Theory and Practice of Science and Technology
2025, VOL. 6, NO. 6, 159-164
DOI: 10.47297/taposatWSP2633-456932.20250606

Analysis of the Intelligent Bus Scheduling System Architecture Based on Hybrid Control

Aojie Liu

School of Traffic & Transportation Engineering, Central South University,Changsha, Hunan, 410083, China

ABSTRACT
The bus dispatching system is an important part of urban public transportation. We need to be able to promptly detect changes in the current operation status and passenger flow, so as to effectively improve the performance of the Intelligent Bus Scheduling System in a dynamic environment. This paper proposes an adaptive PID and Robust Control Hierarchical Hybrid Architecture. The online adjustment method of PID parameters using BP Neural Network is used to achieve rapid and accurate dispatching of vehicles. Among them, the upper layer uses the Robust Control controller based on LMI Optimization to control the robustness, and is paired with a Disturbance Observer for control, which can effectively suppress external interference and parameter changes. The adaptive module that combines NSGA-II Multi-objective Optimization and Deep Reinforcement Learning can not only perform Dynamic Weight Distribution in real - time, but also pre - adjust the parameter values. Considering factors such as passengers' waiting time, equipment energy consumption, and Safety Redundancy in combination with the real - time passenger flow, and training the dispatching system with historical data, the dispatching system can foresee the occurrence of emergencies and enhance the system's self - learning ability. Three types of scenarios (normal passenger flow scenario, passenger flow fluctuation scenario, and communication delay scenario) are tested through the built Digital Twin platform. Compared with the traditional PID Control, this algorithm has the advantage of small Steady-state Error. Compared with single Robust Control, the recovery time is significantly reduced. When facing multiple conflicting objectives, it achieves a coordinated balance between energy consumption and waiting time. This method can obtain a dispatching method with high accuracy and Disturbance Rejection for application in the Intelligent Transportation Hub.

KEYWORDS
Robust control; Bus scheduling system; Objective optimization; Model architecture

1 Introduction

1.1 Research background

Against the backdrop of accelerating global urbanization and the implementation of the "dual carbon" goals, smart cities have become a key development direction for developing countries. China's "14th Five-Year Plan for Modern Integrated Transportation System Development" explicitly proposes leveraging new technologies such as artificial intelligence and Internet of Things to enhance the accuracy and safety of transportation hub scheduling, while coordinating new infrastructure to promote transportation development. As the "vascular network" of urban operations, the transportation system urgently requires intelligent upgrades. With the intelligent development of urban public transportation, the control precision and disturbance resistance capabilities of the Station Scheduling System have emerged as critical challenges to address at this stage. Thus, for key nodes like the smart platform in transportation hubs, applying advanced control technologies to achieve dynamic resource allocation, orderly crowd flow, energy efficiency, and emission reduction will be of paramount importance.

1.2 Review of domestic and international research status

Public transportation has developed rapidly both domestically and internationally. With the ongoing urbanization, it is imperative to establish a high-capacity, high-speed, and intelligent urban public transportation system. Currently, the development of the Station Scheduling System for buses is in a phase of rapid advancement, and various control algorithms such as PID Control, optimal control, and nonlinear control have been widely applied in the field of public transportation.

