30)	0.17 (61)	0.17 (240)	3.07 (−20)
18	0.01 * (9900)	0.05 ⁻¹ (1,249,900)	5.23 (−11)	0.12 (200)	0.09 (350)	2.75 (−31)	0.23 (117)	0.18 (260)	3.41 (−12)
19	0.02 ⁻¹ (1900)	0.12 ⁻¹ (2,999,900)	5.17 (−12)	0.07 (75)	0.09 (350)	2.62 (−34)	0.16 (51)	0.18 (260)	3.32 (−14)
20	0.05 ⁻¹ (4900)	0.12 ⁻¹ (2,999,900)	5.17 (−12)	0.09 (125)	0.10 (400)	2.65 (−33)	0.20 (89)	0.18 (260)	3.46 (−10)
21	0.01 ⁻¹ (900)	0.04 ⁻¹ (999,900)	5.24 (−11)	0.09 (125)	0.09 (350)	2.54 (−36)	0.18 (70)	0.18 (260)	3.02 (−22)
22	0.03 ⁻¹ (2900)	0.04 ⁻¹ (999,900)	5.24 (−11)	0.13* (225)	0.09 (350)	2.60 (−35)	0.22 (108)	0.19 (280)	3.27 (−15)
23	0.01 ⁻¹ (900)	0.09 ⁻¹ (2,249,900)	5.17 (−12)	0.08 (100)	0.10 (400)	2.23 * (−44)	0.19 (80)	0.18 (260)	2.72 (−29)
24	0.03 ⁻¹ (2900)	0.09 ⁻¹ (2,249,900)	5.17 (−12)	0.13 * (225)	0.10 (400)	2.26 (−43)	0.42 * (297)	0.20 (300)	2.73 (−29)

Unit: AN (m/s²), Std.LP (m), Avg.HW (s), Δ AN (%), Δ Std.LP (%), Δ Avg.HW (%). * Hazardous section.

A higher rate of change in the evaluation index refers to poorer driving safety. The section with the highest rate in the evaluation index is defined as the hazardous road section of driving safety in this study. The hazardous road sections for the mixed pairs of vehicles are presented in Table 4. It was identified that the longitudinal driving safety was poor in the road section where the length of the horizontal curve was 1000 m and at 3% grade. With regard to lateral driving safety, a road section with a 500 m right curve and 1% downhill is relatively vulnerable in terms of the driving safety of the mixed pair. Inter-vehicle safety would deteriorate in a combined alignment section where the length of the horizontal curve is 1000 m while going downhill.

Table 4. Identified hazardous road sections for mixed vehicle pairs.

Evaluation Target	Safety Indicator	Evaluation Index	Mixed Pair
Longitudinal safety	Acceleration noise	ΔAN	1000 m left curve 3% uphill 1000 m left curve 3% downhill 1000 m right curve 3% uphill
Lateral safety	Standard deviation of lane position	$\Delta Std.LP$	500 m right curve 1% downhill
Inter-vehicle safety	Average of headway	$\Delta Avg.HW$	1000 m right curve 3% downhill 1000 m left curve 1% downhill

The existing roads have been designed based on ensuring the safety of MV pairs, and the traffic operation system has been continuously operated to prioritize the safety of MVs. To ensure safe operation in mixed traffic flow, it is necessary to understand the driving behavior of mixed pairs and AV pairs. Mixed pairs and AV pairs showed a difference in safety under different road conditions compared to MV pairs. For instance, in terms of longitudinal safety, the 24th section is the most vulnerable in MV pairs, while in the mixed pairs, both the 24th and 14th sections showed the lowest safety. Section 24 has a downhill slope, whereas Section 14 has an uphill slope. From a traffic management system perspective, Sections 24 and 14 have a compound alignment with a left curve and an uphill slope. In-vehicle warnings based on V2X for MVs can reduce crash potential due to safe driving behavior. Regarding safety due to interactions between preceding and following vehicles, Sections 16 and 23 show hazardous road conditions in mixed pairs. Although Sections 16 and 23 have different longitudinal slopes, they share the characteristics of having a downhill slope. From a road design perspective, installing transverse grooving for downhill slopes can prevent speeding and enhance safety. The results of this study can be used to prevent accidents in mixed traffic flow scenarios.

5. Conclusions

Understanding the characteristics of mixed car-following situations is of high importance for preparing for emerging automated driving systems because it is unlikely that the AV market will grow rapidly and soon. A variety of simulation experiments have been conducted to evaluate the impact of AVs on traffic stream performance and to identify the characteristics of AV maneuvering. However, we are not aware of any study that addresses the driving safety of the mixed car-following pair consisting of an AV and MV using different road-alignment conditions. The purpose of this study is to propose a methodology to identify what kind of geometric conditions would have a negative impact on the driving safety of mixed car-following situations on freeways.

A notable feature of this study is to adopt an MADS method to simulate the maneuvering of AVs and to evaluate the responsive behavior of MVs following AVs. Three safety indicators, including the acceleration noise, the standard deviation of the lane position, and the headway, were used to characterize the maneuvering behavior of the mixed car-following pairs in terms of driving safety. Then, the rate of change in the safety indicator compared to the baseline case, which is a flat tangent road section resulting in stable maneuvering, was applied to identify road-alignment conditions where mixed car-following pairs would experience relatively more hazardous situations. The evaluation results showed that a set of road sections with combined alignments led to higher risks to driving safety. The outcome of this study can be used to identify the road-alignment conditions in which mixed car-following pairs would experience hazardous situations. In addition, the outcome is expected to be used as a fundamental for the development of novel V2X-based traffic information content that enables ODD expansion of AVs and supports the more effective decision-making of MV drivers.

Although valuable insights were obtainable using systematic simulation experiments, several further studies should be conducted to draw more generalized results and create practice-ready outcomes. First, more efforts need to be made to develop maneuvering

control logic for AVs. This study adopted publicly released general control schemes for following preceding vehicles. However, there are valuable opportunities to improve the control logic used in driving simulation experiments. To do this, real-world AV-maneuvering data will make our simulation experiment more realistic. Additionally, more extensive simulation experiments with a larger participant group need to be conducted. Connection and synchronization of more than two driving simulation environments would allow for more valuable results, which are fundamental to developing effective traffic management strategies to address mixed traffic conditions. Rather than simply comparing the evaluation index with the baseline case, a more sophisticated method could be devised. Lastly, in addition to the three safety indicators used in this study, continuous efforts are needed to find more salient indicators. Although there are various safety indicators, there is a need to consider the method for prioritizing safety indicators that can well represent the safety concerns of mixed traffic flow. Prioritized safety indicators for the safety evaluation of mixed traffic flow could enhance the quality of research and should be conducted in future studies.

The safety of mixed traffic flow can vary depending on the MPR of the AVs. Therefore, the AVs' MPRs are important to consider in mixed traffic flow. However, the scope of this study does not cover it. For further research, safety analysis incorporating diverse mixed pair scenarios regarding AVs' MPRs is essential. Furthermore, road conditions with poor safety will be similar to those of MV pairs in a low-level MPR scenario where an AV does not affect changes in driving safety among mixed pairs. The marginal point of AVs' MPRs that influences changes in driving safety should be identified within the mixed pair. If hazardous road conditions are identified based on an AV's MPR through further research, the results can be used as fundamental data for traffic management agencies to build or enhance road infrastructure according to actual AVs' MPRs.

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