Strategic Lane changes for Autonomous Buses: A Clustering Method to Approaching Vehicles

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SHORT SUMMARY

Globally, automated buses are anticipated to replace conventional buses but face challenges in lane changing due to intersection demands, requiring manual control. This study proposes a lane-changing strategy for fully autonomous operation by clustering approaching vehicles and utilizing spaces between them for smoother transitions. The strategy's effectiveness was evaluated using metrics such as lane-changing time, conflict rates, and speed variability of following vehicles. Results show a 4.7-second reduction in lane-changing time, a 24.3% decrease in conflict rates, and a 3.17 km/h reduction in speed variability, enhancing operational efficiency, safety, and traffic flow stability. These improvements are expected to increase passenger satisfaction and support traffic continuity, contributing to more stable and efficient automated bus operations.

Keywords: Automated Bus, Clustering, Lane Change, Vehicle Platoon

1. INTRODUCTION

Automated vehicles (AVs) are transforming traffic networks worldwide, with AV-based mobility services implemented across various scenarios (Fagnant et al., 2015). While autonomy in controlled settings has shown success, achieving fully autonomous operations in complex urban environments remains challenging. Urban applications of autonomous mobility, including public transportation and logistics, involve critical interactions such as deceleration, acceleration, turning, and roadside stops. For autonomous buses, these tasks include boarding and alighting passengers and performing lane changes, often requiring manual control due to safety concerns (Pendleton et al., 2017; Qu et al., 2022). This trade-off between safety and efficiency complicates operations, limiting autonomy.

Prior research has addressed lane-change strategies by enhancing AV algorithms and exploring cooperative driving models (Phuong et al., 2022). However, many studies fail to incorporate traffic flow conditions or offer strategies enabling independent lane changes for automated buses (Sheng et al., 2022). To address this gap, this study proposes a novel strategy clustering approaching vehicles into platoons and leveraging gaps between them to determine optimal lane-change timing. By minimizing the influence of surrounding traffic, the strategy enhances operational efficiency, safety, and traffic flow stability. Validated through microscopic traffic simulations, the approach demonstrates significant potential to improve automated bus operations while maintaining stable and efficient traffic flow conditions.

