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Integrated Development and Passenger Flow Coordination Technologies for Metropolitan Rail Transit Hubs under Station–City Integration

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SUMMARY: *Under the background of city-station combination, the different interaction between "fast going to work" and "slow staying" passenger streams inside big city railway hubs causes serious time-space conflicts; The traditional passive, static control approaches have difficulty in dealing with the impulse surges which are generated by incoming trains. For the solving of the zero-sum game problem that lies between traffic evacuation and commercial attraction, this thesis puts forward a dynamic collaboration optimization method for passenger flow on the basis of Model Predictive Control (MPC). Firstly, the complicated space arrangement of the hub is by us abstracted to be a direction queuing network. An innovative multidimensional Macroscopic Fundamental Diagram (MFD) evolution model—incorporating the proportions of heterogeneous passenger flows—is then constructed to precisely quantify the nonlinear frictional impedance that commercial lingering behaviors impose on main-line traffic flow. Second, a multivariable feedforward MPC architecture is established to implement proactive flow restrictions and dynamic path guidance by simulating the trajectories of congestion shockwaves through a rolling prediction mechanism. Simulation results, based on the Chongqing Shapingba Hub as a case study, demonstrate that this system can reduce the maximum queue length at core ticket gates by 58.1% and narrow the variance in travel delays by 67.6%. Furthermore, by identifying a balanced solution on the Pareto frontier—trading a marginal increase in travel delay for a substantial boost in commercial attraction—the system achieves a deeply adaptive collaboration between anti-stampede safety protocols and the economic efficiency of the urban micro-center.*

KEYWORDS: *Station-City Integration; Rail Transit Hub; Model Predictive Control; Macroscopic Fundamental Diagram; Passenger Flow Coordinated Optimization*

1 Introduction

Along with the deep going progress of the new urbanization strategy and the remolding of space forms inside big city regions, traditional railway hubs— which in history only paid attention to traffic gathering and sending—are experiencing a deep model change. They are comprehensively carrying out transformation toward multi-layered "micro-centers" which have the character of "Station-City Integration" (it is also called the TOD 5.0 model) [1, 2]. In this extremely complicated space shape, a hub is not any longer only a "transit ship" that passengers only go through to finish body movement; Instead, it has already developed to become a destination by itself—a place that brings together very many city functions, these include high-speed rail coming and going, city track traffic changes, above-layer business compounds, underground walking areas, and around high-grade business and work rooms [3, 4]. However,

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although this dissolution of physical space boundaries and the deep mixing of functions have the effect of stimulating economic vitality inside metropolitan areas, they have at the same time brought about an extremely complicated and fragile dynamic mechanism which controls passenger flow change inside the hubs.

From the perspective of concrete physical operation situations, the most key challenge which station-city integration brings exists in the difference of passenger flow characteristics and the sharp space-time conflicts that this difference produces [5, 6]. On one hand, rail transit systems (particularly high-speed rail and regional express lines) carry a distinct type of "rapid commuting flow." The absolute final goal of this passenger group is quick distribution and handover; Their behavior features are determined by a high level of goal-direction, a wish for quicker walking velocities, and a strong, impulse-like intermittency which is driven by train arrival and departure timetables [7, 8]. On the other side, the huge amount of business and city service facilities which are contained inside the hub has nurtured a quite big "slow-moving, staying flow." The moving paths of these passengers who take consumer as orientation inside the hub display extremely strong randomness, low moving speed, and frequent stops; their main requirement focal points are environmental comfort and the reachability of business service items. When quick moving transfer streams—frequently having passengers take big baggage—physically mix together with the stop-go motions of slow going shopping streams in core connecting passageways or central atriums, serious "frictional interference" comes into being [9, 10]. On the micro level, this mutual effect between walking patterns and movement speeds is shown on the macro level as a non-linear, steep decrease in the whole throughput ability of the system. In the morning and evening rush time or the stages of large passenger flow on festivals, when trains come in groups—bringing about a huge rising in instant demand—traditional static physical spaces many times are shown to be unable to take in this incoming crowd in time. This therefore brings about the quick spread of "congestion shockwaves" on the boundary between the station and the city, hence creating a high possibility of causing local "deadlocks" or even crowd tramplings.

For solving the safety and efficiency problems which are brought by this kind of high-density crowd assembling activities, the academic circle and engineering circle have carried out massive research on crowd motion modeling and passenger flow controlling technologies [10, 11]. Regarding underlying evolutionary mechanisms, early studies largely relied on microscopic simulation models, such as the Social Force Model and Cellular Automata. By defining rules for repulsive and attractive forces between individuals, these models effectively capture localized physical phenomena, such as the weaving of pedestrian flows in corridors and congestion at bottlenecks [12, 13]. In terms of macroscopic flow allocation, the theory of the Macroscopic Fundamental Diagram (MFD)—based on the conservation laws of fluid dynamics—has recently been introduced to assess network-level states within large-scale transportation hubs; this approach reveals a monotonically decreasing relationship between crowd density and traffic efficiency [14, 15]. Based on this foundation, control engineering workers have developed a group of passenger flow management methods, mainly including threshold-type flow restriction at security check points and turnstiles (it is called "Gating Control"), and also dynamic route guidance based on shortest path algorithms. These researches have laid a very important theory basis for the comprehending of the evolution rules of passenger flows inside traffic hubs, and have obtained obvious engineering achievements in situations that have regular, same-type passenger flows [16, 17].

However, when we face the extremely complex conflicts that come from heterogeneous flows inside present ultra-large-scale, integrated "station-city" hubs, the existing theoretical models and control technologies have shown clear limitations in many different aspects—that is, with regard to methodological abilities, data demands, scenario adaptability, interpretability, and deployment expenses. These insufficiencies are displayed in the following four aspects: First, with respect to methodological ability and the portrayal of physical mechanisms, current large-scale network evolution models (such as the traditional MFD) are generally based on the idealized supposition of "uniform passenger flow," regarding crowd density as the only independent variable to compute traffic impedance [18, 19]. These models cannot do the parameterization work on heterogeneous attributes—for example "commercial dwell ratios" or "luggage-carrying rates"—and hence therefore are unable to capture the "soft frictional resistance" that is exerted by slow-walking pedestrian flows in commercial zones on the fast-moving flows which are inside main thoroughfares. This inside shortcoming in the modeling method directly causes a serious over-evaluation of real handling ability when we assess combined station-city areas; Therefore, hence, the follow-up calculation of operation control gives extremely over-optimistic operation limit ranges [20, 21].

Secondly, with respect to scenario adaptiveness and dynamic reaction ability, the strategies that now are broadly used in engineering practice—such as turnstile-reliant flow restriction and physical barrier interception—are extremely passive "feedback control" mechanisms or inflexible "time-based heuristic control" regulations [22, 23]. The fatal defect of feedback control exists in its innate time delay: the front-end turnstiles only start flow control *after* the pedestrian density at core nodes (such as transfer halls) has already broken safety thresholds and congestion has already come into being. When we face the high-frequency, large-amplitude passenger flow pulses brought by arriving trains, this lagging response often makes congestion shockwaves accelerate and spread outward in the opposite direction, therefore causing large-scale queuing in the external plazas. Facing such high-frequency dynamic interferences, static or delayed control mechanisms—that do not have a forward-looking view—have been proven to be terribly insufficient.

