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Dynamic passenger flow assignment in metro stations using density–queue feedback

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Abstract: Simulation studies of passenger flow management in metro stations often compare predefined diversion schemes, although fixed assignment ratios may shift congestion when local loads change. This study develops a dynamic assignment method based on density–queue feedback. The controller combines density and queue length into a composite pressure measure and uses it to update route probabilities through Softmax mapping, a probability lower bound, and exponential smoothing. In an analysis of the National Convention and Exhibition Center Station in Tianjin, AnyLogic is used to model passenger flow, while Python is responsible for executing feedback computations and updating probabilities. Each of the three schemes—fixed equal probabilities, a fixed assignment ratio, and dynamic feedback—is tested in 30 independent runs. Component ablation and parameter sensitivity analyses are also conducted. Relative to the fixed equal-probability scheme, dynamic feedback reduces mean public-node density, mean public-node queue length, and passenger-weighted mean dwell time by 34.1%, 20.6%, and 12.2%, respectively. Relative to the fixed-ratio scheme, it reduces mean density at monitoring node 2 by 16.9% and maximum queue lengths at monitoring nodes 1 and 2 by 20.7% and 27.3%, respectively. Simulation completion time does not differ significantly among the three schemes. The ablation results show that queue feedback identifies persistent service backlogs and exponential smoothing limits probability fluctuations. Under the modeled conditions, the method balances public-node relief, monitoring-node loads, and passenger flow efficiency.

Keywords: metro station; passenger flow assignment; agent-based simulation; feedback control; Softmax; queueing

1. Introduction

During major events, the influx of people often results in short-lived, highly directional surges in the demand for station entry. When passengers entering from various points are not evenly spread across available fare-gate zones, it can lead to a swift rise in local crowding and queue lengths. Additionally, using a constant diversion ratio might simply transfer congestion to different locations. Consequently, route allocation must adapt to the current conditions of fare-gate zones, considering local crowd levels, the distribution of loads across different areas, and the efficiency of passenger movement.

Passenger flow control in urban rail transit is generally studied using offline optimization or online control. Yang et al. [1] coordinated passenger inflow across stations using station-to-line spatiotemporal relationships. Their approach represents demand and capacity constraints at line and network levels but depends on demand forecasts and efficient computation. Liang et al. [2] adjusted metro-line control decisions online as demand changed. Both studies focus mainly on station admission or line-level flows. They do not directly model how pressure at individual facilities changes route probabilities between station entrances and fare-gate areas.

Passenger route choice is commonly modeled with utility functions, discrete choice models, or behavioral rules. Tong and Bode [3,4] examined general route-choice principles and the effects of building layout on route choice and recall. Snopková et al. [5] related evacuation route choice

to isovist compactness and stairs. Together, these studies identify distance, layout, visibility, perceived crowding, and familiarity as relevant factors. Applying such models still requires observed routes and calibrated parameters.

Real-time guidance converts operating conditions into route recommendations or choice information. Krall et al. [6] studied how digital route information affects delay-induced congestion, and Mayr and Köster [7] compared guidance strategies under limited compliance. Zhang et al. [16] used network states in a graph neural network model for evacuation route recommendation. For service-facility control, however, density alone cannot distinguish brief crowding from sustained service backlogs. Route probabilities may also fluctuate between control intervals unless bounds and smoothing are applied.

Microscopic pedestrian simulation generally uses social force models or agent-based rules to describe walking, collision avoidance, queueing, and service processes. Yang et al. [8] reviewed crowd simulation and modeling methods, while Dang et al. [9] proposed a multilevel crowd simulation framework and discussed model calibration and validation. In rail transit applications, Wang et al. [10] investigated metro station passenger flow control plans using a social force model, and Liu et al. [17] analyzed deadlock in bidirectional pedestrian flow on stairs using a personal space model. Experimental studies have also compared virtual and physical methods for examining pedestrian responses [14] and quantified how people with disabilities affect bottleneck dynamics [15]. These studies support the identification of local bottlenecks, the analysis of congestion, and the comparison of passenger flow management schemes. Ni et al. [11] and Tian et al. [12] applied AnyLogic to metro station passenger flow management and simulation-based optimization, demonstrating its suitability for representing spatial layouts, service processes, and passenger routes.

Simulation can evaluate a control scheme, but the decisions must come from rules or optimization. Wang et al. [13] combined a queueing network and a surrogate model to optimize station-level control for large passenger flows. This approach can search for control parameters and management schemes, but it requires model training and repeated simulation. A fixed route ratio also omits feedback from current facility conditions to subsequent passenger choices.

The existing methods serve different purposes. Line-level optimization regulates station admission, route-choice models explain individual behavior, and microscopic simulation evaluates proposed schemes. Station-level assignment among multiple service areas still needs a simple feedback rule that converts local occupancy and queueing into feasible, stable route probabilities. The method developed here updates probabilities from density and queue states and constrains them with a lower bound and exponential smoothing.

The study addresses three questions: how to convert facility density and queue states into route probabilities; whether feedback can reduce public-node loads without sustained accumulation at side nodes; and how density feedback, queue feedback, and exponential smoothing affect control performance.

We develop a set-based feedback framework for multiple entrances and service facilities. AnyLogic simulates passenger movement, and Python updates route probabilities from density and queue length. Baseline comparisons, component ablation, and parameter sensitivity experiments evaluate the controller. The framework supports entrance groups with two or more candidate facilities, while demand and parameter values remain case-specific.

2. Methods

Fig. 1 presents the network representation, feedback loop, and evaluation design. At each control interval, the controller reads the monitoring-node states and updates route probabilities for the next interval.

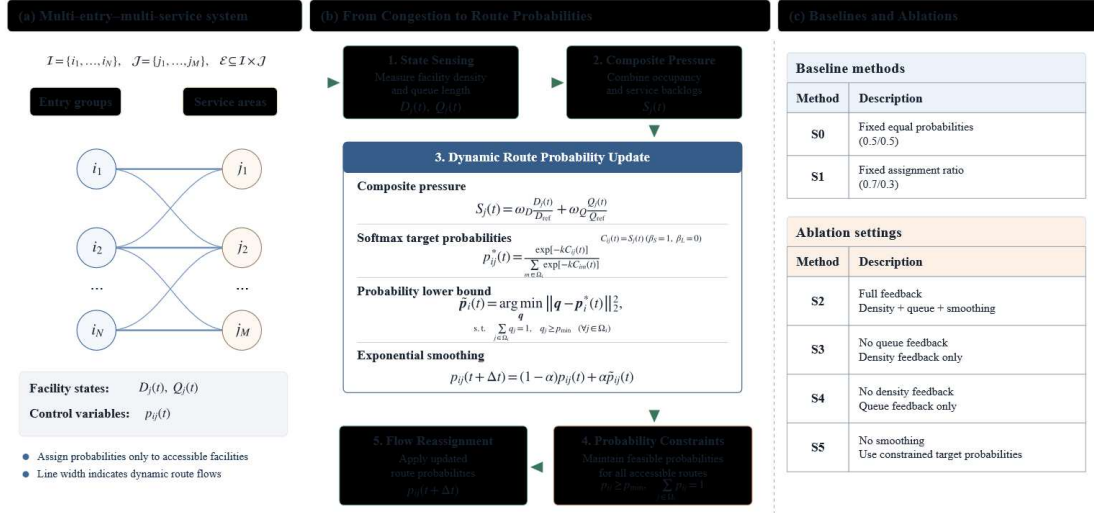


Fig. 1. General framework and evaluation procedure for dynamic passenger flow assignment using density–queue feedback.

