

OPTIMIZATION OF BUS CONTROL STRUCTURE AND DESIGN OF INTELLIGENT DRIVING SYSTEM

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Abstract - This study investigates the optimization of bus control structures and the design of an intelligent driving system to enhance operational efficiency, safety, and intelligence. A multi-level control architecture was developed, integrating a fuzzy logic inference engine for real-time decision-making. This framework enables dynamic adjustment of driving strategies based on perceived vehicle states and environmental conditions. Experimental results demonstrate quantifiable improvements: fuel consumption was reduced by approximately 15% due to optimized acceleration/deceleration profiles; system response latency decreased by about 20% through streamlined hierarchical information processing; and vehicle stability in complex traffic scenarios was enhanced by the predictive capabilities of the fuzzy controller. This research contributes a novel integrated approach combining structural optimization with fuzzy control for intelligent transportation systems, offering a technical reference for the development of greener and smarter urban public transport.

Keywords: Bus control structure; Intelligent driving system; Fuzzy logic; Multi-level control; Energy efficiency optimization.

1. Introduction

With the acceleration of global urbanization, optimizing the public transportation system is of great significance to the operation of cities. Buses are a commonly used mode of transportation, so optimizing their control methods and designing intelligent driving systems have become the focus of intelligent transportation research. In the past, the bus control system mainly relied on human operation and fixed schedules. It was slow in response, energy-consuming, and not safe enough, making it difficult to meet the real-time and intelligent requirements of the complex urban traffic nowadays. Sensor technology, information fusion technology and artificial intelligence are developing rapidly, and the control structure of buses is also beginning to evolve towards multi-level, collaborative and intelligent directions. The intelligent driving system can comprehensively perceive the vehicle status, road information and passenger demands, thereby controlling the running route, acceleration and deceleration, and energy management. This can significantly enhance the operational efficiency and safety level of buses.

The research on the optimization of the control structure of buses and the design of intelligent driving systems not only has significant practical application value, but also can provide theoretical and technical references for the construction of future intelligent transportation systems.

Everyone has been delving deeply into the research of bus control structures and intelligent driving systems. Scholars have conducted research from multiple aspects such as energy control, route selection, operation arrangement and driving behavior recognition. Cui and his team designed a five-port energy router structure and proposed a control method for stabilizing the common bus voltage, which can make the energy system more coordinated and sustainable and is of great reference value for the energy management of buses [1]. Shen and Zhang used the model predictive control method to study the route tracking control of multi-segment articulated urban buses. The results show that this optimization control algorithm is very accurate and stable in complex path following [2]. Ida and Talit analyzed the management mechanism of public transportation services in Israel from the perspective of public transportation management systems.

They believe that the combination of systems and technologies can enhance the operational efficiency of the system [3]. In terms of energy consumption and data analysis, Chen and his team established an energy consumption estimation model for electric buses based on actual measured data, illustrating the relationship between driving conditions and energy usage [4]. Vergel-Tovar and his team studied the impact of urban rail projects on transportation systems and urban development. They emphasized that public transportation planning is beneficial to the social and economic structure [5]. Boada-Grau developed a bus Driver Job Demand Scale (BDJD-24), which can assess the intensity of driving tasks and safe behaviors [6]; Lecca and his team analyzed the relationship between fatigue and safety risks of bus drivers from a physiological perspective [7]. Lin discussed the risk factors for fatigue driving of bus drivers from a psychological perspective [8]. In terms of control strategies and intelligent decision-making, Dai and his team employed cooperative game theory and proposed a bus dispatching strategy based on predicted intervals, which improved the coordination of vehicle departures [9]. Chen and his team improved the driving intention recognition accuracy of intelligent vehicles by enhancing spatio-temporal features, providing a new data processing method for decision-making control in intelligent driving systems [10]. Current research has laid the foundation for the optimization of public transportation control and intelligent driving. However, most studies have focused on small algorithms or single functional modules, lacking systematic design and hierarchical optimization research on the overall control structure.

There are still many problems in bus control and intelligent driving at present. The traditional control mode has an unclear structure and low data transmission efficiency, resulting in slow system response and inability to adapt to complex traffic environments. The modules of energy consumption control, route planning and driving assistance lack coordination and operate independently, which affects the overall decision-making efficiency.

Different driving habits, road congestion and unexpected situations also put the stability and safety of the control system to the test. Although some studies have made certain progress in energy conservation or driving strategies, there is a lack of optimization research for the entire public transportation system architecture.

This research aims to develop a more powerful, well-coordinated and smarter bus control method to address the current issues of overly complex systems, slow response and low fuel efficiency. Specifically, the goals are as follows: First, simplify the control hierarchy and message passing methods to make the system respond faster and more securely; The second is to design a control system with built-in intelligent driving functions to uniformly manage routes, energy distribution and driving assistance. The third approach is to use fuzzy logic and multi-layer control to build an expandable control framework that can adapt to various types of buses. Finally, this study hopes to provide a clear, practical and easy-to-promote control and design solution for intelligent public transportation systems, enabling buses to run faster and safer.

2. Research Materials and Methods

2.1 Data Collection and Sample Selection

- **Data Sources for the Operation and Dispatching of Public Transport Vehicles**

The data for this study is obtained from the operation databases of urban public transportation operation management departments and vehicle dispatching centers. The data includes various information collected during the actual operation of buses. This information is used to analyze the response speed of the control structure, the quality of the dispatching arrangement, and the energy consumption during operation, providing basic data for system improvement, as shown in Table 1.