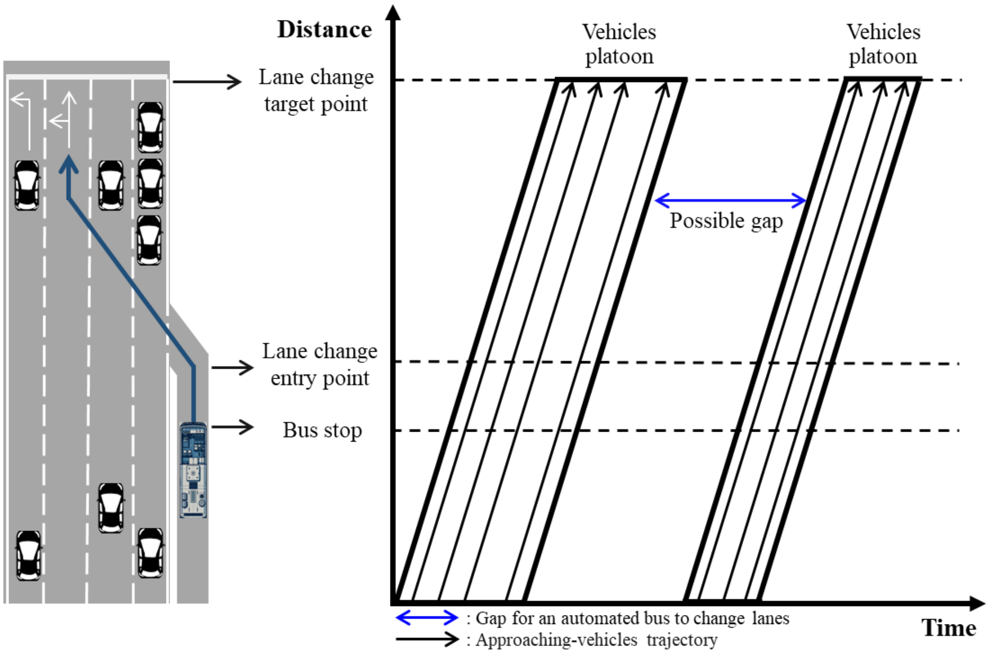
2. METHODOLOGY

Methodology Overview

The objective of this study is to identify gaps between vehicle platoons that allow automated buses to change lanes and to develop a strategy using these gaps for lane changes. Figure 1 illustrates the conceptual diagram of the research. As depicted on the left side of Figure 1, an automated bus departing from a bus stop requires two lane changes before entering an intersection to make a left turn. This research aims to develop a strategy that allows automated buses to change lanes and navigate autonomously without being affected by approaching vehicles, using gaps between vehicle platoons, as shown in the right schematic of Figure 1. To achieve this, the following three specific research objectives have been established:

(1) **Clustering of Approaching Vehicles:** Derive the gaps between vehicle clusters that enable mandatory lane changes for automated buses.
(2) **Development of Lane Change Strategy for Automated Buses:** Determine the optimal departure timing for automated buses to drive and change lanes based on inter-vehicle cluster gaps.
(3) **Validation of Lane Change Strategy:** Validate the lane change strategy using lane change data of automated buses in a simulation environment.

Figure 1: Conceptual Diagram of the Research



This study establishes assumptions to develop a lane-changing strategy for automated buses:

(1) Automated buses stop at bus stops and accelerate uniformly to the lane change entry point, as mandated by Article 26 of Korea's Passenger Transport Service Act.
(2) From the entry to the target point, buses travel at a constant speed, enabling the determination of optimal lane-changing timing unaffected by traffic flow.
(3) Vehicle clustering considers all lanes due to the conservative nature of automated vehicles, which can be influenced by adjacent-lane traffic.
(4) No queue is assumed at the target point, allowing lane changes without delays caused by waiting vehicles.

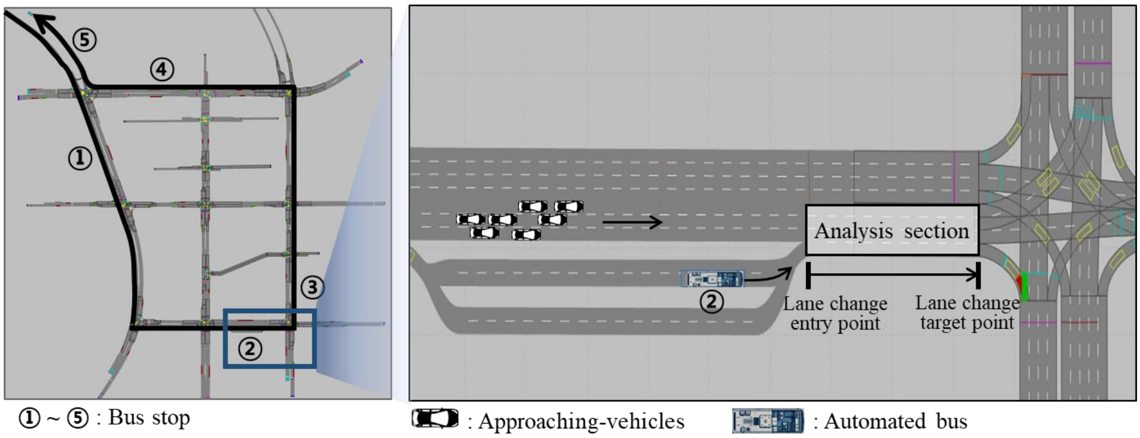
Experimental Approach

The simulation environment was created using VISSIM 2021, focusing on the Pangyo Automated Vehicle Test Zone in Gyeonggi Province, Korea, where the automated bus (PantaG Bus) operates. The network incorporates static and dynamic factors, replicating road geometry with 13 signalized intersections and reflecting off-peak traffic volumes and real TOD signals. Vehicle speeds align with design speeds for Pangyo roads. Figure 2 shows the simulation network and the bus's actual driving path. The simulation was calibrated using the Geoffrey E. Havers (GEH) statistic, confirming accuracy with a reliable microsimulation model(Kabashkin et al., 2017).

$$GEH = \sqrt{\frac{2\times(M-C)^2}{(M+C)}} \quad M = Modelled\ flow, C = Counted\ flow \tag{1}$$

In this study, Directional traffic volumes at nine major intersections were used to validate the simulation. A GEH value of 5 or less in over 85% of points indicates accurate traffic flow representation(Yu et al., 2014), and this study achieved 94.28%, confirming the simulation's reliability. Essential road sections for automated bus lane changes were selected for analysis. Figure 2 shows the analysis section, where the bus performs two lane changes after the entry point. Data, including Vehicle ID, Speed, Vehicle Type, Link ID, Lane ID, and Position, was collected every 0.1 seconds for analysis. Results and discussion.