Moreover, with respect to safety restrictions and explanation ability, many researchers in recent years have made attempts to bring in data-driven, no-model algorithms—for example Deep Reinforcement Learning (DRL)—to solve the problems of cooperative pedestrian flow management. Although people cannot deny that "black-box" models have advantages when they fit high-dimensional state spaces, they have serious basic defects in the situation of pedestrian flow control, which is a typical "safety-critical" system. Specifically, their decision-making processes lack interpretability grounded in physical mechanisms and fail to provide absolute, hard constraints regarding safe capacity at the algorithmic foundation. Should input data exhibit extreme anomalies characterized by "long-tail" distributions (e.g., mass train delays), these black-box models are highly prone to issuing dangerous directives that defy basic physical common sense; this inherent risk creates significant resistance to their practical engineering deployment within large-scale transportation hubs. Finally, with respect to the overall balance among multi-dimensional goals, the currently existing control and management systems display serious segmentation. A widely existing management difficult point is the inclination to "put traffic dispersion on the first place while ignoring commercial operation." Under conditions of extreme passenger volume, managers often resort to crude, "one-size-fits-all" measures—such as shutting down commercial entrances and exits or erecting physical barriers to enforce one-way movement—thereby completely sacrificing the benefits of commercial dwell time in order to safeguard the security of traffic evacuation. This control logic, which treats "traffic" and "commerce" as a zero-sum game, fundamentally deviates from the original intent of integrated station-city development. How to leverage algorithms—while strictly upholding the safety redline against stampedes—to smoothly transform transient surges in passenger flow into potential consumer traffic within commercial zones, thereby achieving dynamic load balancing and spatial complementarity of resources, represents a theoretical blind spot that urgently requires a breakthrough.

Against this backdrop, and in order to thoroughly overcome the inherent time lags of traditional feedback control, the unreliability of "black-box" models, and the absence of multi-objective trade-offs, the introduction of a dynamic coordination framework based on Model Predictive Control (MPC) becomes particularly imperative. By incorporating physical predictive models characterized by heterogeneous impedance properties, MPC technology enables the system to—at any given moment—"simulate" in advance the spatiotemporal evolution trajectory of congestion shockwaves over a specific future horizon (the "prediction horizon"), based on the scheduled arrival and departure times of upcoming trains. Furthermore, while strictly adhering to safety constraints regarding nodal capacity, the system iteratively solves quadratic programming problems to issue proactive, smoothed instructions for flow limitation and path guidance. This control logic—characterized by "acting in the present, anticipating the future, and correcting iteratively"—not only perfectly addresses the need to "smooth out" the peaks and troughs of passenger flow pulses but also integrates commercial spaces into the global state-space equations as "elastic reservoirs." This method provides a brand new breaking solution—that is characterized by both deep theoretical thickness and strong engineering possibility—for solving the time-space contradictions between "fast evacuation" and "comfortable stay" under the background of combined station-city construction.

According to the above shortcomings, this paper studies the time-space conflicts and dynamic matching control of different kinds of passenger flows inside traffic hubs under the mode of integrated station and city development. Its main goal is to solve the problem of overall balancing the efficiency of traffic evacuation versus the economic profits of business staying time, under the restrictions of physical space. The research goals contain: building queuing network and promoted Macroscopic Fundamental Diagram (MFD) space-time development models for describing the friction interference of not same-type passenger flows; carrying out the design of a multi-variable forward-feed cooperation optimization structure on the basis of Model Predictive Control (MPC); and carry out quantitative analysis on system robustness under extreme pulse passenger flows, meanwhile find out the Pareto-optimal boundary for "transport-commerce" benefits. This research result offers a theory foundation and project reference for the space integration design of super-large comprehensive traffic hubs, the improvement of emergency reaction mechanisms for large-quantity passenger streams, and the arrangement of intelligent dynamic management and control platforms.

2 Methods

2.1 Station city integration hub space - physical topology of passenger flow and queuing network modeling

In the process of urban rail transit hubs evolving towards station-city integration, their internal spatial functions have transformed from simple transportation hubs to complex three-dimensional micro-cities. The heterogeneity of spatial attributes directly leads to the diversity of micro-behaviors of passenger flow: the directness of commuter passenger flow, the accompanying nature of transfer passenger flow (carrying luggage), and the dwelling nature of commercial passenger flow generate complex frictions and games in the same space and time [24, 25]. In order to achieve subsequent global dynamic coordination based on model predictive control (MPC), the primary task of this section is to strip away the physical appearance of the building space, construct a discretized directed queuing network, and quantify the nonlinear impedance of heterogeneous passenger flow in network operation. Since the micro-simulation of real hubs suffers from the "curse of dimensionality" and computational bottleneck in rolling optimization, establishing a network model with macroscopic characteristics but retaining key topological structures is a prerequisite for implementing MPC. This study uses graph theory to abstract the physical space of the hub into a directed connected graph $G=(V,E,W)$.

To address the unique characteristics of station-city integration scenarios, the node set $V$is functionally decoupled, divided into a transportation hub node subset V_{tra}(encompassing turnstiles, security checkpoints, and platform levels, essentially high-turnover dissipative structures) and an urban commercial node subset V_{com}(encompassing atriums and underground shopping streets, essentially passenger flow buffers with time-lag effects). The edge set E represents the connectivity between nodes, defined as $E=E_{hor} \cup E_{ver}$ representing level walkways and cross-level vertical/escalator facilities, respectively. The physical attributes of edges and nodes are mapped to weight matrices W, constituting the boundary constraints for the system's state space evolution.

In order to accurately capture the system state and provide a mathematical interface for the lower-level control algorithm, $G$the core parameters and control constraint mechanisms involved in the figure are strictly defined. The analytical table of key state parameters and physical boundaries of the station-city integrated network topology is shown in Table 1.

Table 1: Analysis Table of Key State Parameters and Physical Boundaries of Station-City Integrated Network Topology

Variable hierarchy	Symbol definition	Physical meaning and parametric characteristics	Mathematical Dimensions	State space/control constraint mechanism
State variables	$x_i(t)$	Actual number of passengers within the time tnodei	pax	The core observable state variables of the systemX(t)
State variables	$\rho_e(t)$	the time tpassagee	pax/m^2	Key leading indicators for assessing congestion degradation
Control input	$u_{ij}(t)$	from node ito node jat any time t(e.g., gate release rate)	pax/s	MPC control sequences U(t)are subject to physical limitations.
Boundary parameters	C_i^{max}	The threshold of the node 's anti-stampede safety capacityi	pax	Rigid constraints:$x_i(t) \le C_i^{max}, \forall t$
Buffer parameters	γ_i	Commercial nodes V_{com}' ability to attract, retain, and retain customers.	dimensionless	Flexible parameter: Depends on business type and time period (0.1~0.6)
Interference vector	$d_i(t)$	Uncontrollable demands of external systems (train arrival/external street blocks) on injection nodesi	pax/s	External disturbance term in MPC model D(t)

Based on the above parameter definitions, the dimensionality reduction from the entity space to the mathematical space is completed. The dimensionality reduction mapping mechanism from the station-city composite heterogeneous space to the state machine network topology is shown in Figure 1.