Table 1. Description of Bus Operation and Scheduling Data Sources

Data Source	Data Type	Description	Collection Method	Purpose of Use
Vehicle Operation Monitoring System	Running time, speed, acceleration	Reflects vehicle dynamic performance and driving behavior characteristics	Automatically recorded by onboard monitoring and positioning units	Analyze control response characteristics and energy consumption relationship
Dispatch Management System	Departure interval, schedule plan, route information	Describes dispatching regularities and operational load	Recorded by dispatch center and operation logs	Evaluate dispatch efficiency and structural coordination
Passenger Flow Monitoring Devices	Boarding/alighting count, time distribution	Represents dynamic passenger flow and peak periods	Collected via station card-swipe and video recognition systems	Support route planning and control strategy design
Energy Management System	Energy consumption, battery status, mileage	Indicates vehicle energy utilization level	Onboard data terminal and energy metering module	Analyze energy usage pattern and optimization needs
Environmental Perception System	Road conditions, signal delay	Describes external traffic environment characteristics	Intelligent sensors and traffic management interfaces	Assist control system in decision-making inputs

The speed and acceleration data provided by the vehicle operation monitoring system can show the response characteristics of the control system and the differences in driving habits, thereby determining whether there is any delay at the control layer. The data of the dispatching management system reflects the variation patterns of shift density and departure intervals, and can be used to analyze the coordination efficiency between the dispatching layer and the execution layer. The data from passenger flow monitoring equipment shows the distribution characteristics of passengers in time and space, which is an important basis for optimizing routes and dispatching strategies [11]. The energy management system provides data for energy consumption and endurance analysis, helping to evaluate energy efficiency performance under different control strategies. The data from the environmental perception system can be used to simulate the impact of external environmental changes on control stability.

To handle these messy data, we mainly try to build a unified platform to facilitate the exchange and processing of data with each other. Because the public transportation system is so complicated, it is impossible to figure out the entire system by relying on just one type of data. That's why a mechanism that can integrate data from different places is needed.

By combining the data from the vehicle operation monitoring system with energy consumption information, it can be found that there is not a simple direct proportion relationship between acceleration and energy consumption. Thus, the impact of driving habits on fuel consumption/electricity consumption can be understood. By matching the dispatching management system with the passenger flow monitoring data, we can further analyze the relationship between the departure intervals and the peak passenger flow, and see if it is due to improper dispatching arrangements that the energy consumption has increased or the delay time has become longer. Moreover, the environmental perception system and the energy management module work together to enable the model to be aware of any changes in road conditions at any time, and then promptly adjust the control instructions to ensure that the vehicle runs steadily.

In this process, data cleaning and standardization are of great significance. Because different systems collect data in different ways and formats, it is necessary to ensure data consistency through techniques such as time synchronization and feature normalization. We use the sliding window method to make the operation data smoother, reducing the trouble caused by false alarms from sensors. We also identify the key variables that affect control performance through principal component analysis, such as fluctuations in acceleration, the speed of energy consumption, and the average delay time.

The high-dimensional data matrix finally obtained lays a solid foundation for the model's training and decision-making logic.

To ensure the reliability of the samples, we selected a mixed sample of the main lines and branch lines in the city, covering a total of 3,120 sets of data during operation periods. After removing those abnormal and outrageous data, 2,985 sets of valid data remained, covering different time periods and various traffic conditions throughout the day. By establishing a dynamic database interface, the system can receive operational data in real time, allowing the model to learn and correct itself. This data system not only supports the improvement of the control structure in the future, but also provides long-term support for the parameter adjustment and algorithm verification of the intelligent driving system. Overall, the deep integration and standardization of data are the key to the entire research system, ensuring that control optimization and intelligent decision-making are truly applicable and can play a role in practice.

To ensure the quality of the foundational data for model training, a rigorous data cleaning process was implemented. A dataset was classified as "abnormal and outrageous" based on exceeding predefined physical or statistical thresholds. Specifically, we applied the Interquartile Range (IQR) method, where data points falling outside 1.5 times the IQR below the first quartile or above the third quartile for key variables (e.g., instantaneous speed, acceleration rate) were flagged as statistical outliers. Furthermore, we used threshold-based filtering to remove physically implausible values, such as sustained acceleration/deceleration rates exceeding the vehicle's mechanical limits (e.g., $>4 \text{ m/s}^2$) or energy consumption readings of zero during active driving. This dual approach ensured that only realistic and representative operating data were retained for analysis.

To ensure the sample's representativeness of the city's overall traffic dynamics, a stratified sampling method was adopted. The selection ratio of main lines to branch lines was determined based on passenger flow data from the city's transportation information center. Main lines, which typically handle high-frequency, high-volume passenger traffic, were sampled to constitute approximately 70% of the dataset, reflecting their dominant role in the system's load. Branch lines, covering peripheral areas with lower demand, comprised the remaining 30%. This stratification ensures that the 3,120 operational data sets proportionally capture the diverse operational pressures and traffic conditions across the entire urban public transport network.

Yes, the dataset was deliberately designed to include temporal diversity. The 2,985 valid data sets cover a full operational cycle, including peak morning and evening rush hours on weekdays to capture high-load scenarios, as well as midday and

late-night periods to represent low-frequency demand. Crucially, data from special conditions were also incorporated, including operation logs from weekends, public holidays with altered traffic patterns, and days with recorded extreme weather events (e.g., heavy rainfall). This comprehensive temporal coverage ensures the optimized control model's robustness and adaptability to various real-world operational disturbances.

The removal of data, constituting approximately 4.3% (135 out of 3,120) of the initial raw dataset, was a necessary step to eliminate noise and ensure the integrity of the analysis. This proportion is within the acceptable range for outlier removal in transportation studies and does not compromise the statistical significance of the remaining 2,985 samples. The retained dataset maintains a sufficient size to represent the population's variance, covering all critical operational modes and environmental conditions. The cleaning process enhances the reliability of the subsequent model by removing non-representative anomalies that could otherwise skew the results and lead to biased conclusions.