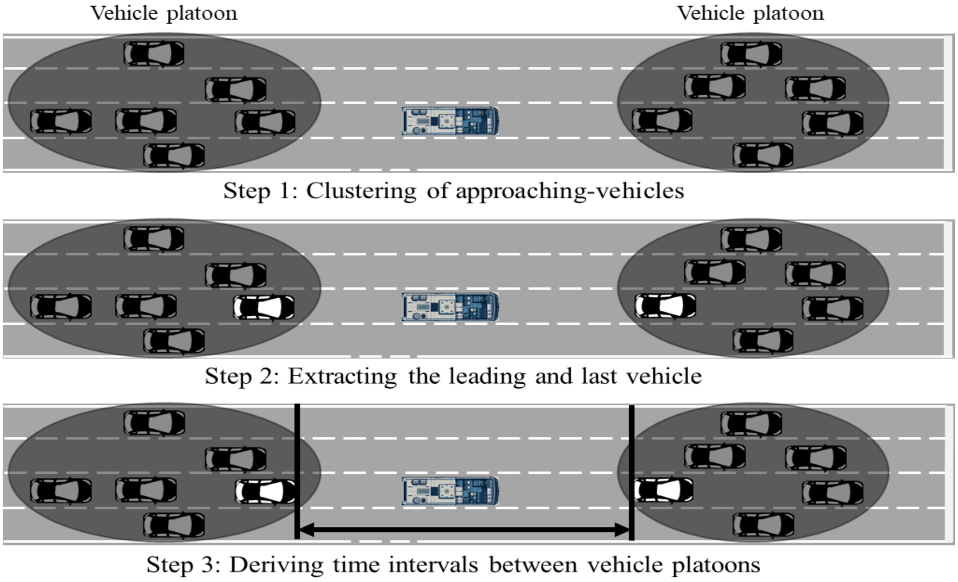
Figure 2: Simulation Network and Analysis Section



Using simulation driving data, clustering is performed to classify approaching vehicles in the analysis section where automated buses require mandatory lane changes. The K-means algorithm is employed to cluster vehicles based on data collected at 0.1-second intervals over one hour, divided into 150-second intervals corresponding to the signal cycle. This results in 24 clustering outcomes.

The dataset is constructed using arrival times at the 'Lane change entry point (d_1)' and 'Lane change target point (d_2)' to identify gaps between vehicle platoons. After clustering, the minimum and maximum arrival times at lane change points for each cluster are extracted to determine platoon gaps. Figure 3 illustrates the procedure and conceptual diagram for clustering vehicles using driving data.

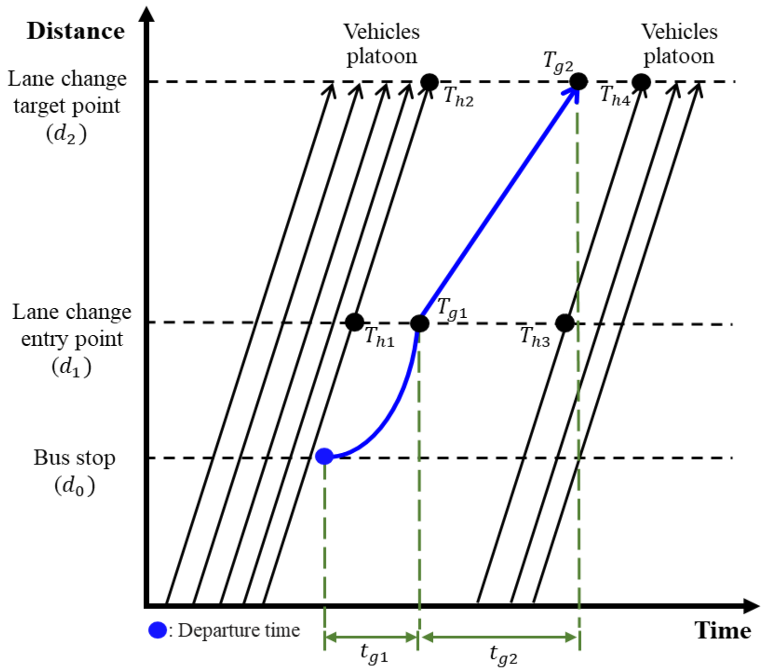
Figure 3: Procedure and Conceptual Diagram for Clustering Approaching Vehicles