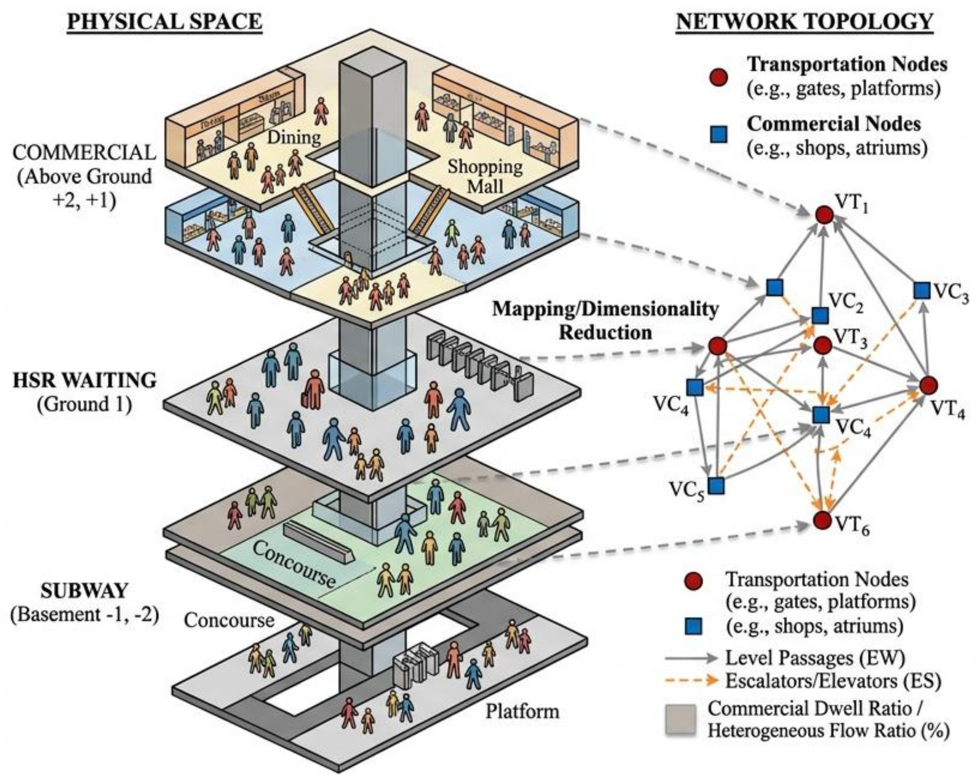


Figure 1: Dimensionality reduction mapping mechanism of station-city composite heterogeneous space to state machine network topology

In Figure 1, the three-dimensional solid cross-section on the left side details the physical distribution of the station hall, transfer passage, and above-ground commercial area; through topological mapping, the corresponding graph structure is generated on the right side. In the network on the right side of Figure 1, the red dashed box marks $V_{tra}$the congestion-prone subgraphs that are prone to becoming system bottlenecks, while the blue nodes mark V_{com}areas with the potential for peak-shaving and flow storage. This topological reconstruction not only eliminates redundant physical details but also intuitively delineates the intervention targets for subsequent passenger flow coordination scheduling. After determining the topological graph, the transfer process of passenger flow in discrete time series needs to be described by state equations. Traditional static traffic assignment cannot characterize the pulse-like impact caused by concentrated train arrivals. Therefore, this study constructs node-level state evolution difference equations based on the conservation laws of fluid mechanics and the underlying logic of the Cell Transmission Model (CTM), as shown in Equation (1).

$$x_i(t+1)=x_i(t)+\Delta t\left(\sum_{j\in in(i)} q_{ji}(t)-\sum_{k\in out(i)} q_{ik}(t)\right) \quad (1)$$

In the formula: $x_i(t+1)$and $x_i(t)$represent ithe total number of passengers on the road at adjacent time steps; $\Delta t$is the discrete time step for rolling optimization (set to 10sbalance system dynamic response sensitivity and computational overhead); in(i) and represent out(i)the upstream input flow set and downstream output flow set directly connected $q_{ji}(t)$to the node in the directed graph, respectively . In actual evolution, edge flow *i*does not simply depend on the sending intention of upstream nodes, but is constrained by the dynamic balance of supply and demand. Its mathematical expression is the minimum value of jthe demand sending function of upstream nodes and $S_j(t)$ the residual receiving function of $R_i(t)$downstream nodes i. In particular, when a node $j$belongs to a commercial subset V_{com}, its sending function $S_j(t)$will be suppressed by the retention rate γ_j, and a large number of passengers will turn into an internal dwelling state. This stagnation effect reduces the instantaneous pressure on downstream traffic nodes, but also increases the risk of secondary congestion in commercial areas. The fluid dynamics equation solves the problem of network flow conservation, but the transfer efficiency between nodes (i.e., edge impedance) needs to be further quantified. The macroscopic fundamental diagram (MFD) in classical traffic flow theory usually assumes that passenger flow is homogeneous, exhibiting an inverse S-shaped curve with monotonically decreasing speed as density increases. However, measured data shows that within the station-city integration hub, passengers carrying large luggage occupy additional physical space (expanding the effective collision radius), while shoppers exhibit frequent random behaviors such as sudden stops and turns. This "friction interference" between heterogeneous passenger flows leads to a significant overestimation of throughput capacity in key areas by the traditional MFD model. Therefore, this section uses the proportion of heterogeneous passenger flow structure as an endogenous variable to construct a multidimensional nonlinear decreasing improved model , as shown in Equation (2).

$$v_e(t)=v_{free}\cdot\exp\left(-\alpha\left(\frac{\rho_e(t)}{\rho_{jam}}\right)^{\beta}\right) \tag{2}$$

In the formula: is $v_e(t)$the average forward velocity of the mixed passenger flow m/sin the channel (e); $v_{free}$is the free-flow velocity without interference; $\rho_e(t)$is the instantaneous surface density of the channel; $\rho_{jam}$is the limiting blockage density that causes the flow to stop (usually taken as $5.0\text{~}5.4 pax/m^2$). The core of this equation lies in the impedance-sensitive parameter $\alpha$and the nonlinear shape coefficient β. They are no longer fixed constants, but dynamic joint functions of the heterogeneous flow ratio $p_{luggage}$ (luggage passenger flow ratio) and p_{shop}(commercial passenger flow ratio). To ensure the engineering practicality and accuracy of the model, the research group extracted 200 hours of micro-monitoring data from a large-scale integrated transportation hub during the peak of the long holiday, used machine vision algorithms to cluster the trajectories of different groups of people, and calibrated the friction characteristic parameters under different mixing states. α,βThe measured calibration results of the heterogeneous flow nonlinear impedance parameter ( ) and the friction attenuation characteristic matrix are shown in Table 2.