In Fig. 1, the left panel defines entrances, service facilities, and feasible connections. The middle panel shows the feedback loop, and the right panel lists the baseline and ablation schemes. The three fare-gate areas in the case study are one instance of this framework. Other layouts require corresponding changes to the accessible sets, accessibility matrix, and equation summations.

2.1 Problem definition and assumptions

Passenger flow management during concentrated arrivals at large events is formulated as a dynamic assignment problem involving multiple entrances and fare-gate areas. Entrances are grouped according to their sets of accessible fare-gate areas, without prescribing the number or spatial positions of the fare-gate areas or whether they belong to a public area. For entrance group i , the set of accessible fare-gate areas is denoted by Ω_i . When $|\Omega_i| \geq 2$, the controller updates the route choice probability from entrance group i to fare-gate area $j \in \Omega_i$, denoted by $p_{ij}(t)$, during each control interval according to the operating pressure at each candidate area. When $|\Omega_i| = 1$, no route assignment choice exists and the probability of selecting the corresponding route remains 1.

The model makes the following assumptions: (1) passengers within the same entrance group share the same set of accessible fare-gate areas and select their routes according to the assigned probabilities; (2) passengers do not reroute after selecting a path; (3) facilities operate normally, with no passage closures, fare-gate failures, or large-scale counterflows; and (4) automatic fare collection (AFC) data constrain total demand only and are not used to infer entrance origins or individual routes.

Route probabilities represent aggregate choice tendencies shaped by accessibility, guidance information, and crowding. Because field data on routes and compliance rates are unavailable, this study compares update rules without estimating individual preference parameters.

To distinguish the types of variables needed to reproduce the model, we divide the model elements into four categories. Exogenous inputs include the entrance-group set I , the fare-gate-area set J , the accessible-route set $\mathcal{E}$, the accessibility matrix A , the accessible fare-gate-area set Ω_i , monitoring areas, entrance arrival rates, maximum arrival counts, fare-gate service times, and the control interval. State variables include $N_j(t)$, $Q_j(t)$, $D_j(t)$, and $S_j(t)$. The control output is the implemented route probability for the next control interval, $p_{ij}(t)$. Evaluation metrics are used only to compare scheme outcomes and do not enter the route probability update.

2.2 Network representation

The connectivity between entrance groups and fare-gate areas is represented as a directed bipartite network:

$$\mathcal{G} = (I, J, \mathcal{E}) \quad (1)$$

Here, $I = \{1, 2, \dots, N\}$ denotes the set of entrance groups and $J = \{1, 2, \dots, M\}$ denotes the set of fare-gate areas, with $M \geq 2$. The accessible-route set satisfies $\mathcal{E} \subseteq I \times J$. In the accessibility matrix $A = [a_{ij}]$, if $(i, j) \in \mathcal{E}$, then $a_{ij} = 1$; otherwise, the entry is 0. The accessible set is defined by $\Omega_i = \{j \in J \mid a_{ij} = 1\}$. This structure can represent any number of candidate fare-gate areas and accommodate both entrance groups with dynamic assignment and those with a single available route.

2.3 State variables and composite pressure

Density in a fare-gate area reflects local spatial occupancy, while queue length reflects the balance between passenger demand and fare-gate service capacity. At time t , let fare-gate area j have a monitored passenger count of $N_j(t)$ and a monitoring area of A_j . Its density $D_j(t)$ is then expressed as:

$$D_j(t) = \frac{N_j(t)}{A_j} \quad (2)$$

To obtain dimensionless quantities, density and queue length are normalized by D_{ref} and Q_{ref} , respectively, to construct the composite pressure $S_j(t)$, with coefficients ω_D and ω_Q . In this case study, $D_{\text{ref}} = 1.2$ persons/m², $Q_{\text{ref}} = 50$ persons, and $\omega_D = \omega_Q = 1.0$. These values are normalization scales and experimental parameters rather than safety thresholds. A higher composite pressure indicates greater resistance to assigning additional passengers to the area.

$$S_j(t) = \omega_D \frac{D_j(t)}{D_{\text{ref}}} + \omega_Q \frac{Q_j(t)}{Q_{\text{ref}}} \quad (3)$$

2.4 Target route probabilities

For entrance group i , the composite impedance associated with choosing fare-gate area j is denoted by $C_{ij}(t)$. Here, L_{ij} is the route distance or equivalent walking cost, L_{ref} is the normalization reference, and β_S and β_L are the state and distance weights. To isolate state feedback in this case study, $\beta_S = 1$ and $\beta_L = 0$ are used; actual walking times are still calculated from spatial routes in AnyLogic. Once field route choice data become available, β_L can be further calibrated, or the utility function can be extended.

$$C_{ij}(t) = \beta_S S_j(t) + \beta_L \frac{L_{ij}}{L_{\text{ref}}} \quad (4)$$

Softmax provides continuous, normalized probability outputs that can be integrated into the AnyLogic route choice module and operational guidance rules. It maps composite impedance to target route probabilities, with higher impedance producing a lower probability. The denominator contains a sum over $m \in \Omega_i$, ensuring that $\sum_{j \in \Omega_i} p_{ij}^*(t) = 1$ remains satisfied when the number of candidate fare-gate areas changes.

$$p_{ij}^*(t) = \frac{\exp[-kC_{ij}(t)]}{\sum_{m \in \Omega_i} \exp[-kC_{im}(t)]} \quad (5)$$

2.5 Probability constraints and updates

A minimum route probability p_{min} is imposed. In the general case, the constrained simplex projection in Eq. (6) ensures that the adjusted probability vector sums to 1 and that every

component is at least the lower bound. To retain adjustment flexibility, $|\Omega_i|p_{\min} < 1$ must hold. When $|\Omega_i| = 2$, the constraint can be written as the componentwise clipping operation in Eq. (7). This case study uses $p_{\min} = 0.10$, giving a probability range of $[0.10, 0.90]$ for each of the two accessible routes.