Teng Jitao [1]et al. studied intelligent bus scheduling by incorporating the genetic algorithm. They used genetic operations to treat the minimum operating cost as the objective function, comprehensively considering factors such as vehicle allocation, time, operational efficiency, and resource utilization. They derived an optimal scheduling sequence and verified through simulation experiments that the genetic algorithm can be effectively applied to bus scheduling problems. Xue Yunqiang[2] conducted a simulation analysis of Route 21 in Nanchang City. Based on uncertainty theory, they categorized bus scheduling schemes into two major types: peak-hour and off-peak-hour scheduling. Peak-hour scheduling can be applied to scenarios with more variable data and larger tolerances, while off-peak-hour scheduling suits situations with low passenger flow and minimal variation in road data variables. On this basis, they constructed a dual-uncertainty multi-objective programming model for mixed vehicle types. Wang Jian[3] addressed bus scheduling issues under specific conditions by proposing an optimization method that considers passenger travel time as a constraint function. They built a scheduling model aimed at minimizing total bus operating mileage and designed a greedy algorithm along with the genetic algorithm to solve for the model's optimal value. This ensures the model can effectively optimize scheduling resources within an appropriate data range. Simulation experiments demonstrated that the proposed model and algorithms exhibit high stability.Axenie[4] et al. proposed a systematic definition of anti-fragility by analyzing the practical issue of varying passenger flow across different time periods. They applied the proposed anti-fragility to traffic signal control, ensuring that traffic signals maintain optimal operation and minimize delays even when traffic flow fluctuates. An adaptive control method was employed to achieve real-time traffic signal adjustment during peak hours. By leveraging the reinforcement learning algorithm, a traffic system reward function was designed to enhance adaptability. Signal control strategies were optimized, and AI models were developed to construct traffic agents, thereby reducing the probability of traffic congestion.

Admas[5] considered the susceptibility of drones to uncertain disturbances during flight and designed a nonlinear PID Control and a high-order sliding mode controller for fixed-wing UAVs. Simulation results under external disturbances showed that the high-order sliding mode controller outperformed the nonlinear PID Control in controlling roll, pitch, and yaw angles, while the opposite was true for airspeed control. In certain scenarios, the system exhibited satisfactory control performance and robustness under nonlinear PID Control.

Qiu[6] integrated Digital Twin with artificial neural network to develop adaptive control for automotive suspension systems. Based on adaptive control models and algorithms, they created a simulation model for vehicle suspension systems and conducted tests to evaluate its applicability across different road conditions and driving scenarios. Experimental results demonstrated strong adaptability of the system to varying levels of road roughness and traffic congestion.

2 Theoretical modeling design

2.1 Process overview

The intelligent Station Scheduling System based on Hybrid Control is grounded in the actual dispatching scenarios of bus stations, conducting in-depth modeling and analysis of operational processes such as vehicle arrival/departure, passenger boarding/alighting, vehicle running time, and inter-station travel time. By constructing a dual-layer control algorithm architecture, the bottom layer employs PID Control to achieve rapid response. Appropriately tuning PID Control parameters enables effective tracking of the system's target state, ensuring precise vehicle scheduling control while enhancing system response speed and steady-state accuracy. The upper layer introduces Robust Control, where a Robust Controler is designed to address uncertainties and disturbances in the smart platform scheduling system, ensuring consistent control performance across a wide range of external disturbances and parameter variations. Simulation and experimental results validate the optimization of the PID control strategy.

2.2 Online tuning of parameters for pid controller

Building on the hierarchical control strategy proposed above, this section first discusses the design of a responsive bottom layer based on the PID Control algorithm. By incorporating an adaptive PID controller model and leveraging neural network algorithms for online tuning of proportional gain Kp, integral time Ti, and derivative time Td, precise tracking in dynamic scenarios is achieved. In the control context established in this study and traditional PID Control, fundamental approaches include proportional control, integral control, and derivative control. Combining these three methods exploits their respective advantages to handle complex control scenarios.

Proportional control adjusts based on the magnitude of error—the larger the error in the control scenario, the greater the applied control effort. In bus scheduling systems, this can be used to swiftly address deviations between vehicles and their scheduled positions. For instance, when a vehicle is delayed, increasing its speed helps minimize the delay duration. The role of integral control is to eliminate accumulated errors and enable the system to ultimately reach a stable state. In bus scheduling, it can address long-standing deviations, such as persistent delays during certain periods. By adjusting departure times based on integral control, the punctuality rate of vehicles during these periods can be improved.

Differential control predicts the trend of error changes to make adjustments in advance. In bus scheduling systems, it can proactively manage vehicle speed and departure intervals based on the direction of speed changes, reducing the impact of sudden situations like congestion or speed fluctuations on the normal operation of the system. The PID Control system is implemented according to the following formula:

$$u_{PID}(t)=K_p e(t)+K_i\int_0^t e(\tau)d\tau+K_d\frac{de(t)}{dt} \tag{1}$$

2.3 Robust control design of upper LMI optimization

After completing the design of the underlying PID Control, the upper-level robust optimization framework can be developed based on this structure. Following the LMI principle, the Robust Control is designed to account for operational time uncertainties, while the Disturbance Observer compensates for external disturbances, ensuring system stability amid parameter variations and optimizing bus scheduling strategies with the goal of minimizing total delay time across all stations.