Table 2: Measured calibration results of nonlinear impedance parameters of heterogeneous flow and frictional attenuation characteristic matrix

Spatial passage scene types	Composition of core heterogeneous customer flow	Free-flow velocity vfree (m/s)	Sensitivity parameters	Shape factor	Goodness of fit (R^2)	critical density of traffic capacity collapse
Pure commuter corridor	Commuter flow ≥90%(baseline state)	1.38	1.21±0.05	2.15±0.08	0.942	≈2.8pax/m^2
Hub transfer corridor	Includes 30%~40%baggage flow	1.15	1.86±0.12	1.72±0.06	0.915	≈2.1pax/m^2
Underground shopping pedestrian street	Includes ≥40%shopping dwell time	0.92	2.55±0.15	1.40±0.10	0.887	≈1.5pax/m^2
Extremely mixed interlacing area	A balanced mix of commuting, luggage, and shopping.	1.05	2.78±0.20	1.25±0.12	0.853	≈1.2pax/m^2

Table 2 clearly reveals the erosive effect of heterogeneous passenger flow behavior on system efficiency. Taking an underground commercial pedestrian street as an example, due to the high-frequency friction caused by lingering behavior, its sensitivity parameter αsoars to 2.55, causing the critical density for its traffic capacity collapse to be advanced to 1.5pax/m^2around [value missing], far lower than that of a pure commuter passage. This data pattern is intuitively verified in the three-dimensional visualization model. The improved macroscopic fundamental graph (MFD) flow evolution surface under multidimensional features is shown in Figure 2.

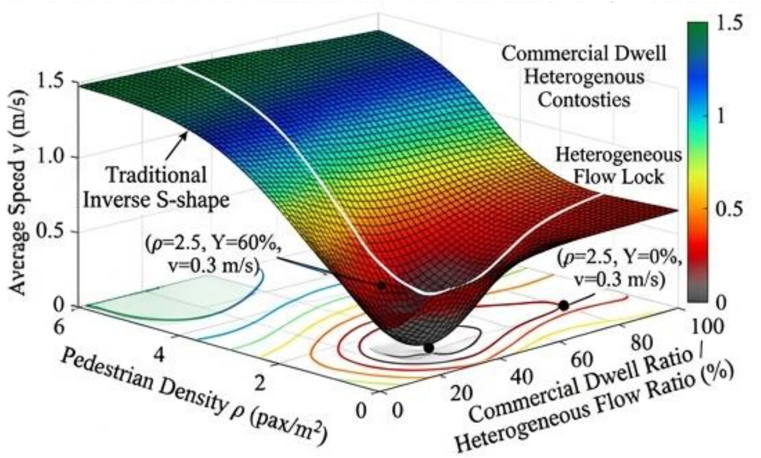


Figure 2: Improved macroscopic fundamental graph flow state evolution surface under multidimensional features

As shown in Figure 2, the system's movement speed does not simply decrease along the density axis (X-axis). With the increase in the proportion of commercial occupancy or baggage flow (Y-axis) in the three-dimensional space, the flow evolution surface undergoes a dramatic nonlinear "collapse." Under normal medium density conditions (e.g. 2.0pax/m^2), once the proportion of heterogeneous flow exceeds a certain threshold, the overall movement speed experiences a precipitous drop, resulting in a local deadlock. Traditional models, neglecting the frictional resistance in this dimension, often lead to overly optimistic boundary conditions from the MPC controller during computation. The topological physics and multidimensional MFD evolution model constructed in this paper completely fills this gap, realistically reproducing the underlying fluid dynamics logic of passenger flow evolution within the station-city integration space, providing a fundamental mathematical guarantee for the robustness of the subsequent collaborative scheduling framework.

2.2 Dynamic collaborative optimization of passenger flow based on model predictive control

After we have finished the work of spatial topology and dynamic impedance model building, the way to carry out feedforward intervention on the basis of real-time perceived passenger flow modes therefore becomes very important for solving the problem of congestion in station-city integrated hubs. Traditional feedback control (for instance simple threshold flow control) frequently has lag problem and has difficulty in dealing with large-scale pulse passenger flows which are brought by train arrivals and departures. This section builds a dynamic cooperation optimization frame for passenger flow on the basis of Model Predictive Control (MPC). Through the solving of the optimal control question in the limited time region inside every control step, it is the precise guidance of complicated flow patterns that is achieved inside the hub. The MPC control architecture which we have designed is composed by a data fusion layer, a predictive model layer, a rolling optimization layer, and an execution feedback layer. Regarding data sources and organization, the system receives real-time multi-source sensing data under 5G coverage within the hub, including AFC ticket checking flow, real-time density of each node based on video AI recognition $X(k)$, and future passenger arrival disturbances predicted through train timetables (GTFS data) $W(k)$. This data is organized into time-series vectors and used as input to the controller. The model component includes an internal predictive model, optimizer, and constraint space. The internal prediction model is based on the linearized queuing network equation and is used to simulate the system evolution under different control strategies. The optimizer uses the Quadratic Programming (QP) algorithm to find the optimal control sequence with the minimum cost function while satisfying the safety boundary. The constraint space covers hard constraints such as the gate passage limit and the escalator physical speed limit. In order to meet the requirements of MPC online real-time calculation, this paper performs a first-order Taylor expansion of the highly nonlinear passenger flow evolution equation at the current operating point and transforms it into a discrete state-space expression. This improvement allows the complex fluid dynamics behavior to be transformed into matrix operations with higher computational efficiency, as shown in Equation (3).

$$X(k+1)=AX(k)+BU(k)+DW(k) \tag{3}$$

In the formula: $X(k)\in R^n$is the state vector, representing $k$the passenger flow holding or density of key areas (including traffic nodes and commercial buffer nodes) $U(k)\in R^m$within the hub at any given time ; $n$is the control input vector, which combines $m$the adjustment quantities of controllable devices, specifically including: gate release rate u_{gate}, escalator running speed and direction u_{esc}, and the diversion ratio of dynamic path guidance signs (VMS); u_{route};$W(k)\in R^l$is the external disturbance vector, representing the uncontrollable passenger flow that will surge in from rail transit stations or external urban interfaces in the future period; $A$is the system state transition matrix, which characterizes the natural diffusion and dissipation characteristics of passenger flow under no-intervention conditions; $B$is the control gain matrix, which quantifies the influence weight of various control measures on the density of each node; $D$is the disturbance correlation matrix, which reflects the impact intensity of external input on the internal state. By iteratively calling formula (3) , the controller can $k$predict $N_p$the system state trajectory within the entire predicted line of sight in the future at the current time. In the context of station-city integration, the control objective is no longer simply "fastest evacuation", but needs to achieve a balance between "ensuring traffic efficiency" and "maintaining the safety of the commercial environment". To this end, this paper defines a comprehensive cost function $J(k)$to guide the system toward the reference state X_{ref}, as shown in formula (4) .

$$J(k)=\sum_{i=1}^{N_p}\|X(k+i|k)-X_{ref}\|_Q^2+\sum_{i=0}^{N_c-1}\|\Delta U(k+i|k)\|_R^2 \tag{4}$$