$$\tilde{\mathbf{p}}_i(t) = \arg \min_{\mathbf{q}} \|\mathbf{q} - \mathbf{p}_i^*(t)\|_2^2, \quad \text{s.t.} \quad \sum_{j \in \Omega_i} q_j = 1, \quad q_j \geq p_{\min} \quad (6)$$

$$\tilde{p}_{ij}(t) = \min\{1 - p_{\min}, \max[p_{\min}, p_{ij}^*(t)]\}, \quad |\Omega_i| = 2 \quad (7)$$

State acquisition, guidance delivery, and passenger responses involve delays. Directly implementing target probabilities may therefore cause abrupt changes between successive control intervals. Equation (8) uses exponential smoothing to update the implemented probabilities for the next interval, where α is the smoothing coefficient and Δt is the control interval. A larger smoothing coefficient allows the implemented probability to approach the target more quickly, while a smaller coefficient moderates changes over short intervals.

$$p_{ij}(t + \Delta t) = (1 - \alpha)p_{ij}(t) + \alpha\tilde{p}_{ij}(t) \quad (8)$$

2.6 Control implementation

AnyLogic simulates pedestrian movement and executes the control loop. At each interval, the model reads passenger counts and queue lengths, calculates composite pressures and target probabilities, and applies the lower bound and exponential smoothing. The resulting probabilities are passed to the route-choice module for the next interval. They affect only passengers who have not selected a route.

The software environment comprised AnyLogic 8.9.5 Professional and Python 3.9 (64-bit). The Python code was developed in IDLE and invoked by the simulation model through the Python library in AnyLogic.

The control loop consists of state acquisition, pressure calculation, target-probability generation, constraint enforcement, smoothing, and route assignment. The accessible sets and matrix define how the same procedure applies to other fare-gate layouts.

Implemented probabilities apply only to passengers arriving at route choice nodes and do not alter the routes of passengers already in passages or queues. In practice, these probabilities could be translated into area-specific guidance intensities delivered through displays, announcements, or staff instructions.

3. Case study and experimental design

3.1 Case study station and accessibility relationships

The case study focuses on National Convention and Exhibition Center Station in Tianjin, China, which has six entrances and three fare-gate areas. Entrances ① and ④ form the Top group, with access to G_L and G_C . Entrances ②, ③, ⑤, and ⑥ form the Bottom group, with access to G_R and G_C . Because G_C serves both entrance groups, it is defined as the public fare-gate area.

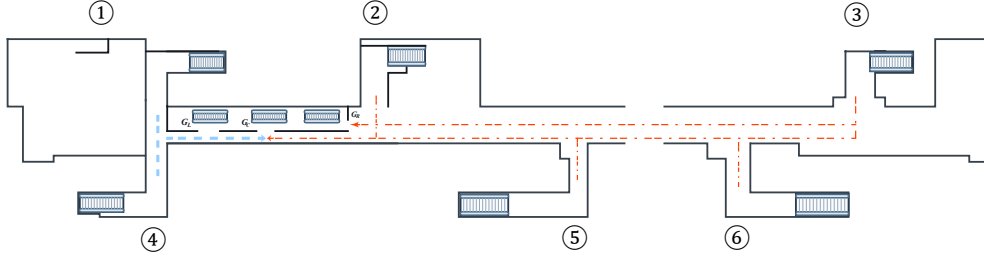


Fig. 2. Entrances, fare-gate areas, and accessibility relationships at the case study station.

3.2 Data sources and demand settings

AFC data determine only the total demand during the concentrated entry period; they do not identify entrance origins, fare-gate choices, or station routes. Only aggregate passenger counts were used, and the study did not access card identifiers, individual trajectories, or other personally identifiable information. Total demand is therefore distributed uniformly across the six entrances so that differences in assumed entrance demand do not affect the scheme comparison.

Based on the peak-hour passenger volume, each entrance was assigned an arrival rate of 11 persons/min and a maximum of 152 arrivals, giving a total input of 912 passengers. Each entrance stopped generating passengers once its cumulative count reached 152. This setting supported controlled comparisons and did not represent the actual distribution of passengers among station entrances.

3.3 Agent-based simulation settings

The AnyLogic model includes arrival, walking, route choice, fare-gate service, and departure processes. Each entrance generates passengers at 11 persons/min and stops after generating 152 passengers. The interval $0 < t \leq 900$ s defines the common window for control and state statistics; arrivals do not necessarily continue until 900 s. Fare-gate service time follows $U(5.0, 6.0)$ s. The areas monitored at monitoring node 1, monitoring node 2, and the public node are 20, 20, and 22 m², respectively, and the control interval is $\Delta t = 1$ s. The simulation ends when all 912 passengers have left the observation area.

All schemes use the same layout, pedestrian parameters, service rules, and statistical definitions. Density, queue length, load balance, and probability variation are calculated from records sampled every second over $0 < t \leq 900$ s, while simulation completion time is reported separately. Because the three monitoring areas differ in size, density is calculated using the corresponding monitoring area and interpreted alongside queue length and passenger flow share.

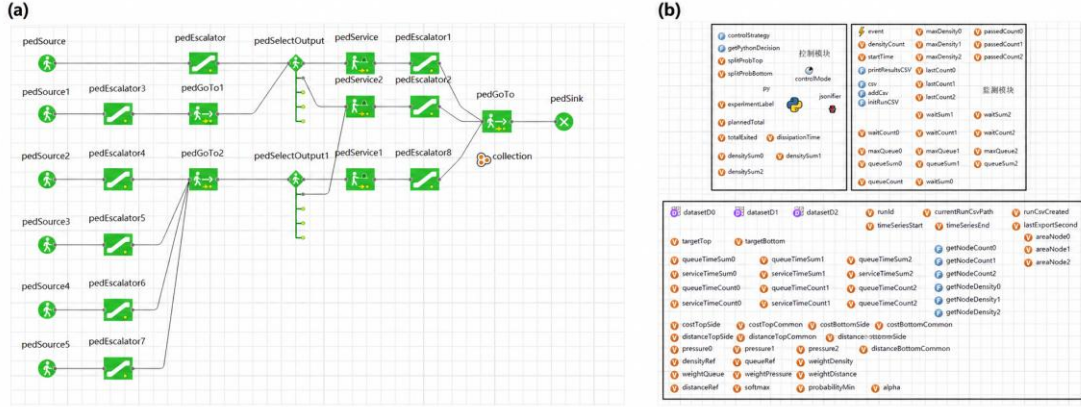


Fig. 3. AnyLogic simulation model: (a) passenger generation, route choice, fare-gate service, and departure; (b) density-queue feedback control, state monitoring, and data logging.

3.4 Comparison schemes

Three schemes are compared. S0 uses fixed equal probabilities: the local-node/public-node probabilities are 0.5/0.5 for both the Top and Bottom groups. S1 uses a fixed ratio of 0.7/0.3 for both groups, without reading density or queue states during a run. S2 uses dynamic feedback: probabilities start at 0.5/0.5 and are then updated in each control interval according to the density and queue states of the candidate nodes. Control parameters and evaluation metrics are listed in Table 1.