This model can incorporate a two-dimensional grid plane to reflect bus station distribution, road connectivity, and alternative station information. The scheduling system can monitor onboard operational data recording systems in real-time to acquire vehicle operation data, calculate and export average travel times for different road segments, and generate a set of passage times for various routes.

Additionally, the system can establish a real-time user feedback mechanism to collect passenger travel information, including desired boarding and alighting points, and forecast passenger flow based on the number of concurrent system users. In these aspects, numerous uncertainties must be considered to construct a robust optimization model, generating corresponding variables, objective functions, and constraints. Even with variable fluctuations, the system can maintain operational stability through control measures.

(1) System state - space modeling

The nonlinear system is linearized at the equilibrium point, yielding the state equation below：

$$\dot{x}(t)=Ax(t)+Bu(t)+D\xi(t) \tag{2}$$

where Jacobian matrices are denoted by letters A, B, and D.

(2) LMI stability constraint design

LMI constraints are established based on Lyapunov stability theory:

$$\begin{cases} A^TP+PA+Q<0 \\ P>0,Q>0 \end{cases} \tag{3}$$

Here, the Lyapunov matrix is denoted by P, and the performance weighting matrix by Q.

The YALMIP toolbox is employed to solve the LMI, obtaining the Robust Control gain matrix K. The resulting control law is:

$$u_{robust}(t)=-Kx(t) \tag{4}$$

(3) Disturbance Observer Design

First, the sliding surface is defined:$s(t)=Gx(t)$

with G as the design matrix, followed by the observer equation:

$$\hat{\xi}(t)=\rho\cdot sign(s(t)) \tag{5}$$

where the gain coefficient$\rho=2\xi_{\max}$ is determined. Finally, the feed-forward compensation control input is established:

$$u(t)=u_{PID}(t)+u_{robust}(t)-\hat{\xi}(t) \tag{6}$$

3 Development and optimization of hybrid control algorithm

3.1 Design of PID parameters with neural network

By leveraging neural networks to design online tuning rules for PID parameters, the system adapts to uncertain environments such as sudden passenger flow changes. Through robust gain adjustment, the Robust Control quantifies the disturbance boundary of the Disturbance Observer and optimizes the compensation loop, enabling adaptive parameter tuning. Based on Model Predictive Control (MPC), with Passenger Waiting Time as the optimization objective, the dynamic priority strategy is designed and implemented by considering both energy consumption and Safety Redundancy, achieving multi-objective collaborative optimization and realizing the target coordination function.

The structure and process of the BP Neural Network are as follows: the input layer consists of tracking error$e(t)=x_{ref}(t)-x(t)$and its rate of change$\Delta e(t)=e(t)-e(t-1)$, the hidden layer is configured as a double-hidden layer with 10 neurons in each layer, and the ReLU function is used as the activation function between neurons in each layer. The output layer provides PID parameters, using the Sigmoid function as the activation function and normalizing the values to a reasonable range. The integral squared error is employed to compute the loss function.

$$J=\frac{1}{T}\int_0^T e^2(t)dt \tag{7}$$

Following the stochastic gradient descent method, the network weights are updated every 10ms after the learning rate is incremented.