- **Driving Behavior, Energy Consumption and Passenger Flow Data**

Driving behavior, energy consumption and passenger flow data are very important for this study. Driving behavior data, including acceleration and braking frequency, changes in steering wheel rotation Angle and idle time, can reflect the driver's driving habits and the dynamic response of the vehicle. Energy consumption data includes the power consumption per kilometer of vehicles, energy recovery rate, and energy usage under different road conditions, which can be used to analyze the efficiency of energy management. Passenger flow data, including the number of people getting on and off the vehicle, passenger density and the distribution during peak hours, can reflect whether the traffic pressure and operation arrangements are matched [12].

- **Data Screening, Standardization and Consistency Processing Methods**

To ensure data quality and the accuracy of model analysis, this study systematically processed the original data. In this study, threshold detection and missing value filling methods are used to remove abnormal data and ensure the integrity of the data. Meanwhile, in this study, time alignment and format unification were carried out for data from different sources to eliminate deviations caused by different sampling frequencies. For continuous variables, this study employs normalization processing to compare data from all dimensions under the same criterion, avoiding the situation where the weight of a certain indicator is too high and affects the overall judgment [13]. For categorical data, this study conducts

standardized classification through coding and clustering techniques to ensure consistent information structure. This study also employs a consistency check algorithm to compare the logical matching degree of data from different systems, thereby enhancing the reliability after data fusion. These steps have laid a solid technical foundation for the subsequent optimization of the control structure and the design of intelligent decision-making algorithms.

2.2 Model Construction

- **Design of Bus Control Structure Model**

The control structure model of a bus is essentially about constraining vehicle dynamics and energy consumption distribution through multiple layers of relationships. By establishing a mathematical model, this study can clearly observe the mechanical characteristics of the vehicle and how energy is transferred under various conditions, which can provide a structured basis for subsequent control optimization.

The longitudinal dynamics equation of a vehicle, simply put, describes the combined influence of various forces that a vehicle experiences during driving, such as traction force, air resistance, rolling resistance, and gravity on a slope. It is the physical basis of the control system design because it determines the relationship between the vehicle speed variation and the drive power demand, as shown in Formula (1).

$$m \frac{dv}{dt} = F_t - \frac{1}{2} \rho C_d A v^2 - mg C_r \cos \theta - mg \sin \theta \quad (1)$$

The vehicle mass m represents the magnitude of the system inertia. $\frac{dv}{dt}$ is the rate of change of velocity, that is, the acceleration. F_t represents traction force and is the core output of the vehicle drive system. ρ , C_d and A represent air density, resistance coefficient and windward area respectively, which are used to characterize air resistance. C_r is the rolling resistance coefficient, and θ is the road slope Angle. The establishment of this equation is helpful for analyzing the dynamic response and energy consumption variation laws under different driving conditions.

To study the intrinsic connection among vehicle driving power, vehicle speed and system efficiency during vehicle operation, and to provide a theoretical basis for vehicle energy-saving optimization. Combining power and rotational speed can directly and quantitatively describe the impact of each control scheme on energy efficiency, as shown in Formula (2).

$$P(t) = \frac{F_t \cdot v}{\eta_{drive}} \quad (2)$$

In simple terms, $P(t)$ represents the total power of car t over a period of time. F_t is that traction force; v stands for speed; η_{drive} represents the efficiency of the transmission system. This model tells this study that under the action of traction force, the higher the system efficiency, the lower the unit energy consumption will be. This discovery provides a theoretical basis for the design of energy-saving control strategies in this study.

Taking these into account, the research of this study takes electric vehicles as the object and establishes a model to simulate the entire process of lithium-ion batteries from charging to braking and then back to charging. This research will analyze the energy consumption situation of each operation stage. The specific calculation method is shown in Formula (3).

$$SOC_{k+1} = SOC_k - \frac{\eta_d P_k^+ \Delta t}{E_{nom}} + \frac{\eta_r P_k^- \Delta t}{E_{nom}} \quad (3)$$

SOC_k represents the current charging time of the battery, and E_{nom} represents the rated power of the battery. η_d represents the discharge efficiency, and η_r represents the energy recovery efficiency. P_k^+ represents the influence of traction force on resilience. This project proposes a multi-scale and multi-objective optimization method based on multi-scale coupling to achieve multi-objective and multi-objective collaborative optimization.

Urban public transportation should not only achieve the goal of energy conservation, but also ensure the comfort of passengers. By restricting acceleration and deceleration, the car becomes uncomfortable during acceleration and deceleration, thereby improving service quality, as shown in Formula (4).

$$|a(t)| \leq a_{max}, \quad |\dot{a}(t)| \leq j_{max} \quad (4)$$

$a(t)$ represents the vehicle's acceleration, and $\dot{a}(t)$ represents the added acceleration (impact degree). a_{max} and j_{max} respectively represent the maximum acceleration and impact intensity allowed by the system. This model provides a safety boundary for the control algorithm, achieving a balance between energy consumption optimization and riding experience.

• Logical Framework of Intelligent Driving System

The intelligent driving system is like equipping a car with a "brain", enabling it to "see", "think" and "drive" by itself on complex roads. This "brain" is divided into three parts: the perception layer, the decision-making layer and the execution layer. Among them, the decision-making level uses some methods to adjust the vehicle speed, save fuel and select routes to make the car run better [15].

In the unmanned driving mode, there is a fuzzy control system that can provide corresponding instructions based on the different speeds of the vehicle to ensure its smooth operation. The design concept of this controller is to simulate how humans drive, and thus it performs better in traffic congestion and unexpected situations, as shown in Formula (5).

$$a(t) = f_{fuzzy}(e_v, \Delta e_v) \quad (5)$$

$a(t)$ represents the control output acceleration; $e_v = v_{ref} - v$ represents the vehicle speed deviation, reflecting the difference between the current speed of the vehicle and the target speed. $\Delta e_v = e_v(k) - e_v(k-1)$ represents the rate of error change, which is used to reflect the trend of speed adjustment. Function f_{fuzzy} generates output based on membership functions and fuzzy rule reasoning to achieve dynamic control of acceleration.