The per-second CSV records confirm the implemented assignment rules. Local-node probabilities remain at 0.5 in S0 and 0.7 in S1 but vary with monitored states in S2. All other demand, facility, service, monitoring, and statistical settings are identical across schemes.

3.5 Statistical analysis

Each of the three main schemes was simulated independently 30 times, yielding 90 runs. Each run was treated as an independent statistical sample; time steps and individual passenger records were not treated as independent replicates. Density, queue length, peak values, and density- and queue-balance metrics were calculated from records sampled every second over 0–900 s. Passenger-weighted mean dwell time, passenger flow shares, and simulation completion time were calculated from full-run summaries. Continuous variables were summarized using run-level means, standard deviations, and 95% confidence intervals. To accommodate potentially unequal variances, overall comparisons among the three groups were conducted using Welch's one-way analysis of variance, followed by Games–Howell post hoc tests. Cohen's d was reported as the standardized effect size. Pairwise comparisons were two-sided, and the significance level was set at 0.05.

The density-balance and queue-balance coefficients of variation (CVs) are calculated according to the model's export definitions. Within each run, per-second TIME records over $0 < t \leq 900$ s are first used to obtain the time-averaged density $\bar{D}_j$ and queue length $\bar{Q}_j$ for each fare-gate area. The between-area CV is then calculated using Eq. (9). Here, X denotes either density D or queue length Q , and $\mu_X = |J|^{-1} \sum_{j \in J} \bar{X}_j$. If the denominator is no greater than 10^{-9} , the model assigns a CV of 0. A smaller CV indicates more similar time-averaged loads across areas, although it must be interpreted alongside monitoring areas, accessibility relationships, and local loads. Passenger-weighted mean dwell time is calculated as $\bar{T} = \frac{\sum_j n_j \bar{T}_j}{\sum_j n_j}$, and the range of route probability variation is calculated as $\Delta p_i = \max_t p_i(t) - \min_t p_i(t)$, where i denotes the Top or Bottom entrance group.

$$CV_X = \frac{\sqrt{|J|^{-1} \sum_{j \in J} (\bar{X}_j - \mu_X)^2}}{\mu_X}, \quad X \in \{D, Q\} \quad (9)$$

Table 1. Model parameters, experimental settings, and evaluation metrics.

Category	Parameter or metric	Value or definition	Description
Passenger input	Entrance arrival rate	11 persons/min	Identical at all six entrances
Passenger input	Maximum arrival count	152 persons/entrance	912 passengers in total
Fare-gate service	Service time	Uniform distribution, 5.0–6.0 s	Identical across the three schemes
Monitoring area	Monitoring node 1 / monitoring node 2 / public node	20, 20, 22 m ²	Correspond to CSV fields node, node1, and node2, respectively; used to calculate density
Control parameter	$D_{\text{ref}}, Q_{\text{ref}}$	1.2 persons/m ² , 50 persons	Normalization references for density and queue length
Control parameter	ω_D, ω_Q	1.0, 1.0	The two normalized components enter the composite pressure with equal coefficients; the coefficients need not sum to 1
Control parameter	$k, p_{\min}, \alpha, \Delta t$	1.0, 0.10, 0.15, 1 s	Determine the Softmax response, probability lower bound, smoothing rate, and update interval, respectively; $p_{\min} = 0.10$ gives a probability range of [0.10, 0.90] for the two accessible routes
Control parameter	β_S, β_L	1.0, 0	The case study focuses on the state-pressure term
Control parameter	Initial implemented probabilities	0.5/0.5	S2 initially assigns equal probabilities to the two accessible routes of each entrance group, then updates them using feedback in every control interval
Simulation replication	Number of runs	30 runs/scheme	Independent stochastic runs, summarized using run-level means, standard deviations, and confidence intervals
Evaluation metric	Density and queue length	Mean, maximum, CV	Describe local operating pressure and load balance across areas
Evaluation metric	Efficiency metrics	Passenger flow share, mean dwell time, simulation completion time	Describe assignment outcomes and passenger flow efficiency

3.6 Model verification

Verification covers model structure, inputs, control rules, and statistical procedures. Behavioral calibration would require observations of entrance origins, route choices, and compliance, while external validation would require independent field data. The field observations required for these procedures are unavailable in this study.

All schemes receive 912 passengers and use identical service times, layouts, monitoring areas, and control intervals. S2 updates probabilities only for passengers who have not yet selected a route. Each main scheme and each ablation scheme was evaluated using 30 independent runs; replication counts for the parameter sensitivity experiments are specified separately in Section 4.10.

3.7 Behavioral calibration and external validation

AFC data do not identify entrance origins, actual routes, or compliance with guidance. Accordingly, the corresponding behavioral parameters were not estimated, and errors between simulation outputs and field observations were not calculated.

3.8 Reproducibility information

The model description specifies entrance groups, accessibility, demand, service times, monitoring areas, control parameters, metrics, statistical windows, and replication counts. CSV fields `node`, `node1`, and `node2` correspond to monitoring node 1, monitoring node 2, and the public node. `TIME` records over 0–900 s provide density, queue, peak, and balance metrics; full-run `SUMMARY` records provide dwell time, flow shares, and completion time. Reproducing the study also requires the AnyLogic model, random seeds, monitoring boundaries, software versions, and analysis scripts.

4. Results

The main experiment compares fixed equal probabilities (S0), a fixed 0.7/0.3 ratio (S1), and dynamic density–queue feedback (S2). Ablation experiments test density feedback, queue feedback, and exponential smoothing. Each simulation run is one statistical observation.

4.1 Public-node load reduction

Fig. 4 shows the main operating metrics, and Table 2 reports the run-level results for 30 runs per scheme. Relative to S0, S2 reduces mean public-node density from 0.2315 to 0.1525 persons/m² and mean queue length from 34.38 to 27.29 persons, representing reductions of 34.1% and 20.6%, respectively. Maximum density falls from 0.886 to 0.594 persons/m², and maximum queue length falls from 66.97 to 51.13 persons. Dynamic feedback therefore lowers both average and peak public-node loads under the tested conditions.

S1 achieves a larger reduction in public-node load but directs more passengers to the two monitoring nodes. Public-node density and queue length are higher in S2 than in S1. Results for the public node alone therefore do not establish that S2 is superior to the fixed-ratio scheme across all metrics.