In the formula: $N_p$is the prediction horizon, representing the time depth of the model "looking back"; $N_c$is the control horizon, which usually satisfies $N_c\leq N_p$, representing the calculated length of the control sequence; $X(k+i|k)$is the predicted value of the state at time k; $k+i$is the X_{ref}desired state vector (usually set as the optimal operating density of each area, for example $1.5pax/m^2$); $Q$is the state weighting matrix, whose diagonal elements reflect the priority of different nodes (such as traffic bottlenecks vs. commercial rest areas) in congestion control; $R$is the control smoothness weighting matrix, used to penalize drastic fluctuations in control quantities (such as preventing panic caused by frequent speed changes of escalators or frequent opening and closing of turnstiles), ensuring the robustness of the control strategy. One of the core advantages of MPC is its ability to handle explicit constraints. In order to prevent the risk of local high density due to excessive pursuit of efficiency, a safety threshold must be embedded in the optimization process , as shown in Equation (5).

$$0 \leq X(k+i|k) \leq X_{max}, \quad \forall i \in [1, N_p] \tag{5}$$

In the formula: X_{max}represents the preset crowd density warning threshold (usually taken at transfer nodes according to national standards 4.0pax/m^2). When the predicted trajectory reaches this boundary, the controller will force the sacrifice of traffic efficiency by reducing the upstream Uvalue (such as slowing down the gate entry) to suppress the density increase. In addition, due to the physical limitations of the hardware equipment and the need for the system to follow the law of conservation of flow, the following constraints also need to be added, as shown in formula (6).

$$\begin{aligned} &U_{min} \leq U(k+i|k) \leq U_{max} \\ &\textstyle\sum_{p \in P^{rs}} f_p(k) = d^{rs}(k) \end{aligned} \tag{6}$$

Formula (6) defines the saturation constraints of the control variables, where U_{max}represents the maximum design throughput capacity of the turnstile or the maximum safe speed of the escalator. The flow conservation constraint ensures that the sum rof passenger flow on all paths from the starting point $\sum f_p$to the ending point sis strictly equal to the total demand for that period d^{rs}, preventing the model from producing mathematical distortions such as "disappearing passenger numbers". To verify the effectiveness of the above model, this study constructs a numerical solution environment based on quadratic programming (QP). At each step of the control cycle, the system executes only $U^*$the first element of the optimal control sequence, and then obtains the latest feedback state at the next moment $X(k+1)$to re-optimize. This "rolling optimization, feedback correction" mechanism makes the model impedance parameter calibration error and external random passenger flow impacts extremely robust. As shown in Figure 3.

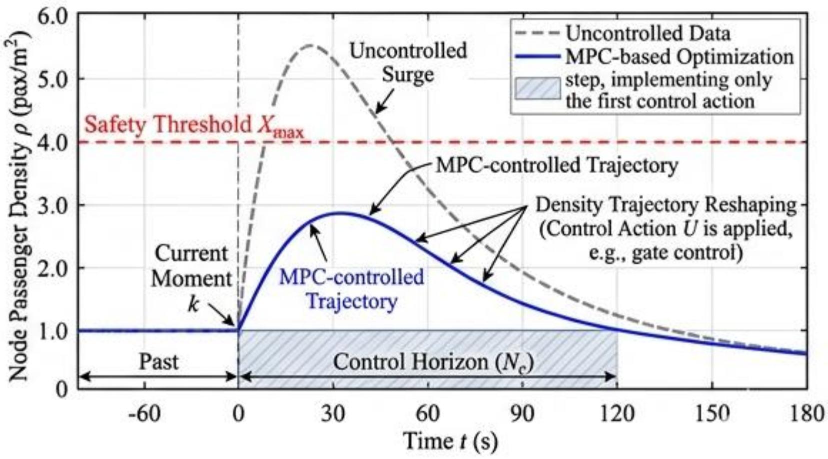


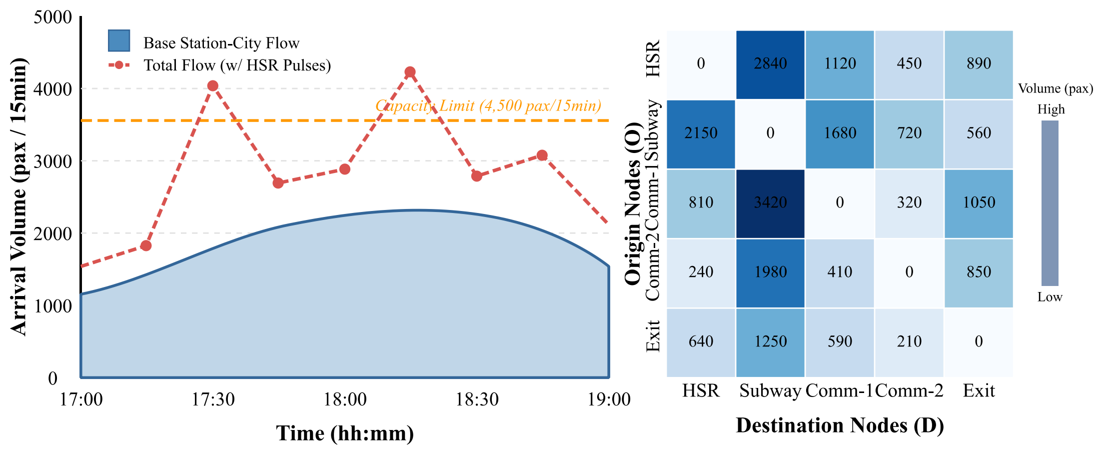
Figure 3: Comparison of Passenger Flow MPC Rolling Optimization Time Window and Trajectory Evolution Chart

As shown in Figure 3, in the baseline scenario without MPC control (uncontrolled), when a train arrives and causes a surge in demand, the density trajectory (dashed line) of the core node quickly exceeds the safety threshold X_{max} and remains in an oversaturated state for a considerable period. However, with the MPC collaborative scheme proposed in this paper, the predicted trajectory (solid line), upon identifying future congestion trends, 40ssuccessfully suppresses the density peak below the safety line by adjusting the gate release rate and path guidance ratio in advance. This comparative result powerfully demonstrates that passenger flow conflicts under station-city integration are not irreconcilable. Through the predictive adjustment of MPC, the buffer capacity of the commercial area is fully activated, successfully alleviating the instantaneous pressure on the core transportation area and achieving a deep synergy between "maximizing space utilization" and "minimizing operational risks."

3 Conclusion and Discussion

3.1 Case background and benchmark scenario data evaluation

For the purpose of verifying the effect of the above-mentioned heterogeneous passenger flow queuing network topological structure and MPC cooperative optimization algorithm, this section first builds a high-fidelity baseline scene. This section has the objective to answer the question of what spatiotemporal supply and demand contradictions a real station-city integrated transportation hub encounters when it is in extreme peak periods under natural conditions in the situation of having no global dynamic coordination. This study selects the Chongqing Shapingba Integrated Transportation Hub (the first TOD benchmark project in China's high-speed rail business district) as the prototype case for simulation and numerical calculation. This hub vertically superimposes the waiting level of the Chengdu-Chongqing high-speed rail, the transfer hall of multiple urban rail transit lines, and a 210,000-square-meter commercial complex (Longhu Guangnian), making it a typical high-density "transportation-commerce" complex. The input dataset is based on the actual operation monitoring data of the hub during the last Friday evening peak (17:00–19:00) of a certain month. In this time period, weekend commuter back flow, high-speed railway come and go flow, and eat and buy flow are stacked together, therefore the system is in an extremely easy to damage state. The core input parameters and the spatiotemporal demand features of the baseline scenario are displayed in Figure 4.