Theoretical Approach

The automated bus travels with constant acceleration a_g to the lane change entry point (time t_{g1}) and then at constant speed v_g to the target point (time t_{g2}). Arrival times for the last vehicle ahead are T_{h1}(entry) and T_{h2} (target), while for the lead vehicle behind are T_{h3} (entry) and T_{h4} (target). Figure 4 illustrates these variables.

Figure 4: Conceptual Diagram of Defined Variables



To change lanes, the automated bus must arrive at the entry point after the last vehicle in the platoon ahead and before the lead vehicle in the platoon behind. The optimal departure time is determined by Equation 2.

$$\begin{gathered} T_{h1} < T_{g1} < T_{h3} \\ T_{h1} < \textit{Optimal Departure Time} + t_{g1} < T_{h3} \\ \therefore\ T_{h1} - \frac{v_g - 0}{a_g} < \textit{Optimal Departure Time} < T_{h3} - \frac{v_g - 0}{a_g} \end{gathered} \tag{2}$$

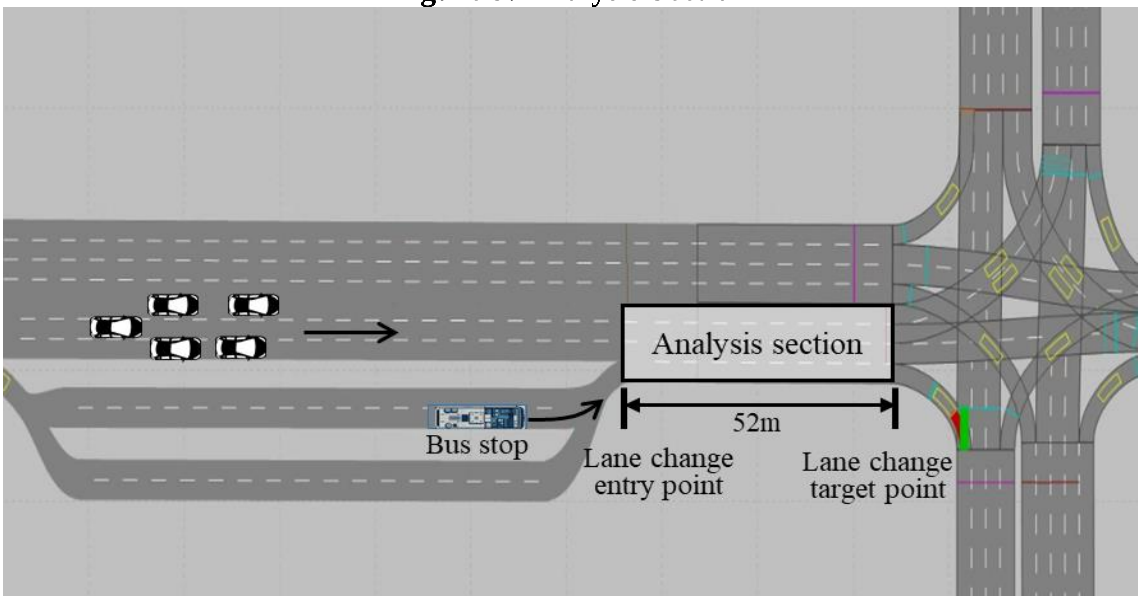
The automated bus must arrive at the target point later than the last vehicle in the platoon ahead but earlier than the lead vehicle behind, as ensured by Equation 3.