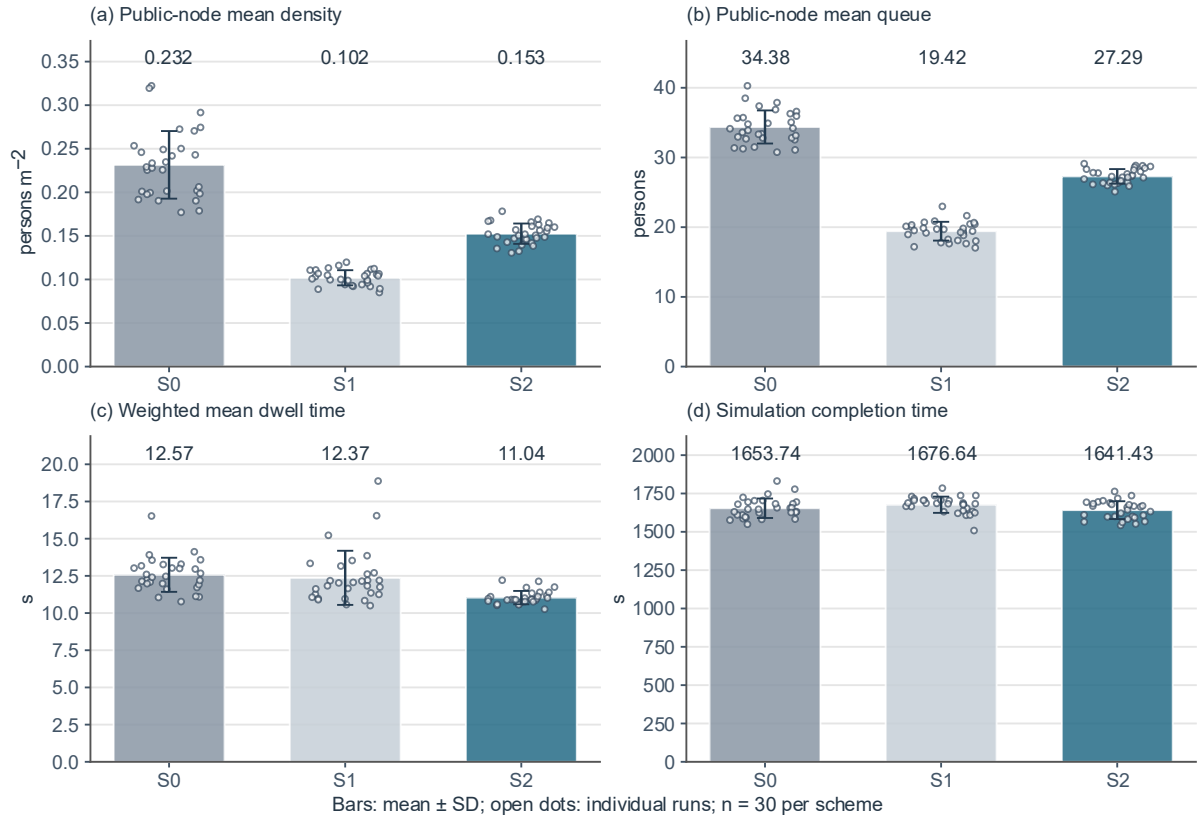


Fig. 4. Main operating metrics for the three control schemes. Bars represent means from 30 independent runs, error bars indicate standard deviations, and open points show individual runs.

Table 2. Run-level results for the three control schemes (mean $\pm$ standard deviation; 30 runs per group).

Metric	S0: fixed equal probabilities (0.5/0.5)	S1: fixed ratio (0.7/0.3)	S2: dynamic feedback
Public-node mean density (persons/m ²)	0.2315 $\pm$ 0.0388	0.1019 $\pm$ 0.0087	0.1525 $\pm$ 0.0117
Public-node maximum density (persons/m ²)	0.886 $\pm$ 0.214	0.450 $\pm$ 0.072	0.594 $\pm$ 0.114
Public-node mean queue length (persons)	34.38 $\pm$ 2.37	19.42 $\pm$ 1.35	27.29 $\pm$ 1.05
Public-node maximum queue length (persons)	66.97 $\pm$ 7.00	38.23 $\pm$ 4.26	51.13 $\pm$ 3.73
Passenger-weighted mean dwell time (s)	12.57 $\pm$ 1.15	12.37 $\pm$ 1.82	11.04 $\pm$ 0.45
Simulation completion time (s)	1653.74 $\pm$ 63.58	1676.64 $\pm$ 52.94	1641.43 $\pm$ 58.10
Density-balance CV	0.217 $\pm$ 0.034	0.462 $\pm$ 0.093	0.280 $\pm$ 0.041
Queue-balance CV	0.828 $\pm$ 0.043	0.390 $\pm$ 0.064	0.656 $\pm$ 0.026
Dwell-time-balance CV	0.229 $\pm$ 0.069	0.197 $\pm$ 0.113	0.096 $\pm$ 0.025
Monitoring node 2 mean density (persons/m ²)	0.2664 $\pm$ 0.0172	0.3254 $\pm$ 0.0738	0.2706 $\pm$ 0.0184
Monitoring node 1 maximum queue length (persons)	20.03 $\pm$ 2.41	28.17 $\pm$ 3.10	22.33 $\pm$ 2.44
Monitoring node 2 maximum queue length (persons)	13.93 $\pm$ 2.29	21.97 $\pm$ 5.60	15.97 $\pm$ 2.31

Metric	S0: fixed equal probabilities (0.5/0.5)	S1: fixed ratio (0.7/0.3)	S2: dynamic feedback
Public-node passenger flow share (%)	50.13±1.83	29.80±1.58	41.68±0.97

4.2 Load transfer to monitoring nodes

Fig. 5 shows the spatial redistribution of loads that accompanies the reduction in load in the public area. Compared with the fixed 0.7/0.3 assignment ratio, dynamic feedback reduces passenger accumulation at the monitoring nodes.

Public-node flow shares are 50.13%, 29.80%, and 41.68% for S0, S1, and S2, respectively. The intermediate share under S2 reflects state-dependent adjustment rather than continued use of the fixed 0.7/0.3 ratio.

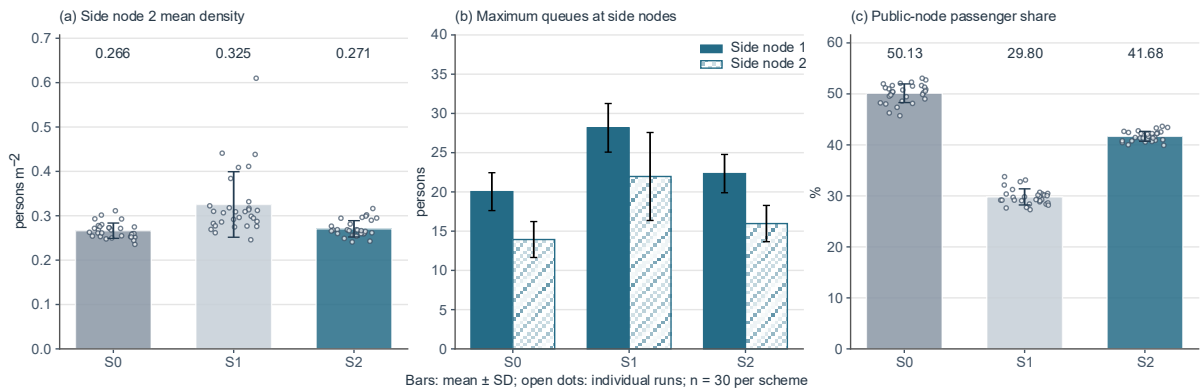


Fig. 5. Monitoring-node loads and public-node passenger flow shares under the three control schemes. Bars represent means from 30 independent runs, and error bars indicate standard deviations.