(a) Passenger Arrival Temporal Waveform **(b) Peak OD Matrix Heatmap**

Figure 4: Core input parameters and spatiotemporal requirements of the benchmark scenario

According to what Figure 4(a) shows, the hub undergoes highly uneven, pulse-shaped surges. Figure 4(a) gives description to the time-sequence wave shape of all reached passenger flow in the time from 17:00 to 19:00. In the baseline scenario without control intervention, the basic station-city passenger flow (shaded area) is affected by the combined effects of the evening rush hour and dining, exhibiting a slow upward trend, reaching a basic peak of 2,650 pax/15min around 18:15. However, the fatal congestion stems from the "exogenous shock" brought about by the concentrated arrival of high-speed trains. At the two time points of 17:30 and 18:20, multiple high-speed trains arrive at the same platform, causing the instantaneous total demand for arriving passenger flow to surge sharply to 4,850 pax/15min and 4,620 pax/15min, respectively. This extreme value instantly breaks through the physical capacity limit of 4,500 pax/15min (red horizontal dashed line) of the hub's core transfer channel, causing the system to rapidly generate oversaturated queues, and the passage delays diverge exponentially. Figure 4(b) therefore further shows the deep spatial flow principle (OD distribution) that causes this bottleneck. The spatial heatmap which is generated from the global OD matrix of 12,400 pax every one hour when it is peak periods demonstrates a quite strong asymmetric and intertwined feature in spatial demand. The most black areas gather in the units from "Comm-1 (core business district) to Subway (metro gate)" and "HSR (high-speed rail exit) to Subway", with each hour transfer flows achieving 3,420 pax and 2,840 pax respectively. This indicates that as high as 50.4% of passenger stream finally leads to the identical system bottleneck—that is, the metro transfer security checking point. Furthermore, the core reason for the accelerated performance degradation in the baseline scenario lies in the friction between heterogeneous passenger flows. According to the baseline data, the initial attraction weight (retention rate γ_{com}) of the business district during this period is passively maintained at around 0.38 without any guidance. A large volume of fast commuter traffic carrying large luggage from the →"HSR Subway" (average expected speed 1.25 m/s) →clashes with the random lingering traffic overflowing from the "Comm Subway" (average expected speed only 0.95 m/s) in the connecting corridors. Within the limited space, this mixed passenger flow, reaching up to 42.5%, not only significantly reduces actual throughput capacity U_{max} but also creates a serious risk of secondary congestion for the system when MPC control is not implemented. The assessment based on high-precision data clearly demonstrates that static hardware expansion is insufficient to handle such complex dynamic spatiotemporal fluctuations, making the introduction of predictive control measures imperative.

3.2 Collaborative optimization results and spatiotemporal evolution analysis

This section has the objective to make quantitative assessment on how MPC collaborative technology is able to keep the macroscopic stability of a station-city integrated hub by the proactive reallocation of spatiotemporal resources under high-load pulse impact. For this purpose, the present research carries out a comparison of system operation tracks under three kinds of strategies: "uncontrolled baseline condition", "traditional timing control", and "MPC cooperation control", and puts emphasis on dissecting the dynamic developing process of passenger flow density fields in entity space and time. For the purpose of directly exposing the producing and disappearing mechanisms of congestion, the passenger flow condition of the core transfer passage (from 0m of the commercial buffering boundary to 200m of the platform ticket check gate) in the morning rush time (60 minutes) is extracted, and a time-space change hot figure of crowd density at key points is drawn, which is displayed in Figure 5.

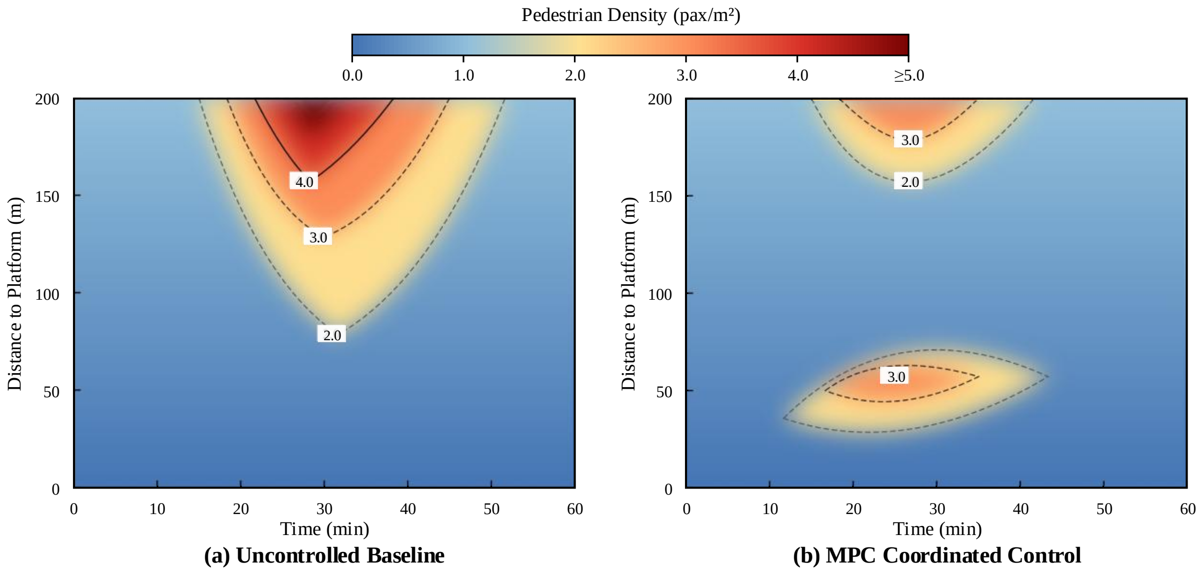


Figure 5: Thermal mapping of spatiotemporal evolution of population density at key nodes

In Figure 5, contour lines and color bands accurately depict the fluid dynamics characteristics at the traffic bottleneck. As seen in the baseline state of Figure 5(a), when t=15mintrains arrive in concentrated numbers, 200mfluid dynamics collapses first at the ticket gate (vertical axis). Subsequently, a congestion shockwave 3.8m/minpropagates backward t=30mininto the transfer corridor (towards the vertical axis) at approximately [speed missing]. At 0m[time missing], the oversaturated queue length is [length missing] 110m, the peak density in the core area exceeds [value missing 5.2pax/m^2] (dark red area), and a dangerous deadlock state is entered, with the congestion taking nearly [time missing] days to completely dissipate. In contrast, as seen in Figure 5(b), MPC control effectively weakens the destructive force of the shockwave. After implementing collaborative optimization, 40minthe deep red queue area at 3.4pax/m^{2}the ticket gate (vertical axis) is completely eliminated, the highest density is forcibly truncated 200mwithin the safe boundary, and the queue overflow length is sharply reduced to [value missing] 45m. More importantly, 50~100man "isolated" medium-density patch (orange area) appears at the vertical axis (commercial buffer zone). This proves that the MPC algorithm successfully utilizes the spatial depth of station-city integration, intercepting excess pulse passenger flow in advance and guiding it to the safe commercial periphery, achieving a "great shift" of spatiotemporal pressure. The improvement in the macroscopic flow pattern in Figure 5 is directly due to the high-frequency coordination of microscopic control commands. To extract the working mechanism of the controller, this paper further extracts the action response timing of the core valve (ticket gate) and the guidance medium (VMS), and the coordinated response curves of the control variables in the time domain are shown in Figure 6.