3.2 Implementation of NSGA - ii multi-objective optimization algorithm

The implementation primarily involves encoding and population initialization. First, chromosome encoding is performed by setting control weight vectors$[w_1,w_2,w_3]$ to represent passenger waiting time, energy consumption, and Safety Redundancy conditions. Then, the population size is set to N=100, with weights ($w_i \in [0,1]$and$\sum w_i = 1$)initialized randomly. Subsequent genetic operations are conducted. Non-dominated sorting is achieved by stratifying the solution set based on objective function values, followed by crowding distance calculation to ensure uniform Pareto front distribution. The target weights are adjusted dynamically according to real-time Passenger Flow Density:

$$w_1 = \frac{\rho(t)}{\rho_{\max}}, w_2 = 1 - w_1, w_3 = 0.1 \tag{8}$$

3.3 Deep reinforcement learning (DRL)-driven parameter adjustment

First, design the state-action space. This design is based on the DPG algorithm framework. The algorithm framework includes an actor network and a critic network. The actor network part includes the input state composed of historical passenger flow and device status, as well as the output actions generated by the PID parameter incrementsΔK_p,ΔT_i,ΔT_d. The critic network includes the actor network and the estimation function of the output Q value. Next, the design work of the reward function will be carried out to estimate the energy consumption status. The design formula is as follows:

$$R_t = -0.5 \cdot |e(t)| - 0.3 \cdot |\Delta u(t)| + 0.2 \cdot (E_b - F_e) \tag{9}$$

Eb represents the energy consumption benchmark, and fe represents the actual energy consumption.

4 Simulation platform construction and performance evaluation

A station dispatching simulation environment is constructed based on the Simulink simulation platform. Urban bus station passenger flow data is collected, such as peak passenger flow times, passenger volume, and average intersection crossing time; real-time data from onboard equipment sensors, such as fuel consumption per kilometer and communication latency, are transmitted to the computational database. Subsequently, data processing methods are applied to mathematically process the collected data, such as using KNN interpolation to repair missing values and employing wavelet transform to eliminate sensor noise, obtaining reliable data that reflects the actual system operation. Finally, standardization is performed, applying Min-Max normalization to the multi-source data. Actual passenger flow data and equipment parameters are integrated to build a Digital Twin platform.

After the simulation platform is established, a comparative experimental method is employed, comparing traditional PID Control and single Robust Control methods to evaluate the advantages of the Hybrid Control algorithm in terms of Steady-state Error, Overshoot, and anti-interference capability. The comparative experiments can be conducted according to the following experimental design: Scenario 1, setting uniform data, performing error calculations, and comparing the Steady-state Error of Hybrid Control with traditional methods; Scenario 2, simulating a Sudden Passenger Flow Peak with ±50% fluctuations to evaluate Overshoot and recovery time; Scenario 3, simulating equipment failure by introducing a 20-millisecond communication delay to test the system's robustness metrics.

5 ExIsting limitations and prospects

5.1 Existing problems

Station scheduling needs to simultaneously optimize objectives such as passenger waiting time, Equipment Energy Consumption, and Safety Redundancy. However, most existing methods rely on simplified approaches like the Weighted Sum, which fail to achieve multi-objective coordination and lack mechanisms for dynamic priority adjustment. This often leads to Local Optimum or System Instability. Traditional bus station scheduling systems mostly depend on manual experience and single control methods, which also exhibit weak Parameter Adaptation capabilities under Dynamic Load. These systems struggle to handle complex dynamic scenarios involving multi-objective conflicts, such as Sudden Passenger Flow Peak, equipment failures, and trade-offs between energy consumption and efficiency. With the increasing integration of artificial intelligence across industries, station systems now demand higher levels of intelligent autonomous decision-making. This necessitates combining advanced algorithms and large-scale models to overcome the application bottlenecks of traditional control theories in complex systems.

Current research primarily focuses on theoretical validation of single control strategies, lacking a Global Hybrid Control Framework design for station subsystems. Traditional PID Control struggles to adapt to dynamic environments with fixed parameters and is prone to Overshoot or Oscillation due to External Disturbances like device latency and sensor noise.

Although Robust Control can suppress disturbances, its poor real-time performance makes it difficult to meet the rapid response requirements of station scheduling.

If these issues are not effectively resolved, the following problems may arise: scheduling delays, preventing passengers from boarding or alighting promptly, reducing station throughput and disrupting scheduling operations; unstable control systems leading to cascading failures of equipment clusters due to extreme weather or device malfunctions; and the inability to dynamically adjust departure intervals in real-time based on environmental changes, resulting in either wasted vehicle capacity or insufficient transportation resources.