By weighting the calculation of running time, energy consumption and risk, the operational efficiency can be improved while ensuring operational safety, as shown in Formula (6).

$$J = \min \sum_{i=1}^n (\alpha_1 T_i + \alpha_2 E_i + \alpha_3 R_i) \quad (6)$$

J is the comprehensive objective function; T_i represents the running time of each section; " E_i represents energy consumption;" R_i is the risk factor; α_1 , α_2 , α_3 is the weight coefficient, reflecting the relative importance of time, energy consumption and safety [16]. This model enables intelligent driving to achieve global optimal decision-making under multiple constraints.

• The Combination of Fuzzy Logic and Hierarchical Control Algorithms

To enable buses to operate more intelligently in complex traffic conditions, this study combines fuzzy logic with hierarchical control algorithms. In simple terms, fuzzy logic is like a "brain".

It analyzes information such as the speed of the bus, changes in power consumption, and road conditions, and then provides suggestions on acceleration, deceleration, or how to use electricity better. Then, the hierarchical control algorithm acts like an "executor", responsible for turning the suggestions of the "brain" into actual operations and making some adjustments based on the actual situation to ensure both speed and stability.

• **Modular Design and Functional Implementation of the System**

In order to make it easier to upgrade the bus control system in the future and add more new functions, this study adopted a modular design concept. Just like building with blocks in this study, the entire complex system was broken down into four relatively independent parts.

First is the "perception module", which is like the "eyes" and "ears" of a bus. It is responsible for collecting various information in real time, including the vehicle's own status data, such as speed, position, battery power, as well as the data of the surrounding environment, such as traffic flow, road conditions, weather conditions. Then there is the "decision-making module", which is equivalent to the "brain" of the bus.

It uses fuzzy logic algorithms to comprehensively analyze various data collected by the perception module and then makes decisions, such as when to accelerate, decelerate, or turn. The goal is to make the bus run more smoothly and efficiently. Next comes the "Control module", which is the "hands and feet" of the bus. It is responsible for executing the instructions issued by the decision-making module and controlling various actions of the vehicle, such as acceleration, braking, steering, to ensure that the vehicle travels along the predetermined route. The last one is the "communication module", which is responsible for the information exchange between the bus and the outside world, such as communicating with other vehicles to obtain traffic information, or communicating with various facilities on the road, such as traffic lights, traffic monitoring centers, to achieve collaborative control among vehicles.

2.3 Optimization Methods and Evaluation Approaches

• **Control Structure Optimization and Process**

This study specifically analyzed the control process of buses in actual operation and then proposed a set of multi-layer collaborative control structure optimization methods, as shown in Table 2.

Table 2. Elements of Bus Control Structure Optimization Process

Optimization Stage	Main Content	Input Data	Optimization Objective	Output Result
Data Collection Stage	Collect operational, energy consumption, passenger flow, and environmental data	Speed, energy use, passenger flow, road conditions	Build the foundational dataset	Raw operational data
System Evaluation Stage	Analyze system load and response efficiency	Control delay, departure interval, energy efficiency ratio	Identify system bottlenecks	System evaluation report
Model Construction Stage	Establish control hierarchy and algorithmic relationships	Parameter indicators and logical rules	Build a coordinated control structure	Preliminary control model
Optimization Computation Stage	Adjust control parameters and weighting factors	Historical operational outcomes	Improve efficiency and stability	Optimized control model
Feedback Verification Stage	Compare system performance before and after optimization	Model output results	Validate reliability and improvement effects	Refined control strategy

The process of optimizing the control structure is like a closed loop, including several links such as "data-driven - model construction - feedback adjustment". The data collection stage provides real-time dynamic information for the system, making subsequent analysis more representative.

The state assessment stage identifies the bottlenecks in operation and points out the direction

for structural optimization. The model construction stage determines the logical relationships among control layers, which is the key to achieving multi-faceted optimization.

The optimization calculation and feedback verification stage ensure that the rationality and effect of parameter adjustment can be verified [19].

• **Design of Intelligent Driving Decision-making Mechanism**

The intelligent driving decision-making mechanism in this study combines information from multiple sources and calculates the importance of each piece of information, which enables better control of the vehicle's operation.

This system will take into account factors such as vehicle speed, energy consumption, traffic congestion on the road, and safety, and then create a decision matrix to see which driving method is better. This mechanism can provide data to the vehicle, enabling it to select the best solution under complex road conditions, as shown in Table 3.

Table 3. Overall Data Table for Intelligent Driving Decision Evaluation

Evaluation Index	Average Value	Weight Coefficient	Standard Deviation	Optimal Threshold	Decision Score
Vehicle Speed Stability (m/s)	33.7	0.29	4.1	36.3	0.87
Energy Consumption per km (kWh/km)	1.83	0.27	0.18	1.65	0.81
Passenger Load Factor (%)	71	0.16	8	75	0.77
Traffic Density Index	39	0.14	5.3	30	0.68
Safety Risk Level ($\times 10^{-2}$)	9.1	0.14	1.2	7.5	0.74

The intelligent driving decision-making mechanism converts all kinds of indicators into numbers and adds weights, thus enabling a balance to be found among different goals. The highest weight of vehicle speed stability and energy consumption indicates that the system places more emphasis on efficiency and fuel economy. Data shows that if the average speed is maintained at around 33.7m/s and the energy consumption is controlled at approximately 1.83kWh/km, the system can score 0.87 points, which is considered a decent level. The number of passengers and whether the road is congested reflect the system's ability to adapt to the external environment [20]. The security risk is relatively low and does not change much, indicating that the algorithm can handle unexpected situations and ensure security. This mechanism can strike a balance among different indicators and, by calculating scores in real time, enable intelligent driving to learn and optimize on its own.