4.3 Passenger flow efficiency

Mean completion times are 1653.74, 1676.64, and 1641.43 s for S0, S1, and S2, respectively. The Welch test gives $p = 0.052$, above the 0.05 threshold. The experiment therefore provides no statistical evidence that S2 changes completion time. Route assignment redistributes loads without changing fare-gate service capacity.

4.4 Dynamic probability response

Fig. 6 compares target and implemented probabilities in S2. Higher pressure at the public node raises the target probability for a side node; higher side-node pressure restrains further diversion. The lag between target and implemented probabilities shows the effect of exponential smoothing. The lower bound keeps each accessible route available, while smoothing limits short-term adjustments.

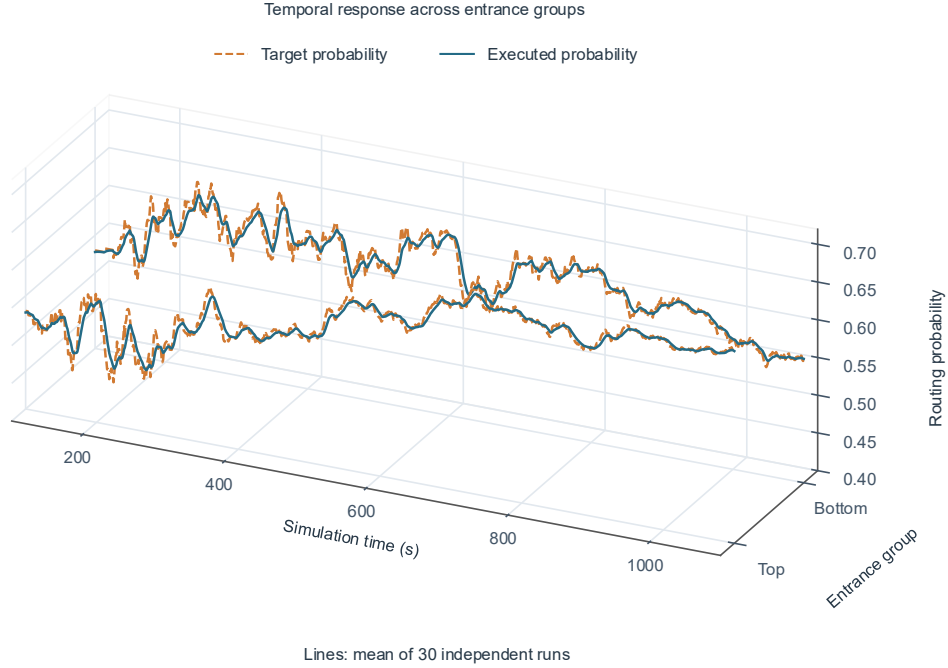


Fig. 6. Dynamic response of target and implemented route probabilities under the full feedback scheme (S2). The difference between the target and implemented probabilities reflects the lower-bound and exponential-smoothing constraints.

4.5 Run-level comparisons

Table 2 shows that S2 reduces public-node density, queue length, and passenger dwell time relative to S0, while increasing the maximum queue lengths at monitoring nodes 1 and 2 by 2.30 and 2.03 persons, respectively. Relative to S1, S2 has higher public-node loads but lower monitoring-node loads and shorter dwell time. S2 therefore balances these outcomes rather than minimizing every metric.

The rankings differ among the three CV metrics. The density-balance CV of S2 (0.280) is higher than that of S0 (0.217) but lower than that of S1 (0.462). Its queue-balance CV (0.656) is lower than that of S0 (0.828) but higher than that of S1 (0.390). Its dwell-time-balance CV (0.096) is lower than those of both S0 (0.229) and S1 (0.197). These metrics describe different processes, so no single CV can summarize the relative performance of the schemes.

Welch tests show overall differences among the schemes for all key metrics except completion time. Table 3 reports Games–Howell comparisons between S2 and the fixed schemes. Because the omnibus test for completion time yields $p = 0.052$, the corresponding pairwise results are treated as descriptive.

Table 3. Omnibus Welch tests and Games–Howell comparisons of key metrics between S2 and the fixed schemes.

Metric	Welch statistic	Omnibus p-value	Comparison	Mean difference (95% simultaneous CI)	Adjusted p-value	Standardized effect size
Public-node mean density	297.38	<0.001	S2-S0	-0.0790 [-0.0971, -0.0609]	<0.001	-2.76
Public-node mean density	297.38	<0.001	S2-S1	0.0506 [0.0442, 0.0570]	<0.001	4.91
Public-node mean queue length	551.17	<0.001	S2-S0	-7.09 [-8.24, -5.94]	<0.001	-3.86

Metric	Welch statistic	Omnibus p-value	Comparison	Mean difference (95% simultaneous CI)	Adjusted p-value	Standardized effect size
Public-node mean queue length	551.17	<0.001	S2-S1	7.86 [7.11, 8.61]	<0.001	6.51
Passenger-weighted mean dwell time	28.32	<0.001	S2-S0	-1.53 [-2.08, -0.99]	<0.001	-1.76
Passenger-weighted mean dwell time	28.32	<0.001	S2-S1	-1.33 [-2.17, -0.49]	0.001	-1.00
Simulation completion time	3.10	0.052	S2-S0	-12.31 [-50.14, 25.52]	0.715	-0.20
Simulation completion time	3.10	0.052	S2-S1	-35.21 [-69.73, -0.69]	0.045	-0.63
Monitoring node 2 mean density	9.02	<0.001	S2-S0	0.0042 [-0.0069, 0.0153]	0.633	0.24
Monitoring node 2 mean density	9.02	<0.001	S2-S1	-0.0548 [-0.0889, -0.0207]	0.001	-1.02
Monitoring node 1 maximum queue length	64.54	<0.001	S2-S0	2.30 [0.79, 3.81]	0.002	0.95
Monitoring node 1 maximum queue length	64.54	<0.001	S2-S1	-5.83 [-7.57, -4.10]	<0.001	-2.09
Monitoring node 2 maximum queue length	27.27	<0.001	S2-S0	2.03 [0.60, 3.46]	0.003	0.88
Monitoring node 2 maximum queue length	27.27	<0.001	S2-S1	-6.00 [-8.70, -3.30]	<0.001	-1.40

Note: Mean differences are calculated as S2 minus the reference scheme. Confidence intervals and adjusted p-values are obtained from Games–Howell tests. Standardized effect sizes are expressed as Cohen's d; negative values indicate lower values in S2 than in the reference scheme.