5.2 Key scientific problems to be solved

5.2.1 How to accurately construct an intelligent station scheduling system by combining mathematical modeling and constraint conditions?

In real-world scenarios, the Station Scheduling System consists of multiple subsystems, requiring the analysis of various complex dynamic processes. If the operational states of individual systems are considered in isolation, it may lead to unbalanced system analysis without focus, thereby failing to achieve the goal of precise control and rapid response. Therefore, accurate modeling of the Station Scheduling System is crucial for effective control and data analysis. This necessitates reasonable simplification of the system model, consideration of uncertainties and disturbances within the system, and the establishment of a mathematical model that not only accurately describes system characteristics but also facilitates control strategy design.

5.2.2 How to implement the dynamic coordination mechanism between pid and robust control?

The Station Scheduling System is a complex integrated system encompassing subsystems such as traffic flow, passenger flow, and equipment clusters. Achieving intelligent scheduling requires addressing coordinated control among these subsystems. The key to coordinated control lies in balancing the rapidity of PID Control and the stability of Robust Control under dynamically changing scenarios. In practical applications, station scheduling is susceptible to environmental fluctuations, which may cause Oscillation or delayed response in the control system. Thus, how to effectively integrate PID Control and Robust Control strategies into the system to ensure information exchange and collaboration among subsystems becomes a critical issue to consider.

5.2.3 How to achieve cross - platform standardization and system scalability?

With the advancement of modern technology and the increase in transportation passenger flow, it is imperative to develop a unified scheduling system applicable across regions. If the station scheduling system can achieve integrated management, it will significantly improve operational and maintenance efficiency. To achieve the universality and scalability of the intelligent station scheduling system across different scenarios, it is necessary to address the issues of strong closed-loop nature and high expansion costs in traditional systems through Modularization and standardized design, promoting the transformation of intelligent stations from "customized development" to "platform-based services." By integrating Digital Twin and Edge Computing, the system can scale its size and functions on demand, flexibly adapting to dynamic changes in requirements. Compatibility testing and code tools can reduce repetitive investments during the operation and maintenance phase, lowering lifecycle costs and facilitating the large-scale deployment of intelligent transportation infrastructure.

5.3 Future prospects

The future Station Scheduling System can adopt methods based on the Dynamic Weight Distribution PID-Robust Hierarchical Control Framework, overcoming the limitations of fixed weight allocation in traditional Hybrid Control. Real-time adjustments can be made using Fuzzy Logic and model prediction, while deep reinforcement learning and Digital Twin technologies can be applied to the Parameter Adaptation module of the scheduling system, maintaining both rapid response and strong robustness. By integrating AI large models to predict peak passenger flow and equipment operating conditions based on historical data, the PID parameters of the adaptive module and the Robust Control gains can be optimized in real time. The combination of the NSGA-II Multi-objective Optimization Algorithm and Lyapunov Stability Theory enhances the system's self-learning capability in dynamic environments. Based on the multi-objective collaborative optimization of Passenger Waiting Time, energy consumption, and Safety Redundancy, dynamic priority adjustment strategies of varying levels can be formulated according to changes in bus departure intervals, enabling adaptive adjustment of bus departure intervals.

6 Conclusion

This paper proposes a Hybrid Control strategy, employing a hierarchical architecture to design an intelligent Station Scheduling System adaptable to dynamic scenarios. This method overcomes the limitations of single-control approaches, achieving high-precision optimization and strong robustness coordination for the Station Scheduling System in dynamic environments. Based on the actual operation of the Station Scheduling System, this study addresses current issues in station operations by employing the Hybrid Control algorithm of Multi-objective Optimization to tackle challenges such as Multivariate Coupling, Nonlinear Disturbance, and insufficient real-time performance in station scheduling.

A smart station scheduling simulation platform is established to validate the effectiveness of the proposed scheduling method, providing a scalable solution for practical engineering applications. This enables precise scheduling and control of platform vehicles, improves operational efficiency and service quality, enhances system robustness and adaptability, and ensures stable performance under varying traffic environments and working conditions.

About the Author

Aojie Liu, 8212220826@csu.edu.cn

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