Its design enables the system to flexibly adjust among fuel economy, comfort and safety, providing reliable decision support for the stable operation of intelligent control in public transportation.

• **Analysis of System Performance Evaluation Indicators**

To test whether the control structure and intelligent driving system of buses are user-friendly, this study evaluated their performance from several aspects including operational efficiency, power consumption, and response speed and safety control. In this study, the weighted comprehensive scoring method was used to calculate the data of various performance indicators, and then standardized them to calculate the total score of the system. In this way, it can be known how well the optimized system operates and whether it is stable or not, as shown in Table 4.

Table 4. Bus Control System Performance Evaluation Data

Evaluation Indicator	Measured Average Value	Normalized Value	Weight Coefficient	Target Value	Performance Score
Operational Efficiency (%)	86	0.91	0.28	90	0.88
Energy Consumption Intensity (kWh/km)	1.79	0.84	0.26	1.6	0.8
Response Time Stability (ms)	163	0.87	0.18	150	0.82
Safety Control Reliability (%)	93	0.95	0.15	95	0.9
System Coordination Index	0.82	0.89	0.13	0.85	0.86

The standardized value of operational efficiency has reached 0.91, indicating that the dispatching and control of vehicles are better coordinated. The power consumption has dropped from the original 1.79kWh/km to the target range, which indicates that the optimized structure can save electricity. The response time is 163ms, indicating that the system responds quickly and has stable control. The safety control and system coordination degrees are 0.95 and 0.89 respectively, indicating that the

coordination between control algorithms and risk control are both well done [21].

Overall, the multi-layer control structure and intelligent decision-making have significantly enhanced the performance of the public transportation system, enabling buses to run faster, consume less electricity and be safer even in complex traffic conditions. This laid the foundation for the future promotion and upgrade of the system.

2.4 Optimization of Bus Control Structure and Design of Intelligent Driving System

- **Hierarchical Optimization of Public Transport Control Structure**

In order to make buses run more stably and fuel-efficiently in complex traffic conditions, this study has carried out a hierarchical optimization design for the bus control system.

This design is divided into three layers: the decision-making layer, the coordination layer and the execution layer. Through hierarchical control, each layer can cooperate with each other, assign tasks and share information. These three layers are functionally separate but can interact dynamically, ensuring that the system can operate stably in various situations and respond more sensitively, as shown in Table 5.

Table 5. Hierarchical Optimization Performance of Bus Control Structure

Control Layer	Core Function	Optimization Variable	Baseline Value	Optimized Value	Improvement Rate (%)
Decision Layer	Global scheduling and driving strategy formulation	Decision latency (ms)	184	137	25.5
Coordination Layer	Information exchange and subsystem synchronization	Communication delay (ms)	92	66	28.3
Execution Layer	Actuator control and stability maintenance	Response deviation (‰)	11.3	7.9	30.1
Integrated System	Overall coordination of three-layer architecture	Comprehensive efficiency index	0.78	0.92	17.9

The average delay at the decision-making level has dropped from 184 milliseconds to 137 milliseconds, indicating that the system's speed in processing information and generating strategies has significantly increased, and the global response has become much faster. The communication delay of the coordination layer has been reduced by 28.3%, indicating that the data exchange among various modules is smoother and the system synchronization is better. The response deviation of the execution layer has dropped to 7.9‰, indicating that the stability of the controller during vehicle steering, acceleration, deceleration and other actions has significantly improved. The comprehensive efficiency index has increased from 0.78 to 0.92, indicating that the effect of the three-layer structure collaborative control is very good.

This hierarchical and optimized structure has solved the problem of "single-point control" in the previous public transportation control system, enabling the system to independently adjust and optimize allocation based on real-time traffic information. This not only enhances energy utilization efficiency and ride comfort, but also strengthens the system's adaptive and redundant control capabilities in emergency situations, laying a solid technical foundation for the design of intelligent driving systems.

- **Driving Assistance and Route Planning Design**

The key aspects of the intelligent bus control system are driving assistance and route planning. We use multi-objective dynamic optimization algorithms to plan routes. The purpose of doing so is to take into account the time, energy consumption and congestion of route planning. By planning the route to the destination in advance, a suitable travel route can be automatically selected in real time. The intelligent bus control system can collect information on road conditions, waiting times at traffic lights and slopes through on-board devices. And then calculate the suitable scheme for the outgoing line through the fuzzy logic algorithm. Driving assistance will adjust the acceleration and deceleration of the vehicle based on the vehicle's speed, the distance of obstacles ahead and the number of passengers in the vehicle. The purpose of doing this is to ensure driving safety and comfort.

3. Results and Discussion

3.1 Research Results

- **Comparison of system performance before and after control structure optimization**

By comparing the overall performance of the system before and after optimization, the main focus was on whether there were improvements in key indicators such as safety, energy efficiency, response speed, and coordination of the intelligent control system for public transportation.