$$\begin{gathered} T_{h2} < T_{g2} < T_{h4} \\ T_{h4} < \textit{Optimal Departure Time} + t_{g1} + t_{g2} < T_{h4} \\ \therefore\ T_{h2} - \frac{v_g - 0}{a_g} - \frac{d_2 - d_1}{v_g} < \textit{Optimal Departure Time} < T_{h4} - \frac{v_g - 0}{a_g} - \frac{d_2 - d_1}{v_g} \end{gathered} \tag{3}$$

Application and Validation of Lane Change Strategy

Figure 5 illustrates the analysis section, where the automated bus performs two mandatory lane changes. Buses departing every 10 seconds are categorized by whether they depart within the 'optimal departure time range' or outside it. Performance is analyzed for efficiency, safety, and traffic flow stability to validate the lane change strategy.

Figure 5: Analysis Section



To validate the lane change strategy, efficiency, safety, and traffic flow stability are evaluated. Efficiency is measured by the time required for lane changes, from bus stop departure to completion. Safety is assessed through conflict counts and Time to Collision (TTC) with following vehicles. Conflict counts indicate collision risks, while TTC estimates the likelihood of accidents. These metrics provide a comprehensive assessment of the strategy's impact. Equation 4 defines the TTC calculation.

$$TTC = \frac{headway}{V_f - V_l}\left(V_f \geq V_l\right) \quad V_f = Following\ vehicle,\ V_l = Leading\ vehicle \tag{4}$$

This study uses the Surrogate Safety Assessment Model (SSAM) to analyze conflicts and TTC for automated buses. Conflicts are identified when TTC is 3.0 seconds or less(Hirst et al., 1997), and severe collision risks are assessed with a TTC threshold of 1.5 seconds(Horst et al., 1993). Traffic flow impact is evaluated using string stability, measured by the standard deviation of average speeds of vehicles following the bus during lane changes. Higher deviations indicate increased accident risk(Jeong et al., 2011), while lower deviations suggest greater stability. These indicators comprehensively assess the strategy's impact on efficiency, safety, and traffic flow stability.

3. EVALUATION AND VAILDATION RESULTS

Experimental Approach

Approaching vehicles were classified into platoons using K-means clustering based on arrival times at the lane change entry and target points. Table 1 shows 96 clusters identified within one hour, with center values for arrival times. For example, Cluster 1's center arrival time is 1814.02 seconds at the entry point and 1816.95 seconds at the target point. These results represent Step 1 in the clustering procedure shown in Figure 3.

Table 1: Results of Approaching-Vehicle Clustering

Classification (Sec)	**Cluster (Platoon)**	**Lane change entry point (d_1) arrival time**	**Lane change target point (d_2) arrival time**
1,800~1,950	1	1814.02	1816.95
	2	1869.00	1872.27
	3	1903.60	1906.64
	4	1933.18	1936.58
1,950~2,100	5	1950.02	1963.82
	6	1965.00	1969.75
	7	2046.27	2049.60
	8	2084.34	2087.89
2,100~2,250	9	2104.95	2108.80
	10	2151.77	2155.77
	11	2199.55	2202.75
	12	2235.84	2239.57
2,250~2,400	13	2252.44	2254.40
	14	2318.73	2322.03
	15	2351.52	2354.95
	16	2384.92	2389.32
…	…	…	…
5,250~5,400	93	5255.80	5263.88
	94	5310.90	5313.50
	95	5359.50	5363.01
	96	5383.01	5388.48

From clustering results, minimum and maximum arrival times at the lane change entry and target points were derived for each vehicle platoon. Table 2 shows these time intervals, indicating when each platoon occupies the analysis section, which can be utilized by automated buses. These results correspond to Steps 2 and 3 in Figure 3.