4.6 Ablation experiments

S3, S4, and S5 were each simulated independently 30 times using identical inputs, facility settings, and statistical definitions. The CSV fields node, node1, and node2 correspond to monitoring node 1, monitoring node 2, and the public node, respectively. Public-node density and queue length were obtained from node2 TIME records over $0 < t \leq 900$ s. The maximum queue lengths at the two monitoring nodes were obtained from node and node1, and the larger value was selected for each run. Mean dwell time was weighted by the passenger flow shares of the three nodes over the full run. Probability variation was calculated from the range of implemented probabilities within the same time window.

4.7 Ablation design

S3–S5 isolate the effects of queue feedback, density feedback, and exponential smoothing. Probability variation is the mean of the probability ranges for the Top and Bottom groups during the first 900 s.

4.8 Ablation results

Fig. 7 reports run-level means and 95% confidence intervals. In Table 4, removing queue feedback (S3) increases mean public-node density, mean queue length, and passenger-weighted dwell time relative to S2, although the larger of the maximum queue lengths at the two monitoring nodes is slightly lower. The control components therefore affect different outcomes.

Table 4. Run-level results for the dynamic feedback and ablation schemes.

ID	Description	Runs	Public-node mean density	Public-node mean queue length	Maximum queue length across the two monitoring nodes	Passenger-weighted mean dwell time	Range of implemented probability variation
S2	Dynamic density–queue feedback	30	0.1525±0.0117 95% CI [0.1482, 0.1569]	27.287±1.049 95% CI [26.895, 27.678]	22.367±2.428 95% CI [21.460, 23.273]	11.038±0.449 95% CI [10.870, 11.206]	0.240±0.029 95% CI [0.229, 0.251]
S3	Density feedback only	30	0.2396±0.0356 95% CI [0.2262, 0.2529]	34.899±1.977 95% CI [34.161, 35.637]	21.433±2.825 95% CI [20.379, 22.488]	12.408±0.874 95% CI [12.082, 12.734]	0.204±0.044 95% CI [0.188, 0.221]
S4	Queue feedback only	30	0.1435±0.0114 95% CI [0.1392, 0.1478]	26.527±1.094 95% CI [26.119, 26.936]	22.533±2.609 95% CI [21.559, 23.508]	11.332±0.960 95% CI [10.973, 11.690]	0.174±0.016 95% CI [0.168, 0.180]
S5	Without exponential smoothing	30	0.1613±0.0131 95% CI [0.1565, 0.1662]	28.177±1.328 95% CI [27.681, 28.673]	23.000±2.289 95% CI [22.145, 23.855]	11.118±0.570 95% CI [10.905, 11.331]	0.283±0.028 95% CI [0.273, 0.294]

4.9 Roles of the control components

Relative to S2, removing queue feedback in S3 increases mean public-node density by 57.07%, mean queue length by 27.90%, and dwell time by 12.41%; the corresponding Cohen's *d* values are 3.28, 4.81, and 1.97. The larger of the maximum queue lengths at the two monitoring nodes decreases by 4.17%. Queue information is therefore most relevant to detecting sustained service backlogs.

Relative to S2, removing density feedback in S4 reduces mean public-node density by 5.91% and mean queue length by 2.78%, but increases the larger of the maximum queue lengths at the two monitoring nodes by 0.75% and dwell time by 2.66%. Lower public-node loads alone do not imply better system-wide performance.

Relative to S2, removing exponential smoothing in S5 increases mean public-node density, mean queue length, the larger of the maximum queue lengths at the two monitoring nodes, and dwell time by 5.79%, 3.26%, 2.83%, and 0.73%, respectively. Probability variation increases by 18.04% (Cohen's *d* = 1.52). Exponential smoothing mainly limits abrupt probability changes.

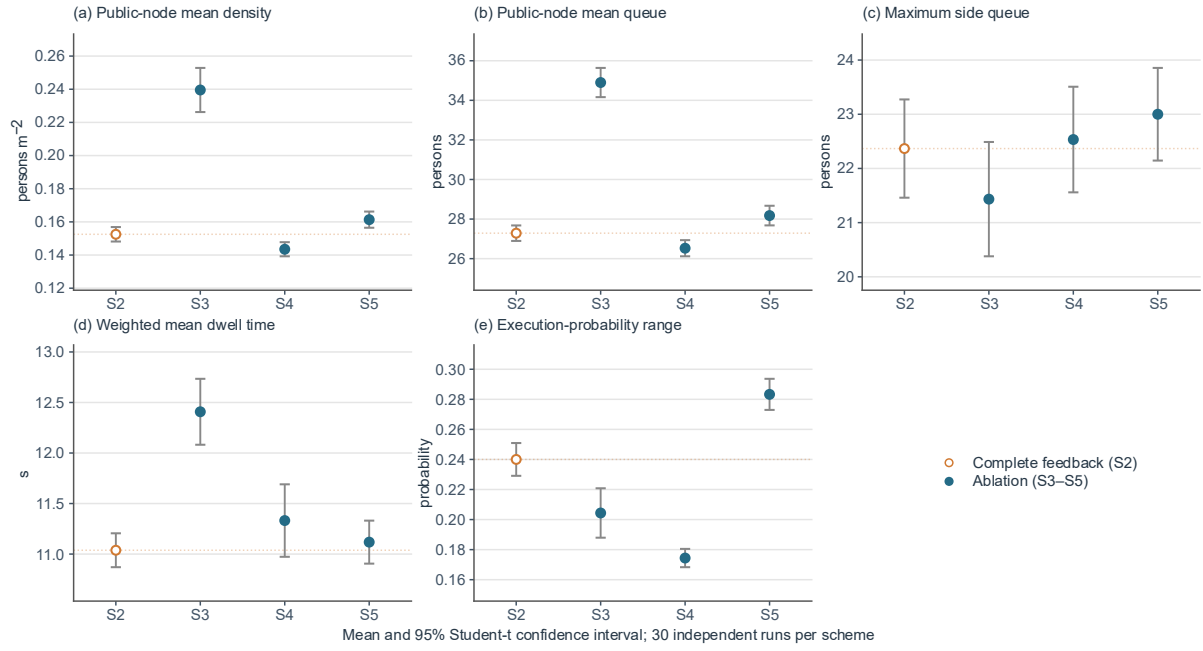


Fig. 7. Run-level comparison of the full feedback and ablation schemes. Points represent run-level means, and error bars indicate 95% confidence intervals.