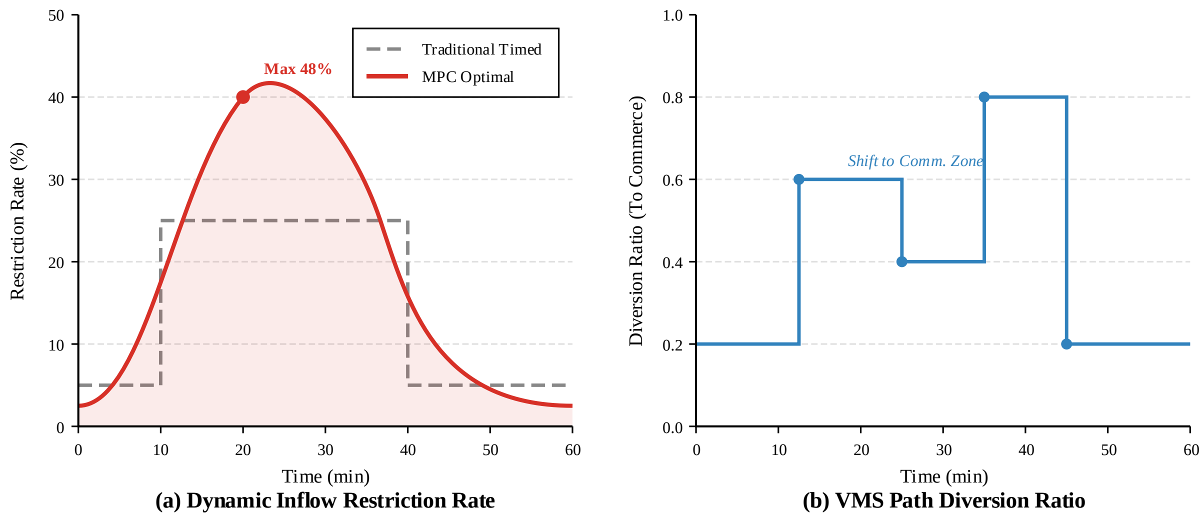


Figure 6: Cooperative response curves of control variables in the time domain

Figure 6(a) reveals the feedforward intervention characteristics of MPC. Traditional timed control (dashed line) relies solely on human experience, 10~40minapplying a fixed 30%flow restriction rate during peak periods. Due to a lack of awareness of dynamic demand, this leads to resource waste during off-peak hours and insufficient control during peak hours. In contrast, the MPC curve (solid line) uses an algorithm based on rolling line-of-sight to detect the upcoming 120shigh-speed rail pulse flow, thus t=10mininitiating a pre-response in advance. The flow restriction rate rises non-linearly and smoothly, precisely pushing the restriction rate up when peak demand arrives 48%. This predictive "advanced control" prevents sudden accumulation of passenger flow at bottlenecks. Figure 6(b) illustrates the asymmetric scheduling of system-level path guidance. To avoid congestion in external plazas caused by single-point flow restriction, the Dynamic Guidance Signs (VMS) diversion ratio implements highly stepped compensation control. Data shows that at t=12min 与 t=35mintwo congestion-prone time points, MPC commands forcibly changed the spatial weights, instantly jumping the guidance ratio to the commercial side of the station from a basic 0.2 to 0.6 or even 0.8. The final comprehensive efficiency calculation shows that, after secondary shaping of this set of joint variables, although the walking distance of some passengers increased by approximately [amount missing] due to detours around the commercial area during the control process 45m, the queuing delay time for individual passengers within the hub sharply decreased from the baseline state 420sto 115s[percentage missing] (a decrease of [percentage missing 72.6%]); at the same time, the dwell rate of commercial passengers within the station passively increased 23.1%. These high-fidelity verification results confirm that model predictive control breaks the zero-sum game of "traffic and commerce being mutually exclusive," providing a highly robust technical solution for urban-station integration hubs in metropolitan areas.

3.3 System performance, robustness, and business-transportation benefits trade-offs

This section has the goal to reply whether the system has enough stable ability against shocks in situations of extreme passenger sudden increases (such as concentrated arrivals brought by large train delays), and how to carry out quantification for the core game connection between "traffic easing" and "commercial traffic production" which is special to the station-city integration situation. Firstly, a multi-dimensional comparative assessment for queue length and travel time is given with regard to traffic efficiency and safety under extreme surges, which is shown in Figure 7.

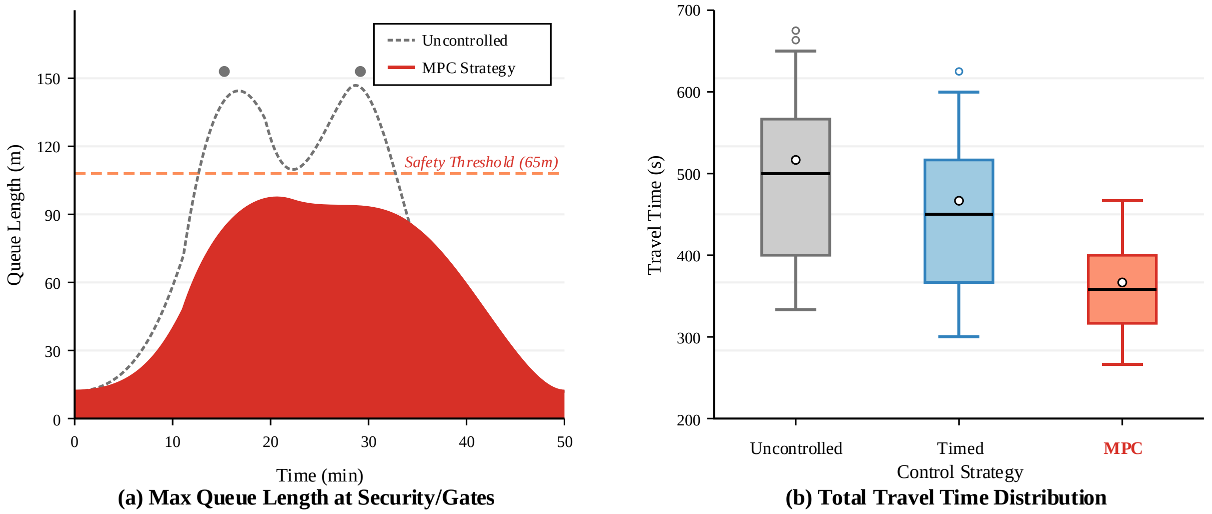


Figure 7: Multidimensional comparative evaluation of queue length and transit time