Table 2: Range of Arrival Times at Lane Change Points by Vehicle Platoon

	Lane change entry point (d_1) arrival time		Lane change target point (d_2) arrival time	
	Minimum value (T_{h1})	**Maximum value (T_{h3})**	**Minimum value (T_{h2})**	**Maximum value (T_{h4})**
1	1806.1	1825.4	1808.7	1828.0
2	1851.2	1880.8	1855.0	1884.1
3	1896.9	1909.7	1900.2	1913.1
4	1922.1	1944.2	1925.6	1948.8
5	1950.0	1950.2	1953.9	1970.3
6	1960.7	1969.3	1967.3	1972.2
7	2035.3	2055.8	2038.7	2059.1
8	2075.8	2094.3	2078.4	2099.5
9	2100.0	2119.8	2100.2	2123.0
10	2139.5	2160.9	2142.3	2165.1
…	...	…	…	…
93	5250.0	5262.8	5258.0	5267.8
94	5310.9	5310.9	5313.5	5313.5
95	5347.6	5370.6	5350.8	5374.5
96	5376.3	5388.7	5382.3	5396.8

Theoretical Approach

Theoretical research determined the optimal departure time for the automated bus using platoon gaps, based on the lane change strategy. T_{h1} and T_{h3} represent forward platoon arrival times, and T_{h2} and T_{h4} represent following platoon times. The bus travels at a constant speed of 7.7 m/s with 2.35 m/s^2 acceleration over a 39.9 m distance. Equations 5 and 6 define this calculation.

$$T_{h1} - 3.27 < Optimal\ Departure\ Time < T_{h3} - 3.27 \quad (5)$$
$$T_{h2} - 8.46 < Optimal\ Departure\ Time < T_{h4} - 8.46 \quad (6)$$

Table 3 documents 83 optimal departure time intervals, ranging from less than one second to 64.21 seconds, derived from Table 2. An automated bus departing within these intervals, such as the first interval (1822.13 to 1846.54 seconds), can perform smooth lane changes unaffected by surrounding traffic.

Table 3: Range of Optimal Departure Time

No.	Optimal departure time range (Beginning)	Optimal departure time range (End)	Possible_gap (Sec)
1	1822.13	1846.54	24.41
2	1877.53	1891.74	14.21
3	1906.43	1917.14	10.71
4	1940.93	1945.44	4.51

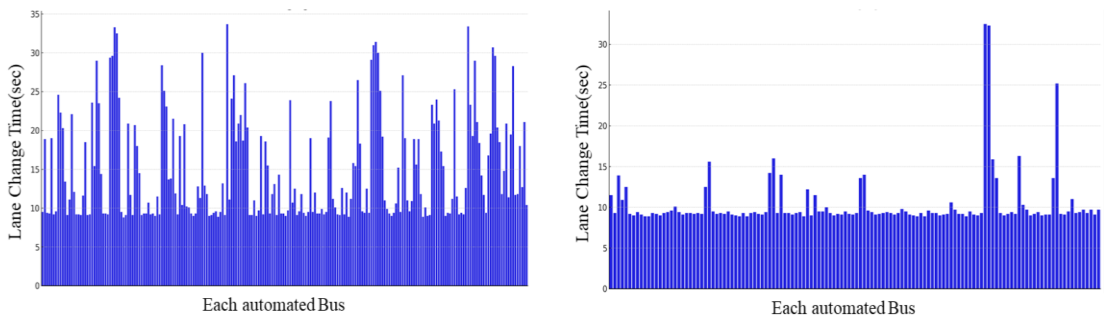
5	1966.03	2030.24	64.21
6	2052.53	2069.94	17.41
7	2091.04	2091.74	0.70
8	2116.53	2133.84	17.31
9	2157.63	2173.24	15.61
10	2210.03	2220.54	10.51
…	…	…	…
83	5367.33	5373.03	5.70

Performance Evaluation

Among the automated buses analyzed, 130 departed within the optimal departure time range, while 216 departed outside this range. The efficiency, safety, and traffic flow string stability of all 346 automated buses were evaluated in relation to their lane-changing behaviors.

The efficiency of automated buses was validated by measuring lane change times. Buses departing within the optimal range averaged 10.3 seconds, 4.7 seconds faster than those outside the range. Figure 6(a) shows 37.0% of buses outside the range exceeded 15 seconds, while only 5.3% of those within the range did, as shown in Figure 6(b). This demonstrates that departing within the optimal range reduces lane change time, enhancing efficiency. Detailed results are presented in Table 4.