4.10 Parameter sensitivity

The sensitivity experiment varies the smoothing coefficient and minimum route probability one at a time. The baseline combination (0.15 and 0.10) is evaluated using the 30 S2 runs; each of the other five combinations is evaluated using five runs. Each full-run SUMMARY record is one sample. Because the non-baseline settings have fewer replications, these comparisons are exploratory. Demand, capacity, service times, and control logic remain fixed except for the parameter being varied.

Table 5. Parameter sensitivity results. The baseline setting is evaluated using 30 independent runs; each non-baseline setting is evaluated using five runs.

α	$p_{\min}$	n	Full-run public-node mean density (persons m^{-2})	Full-run public-node mean queue length (persons)	Maximum queue length across the two monitoring nodes (persons)	Passenger-weighted mean dwell time (s)
0.05	0.10	5	0.1277 [0.1118, 0.1492]	21.15 [18.72, 22.29]	22.20 [21, 23]	11.23 [10.65, 12.79]
0.10	0.10	5	0.1361 [0.1250, 0.1436]	22.67 [21.35, 24.04]	23.80 [22, 26]	11.46 [10.80, 12.23]
0.15	0.10	30	0.1268 $\pm$ 0.0077	21.14 $\pm$ 0.93	22.40 $\pm$ 2.40	11.04 $\pm$ 0.45
0.20	0.10	5	0.1242 [0.1139, 0.1369]	20.78 [19.96, 21.91]	23.40 [20, 27]	11.12 [10.33, 11.84]
0.15	0.05	5	0.1270 [0.1148, 0.1381]	21.47 [20.24, 22.41]	22.60 [20, 26]	10.97 [10.51, 11.41]
0.15	0.20	5	0.1278 [0.1184, 0.1389]	21.41 [20.33, 22.84]	23.00 [20, 26]	10.95 [10.46, 11.49]

Table 5 reports results for the baseline combination as mean $\pm$ sample standard deviation and results for the other combinations as mean [minimum, maximum]. Within each run, the larger of the maximum queue lengths at the two monitoring nodes is selected before the values are summarized across runs. Table 5 uses full-run SUMMARY records, whereas Table 2 uses TIME records from 0–900 s; their absolute density and queue values are therefore not directly comparable.

Fig. 8 shows metric means and changes from baseline. With the minimum probability fixed at 0.10, responses to the smoothing coefficient are nonmonotonic. All four metrics are highest at 0.10. At 0.20, public-node density and queue length are below baseline, but the maximum queue length at the monitoring nodes and dwell time remain above baseline. The settings therefore shift loads among locations rather than improving all metrics together.

With the smoothing coefficient fixed at 0.15, changing the minimum probability from 0.05 to 0.20 produces only small changes in full-run metrics. The lower bound is therefore seldom active in this case. This finding applies only to the tested layout, demand, and parameter range.

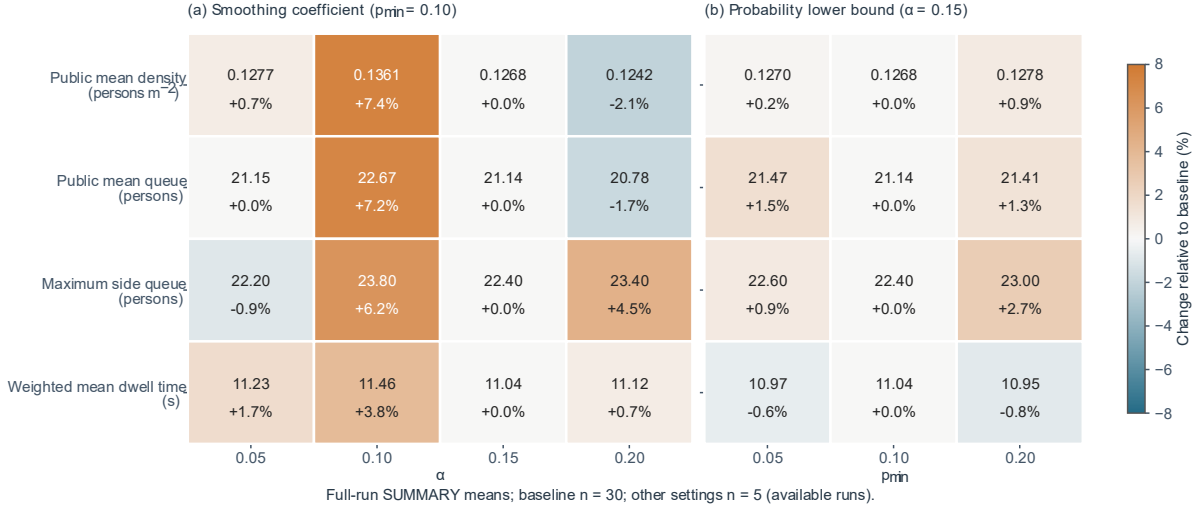


Fig. 8. Sensitivity to the smoothing coefficient and minimum route probability. Heatmaps show metric means and percentage changes relative to the baseline setting.

The ablation results highlight specific functions for each controller component: queue feedback identifies ongoing service backlogs, density feedback monitors spatial occupancy, and exponential smoothing restricts rapid changes in probability over short periods. Within the tested range, the smoothing coefficient affects load transfer more than the minimum probability. The baseline values of 0.15 and 0.10 are suitable for this experiment but are not claimed to be globally optimal.

5. Discussion

Dynamic density–queue feedback changes route assignment as service-area loads evolve. Relative to S0, S2 reduces mean public-node density by 34.1%, mean queue length by 20.6%, and passenger-weighted mean dwell time by 12.2%. Density represents spatial occupancy, whereas queue length reflects service backlog; combining them gives the controller information that either measure alone omits.

Relative to S1, S2 reduces mean density at monitoring node 2 by 16.9% and maximum queue lengths at monitoring nodes 1 and 2 by 20.7% and 27.3%, respectively. Its public-node flow share lies between those of S0 and S1. The controller thus avoids the sustained diversion created by a fixed ratio while retaining part of the public-node relief.

The ablation results support the intended functions of queue feedback, density feedback, and exponential smoothing. In practice, the probabilities could be implemented as guidance intensities through displays, announcements, or staff instructions. The present model does not represent individual compliance, information delays, or facility failures. Field trajectory data and additional station case studies are needed to calibrate passenger behavior and assess the transferability of the method.

Data Availability

The simulation data and processed results generated during this study are available from the corresponding author upon reasonable request.

Code Availability

The Python scripts used for feedback calculations, route probability updates, statistical analysis, and figure generation are available from the corresponding author upon reasonable request. The AnyLogic model is also available upon reasonable request, subject to the applicable software licensing restrictions.

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Author Contributions

G.W. developed the model, performed the simulations, and drafted the manuscript. P.Z. supervised the study and revised the manuscript. D.L. and Z.C. contributed to the methodology. Y.F. assisted with data analysis, and B.Z. provided operational input. All authors reviewed and approved the final manuscript.

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Competing Interests

The authors declare no competing interests.