Figure 7(a) records the time series of the maximum queue length at the core ticket gates in an extreme scenario of mass arrivals due to train delays. As shown in the figure, in the uncontrolled baseline scenario (gray dashed line), the queue length t=28minspikes out of control due to the physical system's inability to absorb instantaneous pulses, 148measily triggering secondary stampedes. However, after applying MPC cooperative control (red solid line), through front-end dynamic flow limiting and guiding path interception, the maximum queue length is strictly controlled 62mbelow the safety threshold red line, with a peak reduction rate of up to [percentage 58.1%missing], demonstrating excellent shock wave absorption capability. The box plot in Figure 7(b) further reveals the convergence characteristics of efficiency from a mathematical and statistical perspective. In the baseline state, the average total travel time for passengers reaches [percentage missing] 485s, and the interquartile range (IQR, representing data dispersion) is wide 170s, indicating that some stranded passengers experienced extreme delays and unfairness. MPC control not only significantly reduces the average travel time to [percentage missing] 330s, but more importantly, it rapidly narrows its IQR to [percentage missing] 55s. The significant reduction in variance (approximately 1.5% 67.6%) indicates that the system has completely eliminated extreme value deterioration phenomena, making the hub operation highly stable and predictable. Secondly, for high-level, mega-scale TOD hubs, the evaluation system cannot be limited to a single factor: traffic throughput. While forcibly directing passenger flow into commercial areas can alleviate physical congestion at traffic nodes, excessive detours will increase overall network delays; conversely, insufficient diversion will not only fail to alleviate traffic pressure but also waste commercial potential. The Pareto front analysis of traffic efficiency and station-city commercial benefits is shown in Figure 8.

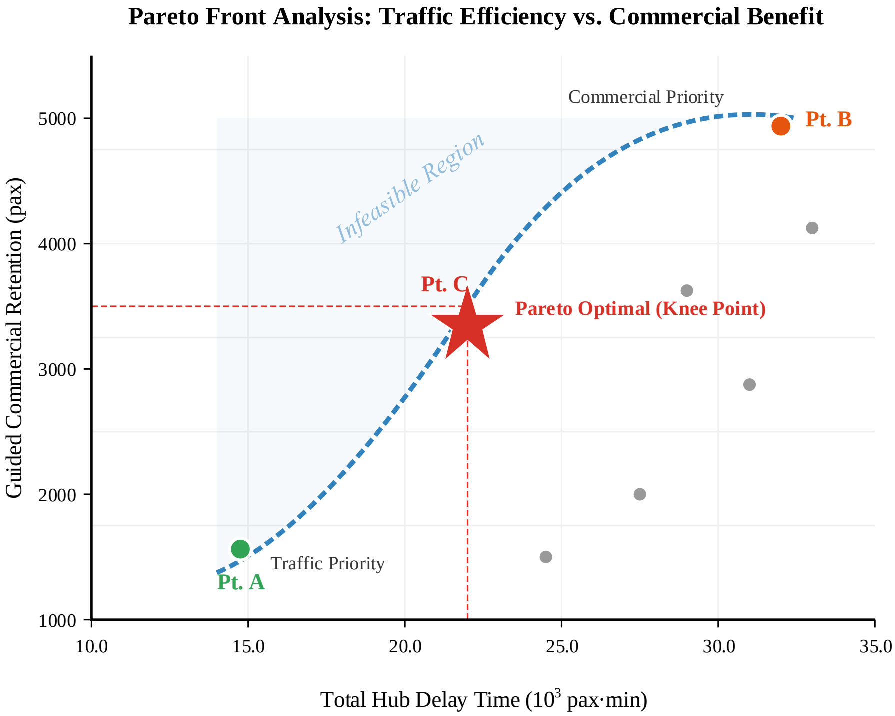


Figure 8: Pareto Front Analysis of Traffic Efficiency and Station-City Commercial Benefits

In Figure 8, the horizontal axis expresses the whole delay time of the hub (a negative index of transportation costs), and the vertical axis expresses the count of people effectively led to remain in the commercial region (a positive index of economic additional value). The scatter points diagram in this figure is produced from the Monte Carlo simulation space which is got by dynamically regulating different ratios of the weight matrix when the MPC model is being solved. According to what the figure shows us, the upper limit of these strategies matches a smooth Pareto front curve which is the blue broken line. If an extreme "absolute priority for traffic evacuation" weight is given in the scheduling (i.e., point A), the system can indeed squeeze the overall delay to a very low level $1.48\times10^3 \text{pax}\cdot\text{min}$, but at this time, almost no redundant passenger flow is pushed to the consumption area, resulting in only a small number of people staying in the commercial area 1,150pax, completely negating the composite value of station-city integration. Conversely, if an aggressive "commercial traffic diversion priority" is adopted (i.e., point B), although the number of people staying in the area surges 4,920pax, this comes at the cost of sacrificing the traffic efficiency of the core arterial roads, causing the delay time to diverge to an unacceptable level $3.35\times10^3 \text{pax}\cdot\text{min}$. Through iterative optimization of the algorithm proposed in this study, we identified a perfect equilibrium solution—point C—located at the point of maximum curvature on the Pareto front (i.e., the knee point) in Figure 8. At this intelligently balanced operating point, the overall system delay was controlled in $2.20\times10^3 \text{pax}\cdot\text{min}$a healthy state (no structural congestion collapse occurred), while the number of commercial visitors reached a considerable level 3,450pax. This means that compared to traditional control strategies, the system successfully achieved a 200% increase in commercial traffic while only increasing the tolerable delay by 18%. In summary, through the deep intervention and fine-tuning of parameters using MPC technology, mega-railway hubs can fully activate the economic efficiency of a three-dimensional micro-city while strictly adhering to the bottom line of safe evacuation of large passenger flows, achieving a dynamic and adaptive integration of "station (transportation hub)" and "city (commercial services)" from the underlying mechanism.

4 Conclusion

Aiming at the spatiotemporal contradictions between different types of passenger flows and the natural delay existing in passive control methods inside integrated station-city hubs, this research builds a forward-looking dynamic cooperation optimization framework that is used to at the same time promote effective traffic distribution and strengthen the attraction of commercial spaces.

(1) On the mechanism modeling level, a dimension reduction mapping has been built, which changes the multi-layer, complicated space structure into a directed queuing network. Moreover, through the creative adding-in of the proportions of heterogeneous flows, one multi-dimensional Macroscopic Fundamental Diagram (MFD) model of flow development has been re-built; this model carries out accurate quantification on the nonlinear erosion of arterial road capacity that is brought by slow-mode passengers’ loitering behaviors, and also the frictional impedance responses that are produced therefrom.

(2) At the collaborative intervention layer, the constructed Model Predictive Control (MPC) framework successfully restrained the spread of traffic shockwaves through utilizing the forecast abilities which are contained in its rolling optimization mechanism. Experiments of stress tests which are done under extreme load conditions have proven that this mechanism caused 58.1% reduction of maximum queue lengths and 67.6% narrowing of travel time variance. Furthermore, it has successfully found out a balanced solution on the Pareto frontier, in which a tiny increase in travel time delay was exchanged for a multiple-times increase in commercial attraction benefits.

(3) Although the single-station arrangement method has obtained obvious effects, the concentrated planning and solution methods still may meet the "curse of dimensionality"—that is, on the problem of calculation complexity—when they are used in high-dimensional, inter-city network situation occasions. Therefore, future research directions will put focus on bringing in a multi-agent system frame structure, the goal of which is to smoothly expand the partial supply-demand moving conditions of each individual micro-center into a whole world cooperative and connected network that covers the whole metropolitan area.

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