Figure 6: Lane Change Time for Automated Buses



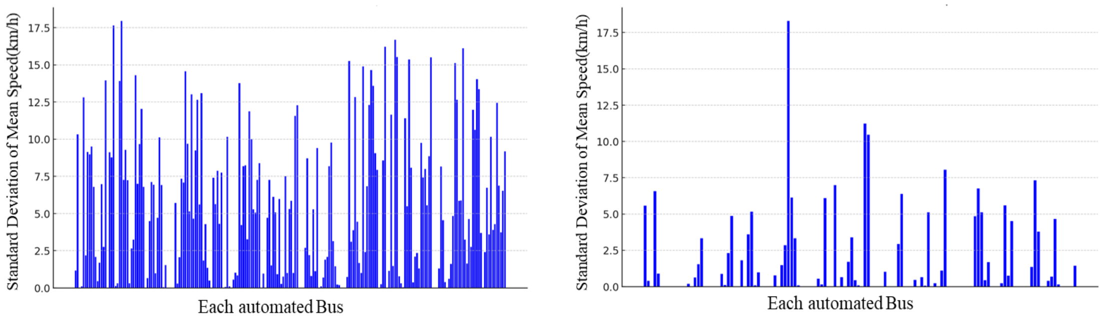
(a) Departing Outside the Optimal Departure Time Range

(b) Departing Within the Optimal Departure Time Range

The safety of automated buses was evaluated using conflict counts, the ratio of conflicting vehicles, and critical TTC occurrences (<1.5 seconds). Departing within the optimal range reduced conflicts from 156 to 26 and critical TTC occurrences from 21 to 0. The conflicting vehicle ratio improved from 38.9% to 14.6%, a 24.3% improvement, demonstrating enhanced safety. Results are detailed in Table 4.

The impact of lane changes on traffic flow was analyzed by validating string stability using the standard deviation of average speeds of following vehicles. For 130 buses departing within the optimal range, 68 instances showed no following vehicles, with an average speed deviation of 2.91 km/h. In contrast, for 216 buses departing outside the range, only 26 instances had no following vehicles, with a higher deviation of 6.10 km/h. (Figure 7(b)) shows overall lower deviations compared to (Figure 7(a)), confirming that optimal departures enhance traffic flow stability.

Figure 7: Standard Deviation of Following Vehicles Mean Speed



(a) Departing Outside the Optimal Departure Time Range

(b) Departing Within the Optimal Departure Time Range

Table 4: Validation Results of the Effectiveness of Lane Change Strategy

<table>
<tr><td colspan="3" rowspan="2"></td><td colspan="2">Classification</td></tr>
<tr><td>Departures outside the optimal departure time range</td><td>Departures within the optimal departure time range</td></tr>
<tr><td colspan="3">Nnumber of departing automated buses(vehs)</td><td>216</td><td>130</td></tr>
<tr><td rowspan="4">Efficiency of Automated buses</td><td rowspan="4">Lane change time(sec)</td><td>Minimum value</td><td>8.8</td><td>8.9</td></tr>
<tr><td>Maximum value</td><td>33.7</td><td>32.5</td></tr>
<tr><td>Mean value</td><td>15.0</td><td>10.3</td></tr>
<tr><td>Median Value</td><td>11.8</td><td>9.3</td></tr>
<tr><td rowspan="3">Safety of Automated buses</td><td colspan="2">Number of conflicts</td><td>156</td><td>26</td></tr>
<tr><td colspan="2">Percentage of vehicles in conflict</td><td>38.9%(84/216)</td><td>14.6%(19/130)</td></tr>
<tr><td colspan="2">Below the threshold for TTC</td><td>21</td><td>0</td></tr>
<tr><td rowspan="2">String Stability of Traffic Flow</td><td rowspan="2">Standard deviation of the rear vehicle's mean speed</td><td>Number of cases without a rear vehicle</td><td>26</td><td>68</td></tr>
<tr><td>Mean value(km/h)</td><td>6.10</td><td>2.91</td></tr>
</table>

This study analyzed the lane change strategy under increased traffic volumes. Automated buses departing within the optimal range showed improved lane change times across all scenarios, with greater efficiency as traffic volume increased. Safety also improved significantly, with fewer conflicts and lower ratios of conflicting vehicles in all scenarios. Departing within the optimal range ensures the strategy's effectiveness in both efficiency and safety, even under higher traffic volumes.