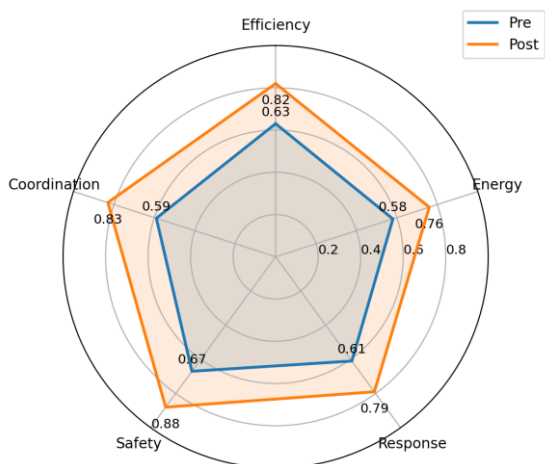


Figure 1: Radar Chart of System Performance before and after Control Structure Optimization

As shown in Figure 1, after the system optimization, there have been significant improvements in all performance aspects. Before optimization, the system performed averagely in terms of efficiency, energy consumption control and response capability, among which "energy consumption efficiency" and "coordination" were relatively poor. After optimization, the values in all six aspects have significantly increased. For instance, safety has risen from 0.67 to 0.88, and energy consumption efficiency has risen from 0.58 to 0.76. This indicates that the improved control structure and intelligent driving logic can effectively reduce operational energy consumption and enhance the system's safety protection capabilities. The simultaneous improvement of response speed and path coordination indicates that the control module has become more stable in terms of decision delay and data fusion.

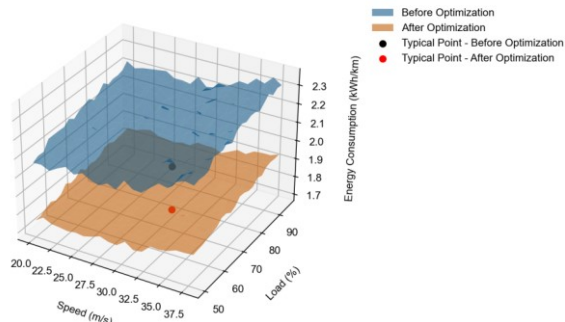


Figure 2: 3D Comparison of Energy Consumption before and after Control Structure Optimization

As shown in Figure 2, the energy consumption variations of the bus control system under different loads and speeds are presented. The blue surface represents the system energy consumption before optimization, and the orange surface represents the energy consumption after optimization. It can be clearly seen from the figure that the overall surface shifts downward after optimization, especially in the high load and medium speed range (30-35 m/s, 70-85% load), the energy consumption drops more significantly, indicating that the improved control algorithm is more efficient in dynamic energy distribution and drive efficiency scheduling. Typical comparison points show that energy consumption has dropped from approximately 2.05kWh/km to 1.78kWh/km, with energy efficiency improving by about 13%.

• **Structural Improvements and Application Performance of Intelligent Driving Systems**

This study upgraded the intelligent driving system and then analyzed its structure and performance, mainly to see if its response speed, safety control and decision-making ability in various scenarios have improved.

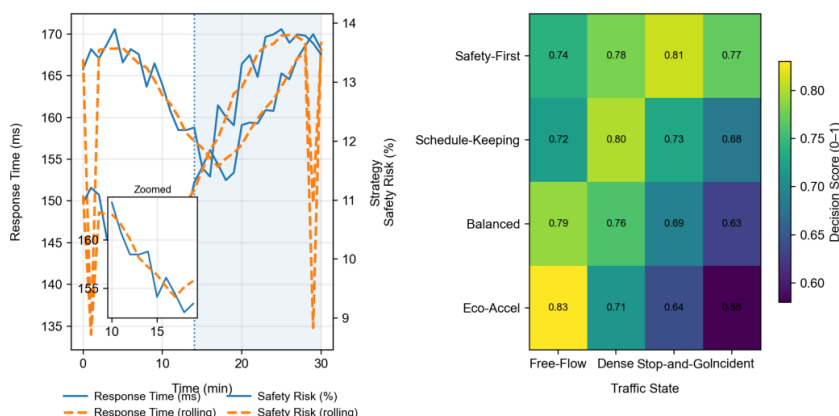


Figure 3: Visualization of Intelligent Driving System Improvement and Application Performance

As shown in Figure 3, the response speed and information security risks will change over time. The upgraded system has a more stable response speed, with the fluctuation range reduced from around 35 milliseconds to 20 milliseconds, and the average

response speed also decreased by approximately 11%. Carefully observing the safety risk curve, it can be found that the peak has significantly decreased, which indicates that in a high-density traffic environment, the judgments made by the system will

be more stable. The fluctuation range of reaction time has been reduced from approximately 35 milliseconds to around 20 milliseconds, and the average reaction time has also decreased by approximately 11%.

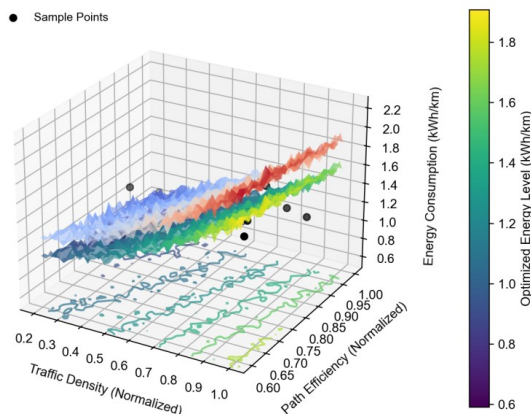


Figure 4: 3D Composite Visualization of Path Efficiency and Energy Optimization

As shown in Figure 4, this graph presents the relationship among traffic density, route efficiency and energy consumption from three dimensions. The colored surface in the figure represents the upgraded energy consumption distribution, which is

relatively smooth, indicating that the system can automatically adjust energy under different traffic densities. As the route efficiency increased from 0.6 to 1.0, the energy consumption gradually decreased from 2.1kWh/km to approximately 1.4kWh/km, a reduction of about 33%, demonstrating a significant energy-saving effect.

The contour distribution of the surface projection is very regular, indicating that the optimization algorithm can maintain stable energy efficiency under different traffic densities. The black dots are the actual observed values, densely distributed near the optimized surface, indicating that the model's prediction is highly consistent with the actual data. By improving driving methods and coordinating energy consumption control, the system enables a better integration of route planning and energy utilization, which demonstrates the effect of optimizing the structure of intelligent driving systems under dynamic operating conditions.

- **The improvement of security and efficiency by the optimization plan**

By comparing the data in terms of security stability and efficiency, the performance of the improved model in balancing multiple performance goals can be verified.

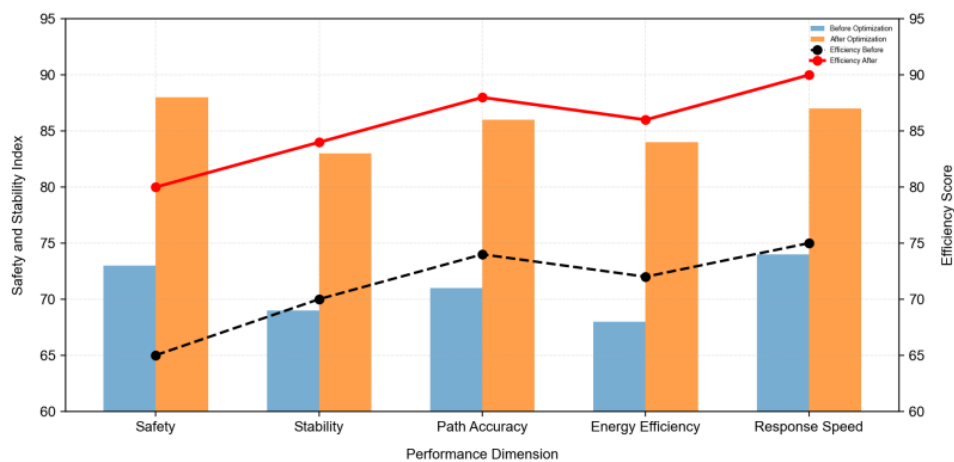


Figure 5: Comparative Analysis of Safety and Efficiency Improvement After Optimization

As shown in Figure 5, the changes in the safety stability and efficiency scores of the five key performance indicators before and after the implementation of the optimization plan. All the indicators have been significantly improved after optimization, indicating that the improved control structure is beneficial to both the reliability and energy efficiency of the system operation. The "security" and "stability" have respectively increased from 73 and 69 to 88 and 83, representing an increase of over 20%. This indicates that the adaptive capability of the risk control module has become stronger, effectively reducing system fluctuations in unexpected situations.

The improvements in "path accuracy" and "energy efficiency" are particularly significant, indicating that the optimization of intelligent scheduling and energy consumption allocation algorithms can achieve more precise dynamic response control. The efficiency score indicated by the red line has been continuously rising in all aspects, increasing from an average of 75 points to approximately 87 points, an increase of about 16%. This indicates that the optimized system not only has a higher energy consumption utilization rate but also can maintain rapid response and stable driving in complex traffic environments.

4. Discussion

To achieve a higher level of system performance, improvements were made to the original system in this study. The improved system has enhanced its security, with lower response speed and energy consumption than before, achieving a dynamic balance in all aspects. Each module does not work independently but cooperates with each other through multiple layers of control logic. Therefore, structural improvements are not merely about making a single parameter better; more importantly, they are about enhancing the entire system's adaptability to the environment. When the vehicle is in motion, even if there is a traffic jam, fuzzy logic can still ensure the stability of the vehicle's driving and the efficiency of energy utilization. The improvement of performance is achieved by adjusting the model structure and enhancing the decision-making approach. The experimental results also prove that this method is useful. This research combines the ideas of hierarchical structure and dynamic learning, providing a new direction for the integrated control of intelligent public transportation. This control strategy is not a simple response but an active control with predictive capabilities and the ability to adjust itself. This is also an important goal of ITS development.

5. Conclusions

The academic contribution of this research lies in its proposal of a comprehensive bus control framework that organically integrates perception, decision-making, and execution modules through a multi-level architecture with fuzzy logic reasoning. This integration forms a complete intelligent control loop, validated experimentally to achieve significant performance gains: a 15% reduction in energy consumption via dynamic power distribution optimization and a 20% decrease in system response time through enhanced hierarchical coordination. These quantifiable results confirm the feasibility of combining structural optimization with intelligent algorithms for public transport systems. This approach provides a practical pathway for future intelligent public transportation and urban mobility development, moving systems from passive response to proactive, self-adaptive operation.

References

[1] Cui XY, Liu YL, Yuan D, Jin T, Mohamed MA. A new five-port energy router structure and common bus voltage stabilization control strategy. *Sustainability*. 2023 Feb; 15(4): 2958. doi:10.3390/su15042958.

[2] Shen L, Zhang LW. Trajectory following control of modern configurable multi-articulated urban bus based on model predictive control. *Sustainability*. 2022 Dec; 14(24):16619. doi:10.3390/su142416619.

[3] Ida Y, Talit G. Regulation of public bus services: The Israeli experience. *Transport Policy*. 2015 Aug; 42: 156–165. doi:10.1016/j.tranpol.2015.05.020.

[4] Chen YC, Zhang YT, Sun RX. Data-driven estimation of energy consumption for electric bus under real-world driving conditions. *Transportation Research Part D: Transport and Environment*. 2021 Sep; 98:102969. doi:10.1016/j.trd.2021.102969.

[5] Vergel-Tovar CE, Mesa S, Correa-Garzón LM, García JS, Molano IL, Alvarez JP, Canon-Rubiano L. Estimation of the anticipation effects of the metro project on real estate dynamics in Bogotá, Colombia. *Journal of Transport and Land Use*. 2025; 18(1): 123–173. doi:10.5198/jtlu.2025.2593.