Figure 8: Mean Lane Change Time by Traffic Volume Scenarios

Figure 9: Percentage of Vehicles in Conflict by Traffic Volume Scenarios

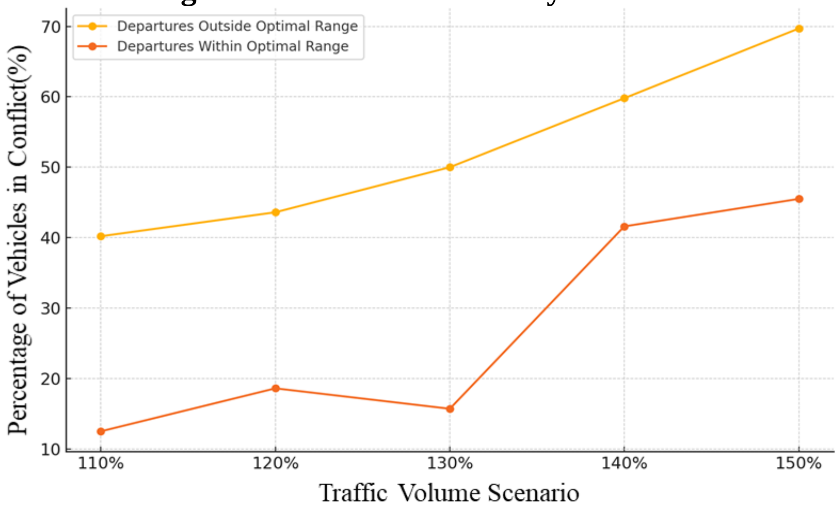
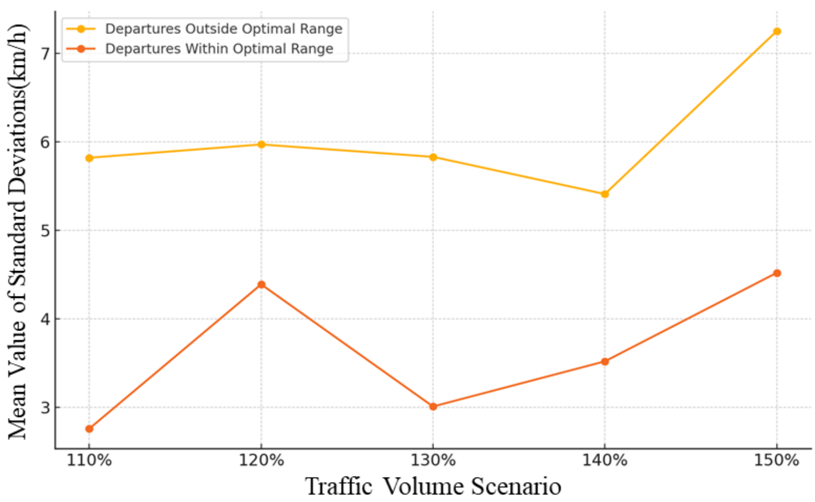


Figure 10: Mean Value of Standard Deviation of Following Vehicles' Mean Speed by Traffic Volume Scenarios



4. CONCLUSIONS

This study developed a lane change strategy for automated buses, addressing urban traffic management challenges. Using K-means clustering, the strategy identifies optimal gaps between vehicle platoons for efficient and safe lane changes. Unlike previous approaches focused on driving algorithms, this strategy emphasizes a traffic flow perspective, allowing buses to change lanes without being affected by surrounding vehicles.

Validated through simulations in the Pangyo Automated Vehicle Test Zone, the strategy reduced lane change times by 4.7 seconds, decreased conflict ratios by 24.3%, and improved traffic flow stability. These benefits were observed in both off-peak and high-traffic scenarios, highlighting its potential to reduce control handovers and enhance autonomy and operational predictability.

Despite promising results, limitations include assumptions about uniform acceleration and constant speed. Future research should explore adaptive strategies for dynamic traffic conditions and validate findings in diverse urban environments. This strategy demonstrates significant potential for enhancing the efficiency, safety, and acceptance of autonomous public transportation.

ACKNOWLEDGEMENTS

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