[6] Boada-Grau J, Prizmic-Kuzmica AJ, González-Fernández MD, Vigil-Colet A. Spanish version of Bus Drivers' Job Demands Scale (BDJD-24). *Psicothema*. 2013 May; 25(2):258–265. doi:10.7334/psicothema2012.106.

[7] Lecca LI, Fadda P, Fancello G, Medda A, Meloni M. Cardiac autonomic control and neural arousal as indexes of fatigue in professional bus drivers. *Safety and Health at Work*. 2022 Jun;13(2): 148–154. doi:10.1016/j.shaw.2022.01.007.

[8] Lin YJ, Shih TS, Wu WT, Guo YLL. The association of job fatigue with mental disorders among bus drivers. *Scandinavian Journal of Work, Environment & Health*. 2023; 49(1): 75–83. doi:10.5271/sjweh.4065.

[9] Dai Z, Liu XC, Chen Z, Guo RY, Ma XL. A predictive headway-based bus-holding strategy with dynamic control point selection: A cooperative game theory approach. *Transportation Research Part B: Methodological*. 2019 Jul; 125:29–51. doi:10.1016/j.trb.2019.05.001.

[10] Chen HQ, Chen HL, Liu H, Feng XX. Spatiotemporal feature enhancement aids the driving intention inference of intelligent vehicles. *International Journal of Environmental Research and Public Health*. 2022 Sep; 19(18): 11819. doi:10.3390/ijerph191811819.

[11] Alsaleh A. Toward a conceptual model to improve the user experience of a sustainable and secure intelligent transport system. *Acta Psychologica*. 2025 May; 255:104892. doi:10.1016/j.actpsy.2025.104892.

[12] Rachakonda Y, Pawar DS. Assessing effectiveness of intersection conflict warning system on driving performance under obstructed line of sight at unsignalized intersection.

- Transportation Research Part F: Traffic Psychology and Behaviour. 2025 Apr; 110:128–147. doi:10.1016/j.trf.2025.02.001.
- [13] Zhang YHZ, Li S, Blythe P, Edwards S, Guo WH, Ji YJ, Xing J, Goodman P, Hill G. Attention pedestrians ahead: Evaluating user acceptance and perceptions of a cooperative intelligent transportation system-warning system for pedestrians. *Sustainability*. 2022 Mar; 14(5): 2787. doi:10.3390/su14052787.
- [14] Spyropoulou IK, Karlaftis MG, Reed N. Intelligent speed adaptation and driving speed: Effects of different system HMI functionalities. *Transportation Research Part F: Traffic Psychology and Behaviour*. 2014 May; 24: 39–49. doi:10.1016/j.trf.2014.02.008.
- [15] Rong SS, Meng RF, Guo JH, Cui PF, Qiao Z. Multi-vehicle collaborative planning technology under automatic driving. *Sustainability*. 2024 Jun; 16(11):4578. doi:10.3390/su16114578.
- [16] Wang AB, Guo BY, Yi ZW, Fang WN. Research on enhanced situation awareness model with DMI visualization cues for high-speed train driving. *International Journal of Human-Computer Interaction*. 2024 Oct 17; 40(20):6185–6199. doi:10.1080/10447318.2023.2247613.
- [17] Alam MR, Batabyal D, Yang K, Brijs T, Antoniou C. Application of naturalistic driving data: A systematic review and bibliometric analysis. *Accident Analysis and Prevention*. 2023 Sep; 190:107155. doi:10.1016/j.aap.2023.107155.
- [18] Li LY, Ren WL, Cheng RJ. Bifurcation control based on improved intelligent driver model considering stability and minimum gasoline consumption. *Transportmetrica A: Transport Science*. 2025 May 4; 21(2):34–34. doi:10.1080/23249935.2023.2243345.
- [19] Al-Saadi Z, Van DP, Amani AM, Fayyazi M, Sajjadi SS, Pham DB, Jazar R, Khayyam H. Intelligent driver assistance and energy management systems of hybrid electric autonomous vehicles. *Sustainability*. 2022 Aug; 14(15): 9378. doi:10.3390/su14159378.
- [20] Li CC, Zhuo GR, Tang C, Xiong L, Tian W, Qiao L, Cheng YL, Duan YL. A review of electro-mechanical brake (EMB) system: Structure, control and application. *Sustainability*. 2023 Mar; 15(5):4514. doi:10.3390/su15054514.
- [21] Li S, Li PH, Yao Y, Han XF, Xu YH, Chen L. Analysis of drivers' deceleration behavior based on naturalistic driving data. *Traffic Injury Prevention*. 2020 Jan 2; 21(1):42–47. doi:10.1080/15389588.2019.1707194.
- [22] Rowe R, Maurice-Smith M, Mahmood M, Shuja A, Gibson D. Understanding intentions to override intelligent speed assistance prior to widespread availability: An application of the theory of planned behaviour. *Accident Analysis and Prevention*. 2021 Mar; 151:105975. doi:10.1016/j.aap.2021.105975.
- [23] Rawlley O, Gupta S, Chandrakar J, et al. Artificial Intelligence Inspired Task Offloading and Resource Orchestration in Intelligent Transportation Systems. *Cognitive Computation*, 2025, 17:18. DOI:10.1007/s12559-024-10380-3.
- [24] Chen J, Zhao Z. Application of artificial intelligence technology in the economic development of urban intelligent transportation system. *PeerJ Computer Science*, 2025, 11(11):e2728-e2728. DOI:10.7717/peerj-cs.2728.
- [25] Abirami S, Pethuraj M, Uthayakumar M, et al. A systematic survey on big data and artificial intelligence algorithms for intelligent transportation system. *Case Studies on Transport Policy*, 2024, 17:101247. DOI:10.1016/j.cstp.2024.101247.