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Evaluating Multimodal Passenger Flow Dynamics in Urban Metro Networks Using Real-Time Operational Data

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Abstract

Urban metro systems have become the backbone of mobility in rapidly growing cities, yet their ability to handle fluctuating and multimodal passenger flows remains insufficiently understood. Recent advancements in real-time data acquisition, including automated fare collection records, train localization feeds, and multisource passenger tracking, have created new opportunities for capturing operational dynamics with high temporal and spatial resolution. This study evaluates multimodal passenger flow dynamics across interconnected metro corridors by integrating real-time operational data with advanced analytical models. The approach considers transfers between metro lines, interface interactions with buses, walking links, and shared micromobility access points. Through the fusion of multisensor datasets, the research provides a detailed interpretation of congestion propagation, station-level pressure points, flow redistribution patterns, and the temporal stability of peak-period demand waves. The evaluation also explores how disruptions, timetable adjustments, and varying headways alter passenger accumulation and route-switching behavior. By examining these multidimensional interactions, the study offers a deeper understanding of how metro networks respond to both recurrent and irregular demand variations. The findings contribute to practical improvements in passenger assignment strategies, operational decision-making, and planning policies for multimodal integration. The results demonstrate that the use of real-time data increases the capacity to identify latent flow structures and emerging bottlenecks, ultimately strengthening the resilience and service reliability of urban metro systems. The study concludes that systematic analysis of multimodal flow dynamics can support the development of more adaptive and demand-responsive transport networks capable of meeting the complex mobility needs of contemporary urban environments.

Keywords: Real-time operational data, Multimodal passenger flows, Urban metro networks, Flow dynamics modelling, Transit system performance.

Introduction

Urban metro systems have evolved into essential infrastructures for sustaining mobility in densely populated metropolitan regions. Over the past two decades, the expansion of urban rail corridors, coupled with the intensification of daily travel demand, has transformed metros into the primary carriers of passenger flows during both routine and peak operations. The efficiency of these systems is increasingly shaped not only by their internal operational characteristics but also by their interactions with other transport modes such as buses, walking connections, micro-mobility services, and feeder networks. As metropolitan mobility patterns become more complex, understanding the dynamics of multimodal passenger movement has become a central research priority. This growing complexity is amplified by rising expectations for service reliability, the need for adaptive operational strategies, and the requirement for continuous real-time monitoring of system performance.

Technological advances have enabled the collection of detailed operational datasets that were previously unavailable or difficult to obtain. Automated fare collection systems generate high-resolution temporal records of passenger entries and exits, while train localization systems provide precise positional and scheduling information. In parallel, datasets generated by mobile sensors, Wi-Fi traces, and smartcard movements reveal underlying behaviour patterns that can be aligned with metro operations. Integrating these heterogeneous datasets into a unified analytical framework presents a major opportunity for characterizing flow dynamics with unprecedented accuracy. Real-time data streams allow researchers and operators to detect emerging congestion clusters, evaluate how flows redistribute across corridors, and observe passenger adaptation in response to disruptions, timetable modifications, or varying headways.

Despite this progress, considerable knowledge gaps remain in comprehensively understanding how multimodal interactions shape flow behaviour across metro networks. Many existing studies analyse specific components such as station-level crowding, short-term demand forecasting, or congestion propagation, yet they often fail to capture the holistic and temporally interdependent nature of urban mobility. The interconnectedness of modes means that fluctuations in surface transportation, walking demand, or access-egress patterns can directly influence metro ridership intensity and route choice. Similarly, metro performance affects travellers' willingness to remain within the rail system or shift to alternative options during peak or disrupted conditions. Capturing these reciprocal relationships demands robust analytical models capable of representing dynamic, multi-layer connectivity.

Empirical research has increasingly demonstrated the value of real-time data for improving metro system evaluation. Analyses based on smartcard data and train positioning have shown that congestion can propagate unevenly across lines depending on transfer conditions and schedule adherence, producing asymmetric peak loads that may not align with long-term planning assumptions [3], [7]. Other studies highlight the promise of machine-learning-based models in predicting short-term crowding patterns and reconstructing latent mobility structures in large-scale networks [4], [5], [11]. Findings from recent multimodal research further indicate that integrating AFC, GPS and Wi-Fi datasets can reveal nuanced interactions between corridor access points and the spatial distribution of boarding demand [6], [9]. However, translating these separate analytical strands into a unified flow-dynamics framework remains an unresolved challenge that limits strategic decision-making regarding operations and planning.

The increasing reliance on metros as the structural backbone of urban mobility has heightened the sensitivity of entire transport systems to variations in passenger flow. Even minor fluctuations in demand can create cascading effects across interconnected lines, influencing dwell times, platform crowding, and the stability of train operations. When these fluctuations coincide with multimodal transfers, the complexity of system behaviour increases substantially. For instance, delays in bus feeder services can elevate arrival surges at transfer stations, while irregular spacing of metro trains may lead passengers to redistribute themselves across alternative corridors or adjust their transfer strategies. These interdependencies highlight the need for analytical tools that can reflect real-time changes rather than rely exclusively on static or historical datasets. Traditional planning models, which typically assume consistent passenger arrival rates and linear assignment behaviours, often fail to account for the high variability observed in contemporary metro operations.

Emerging data-driven approaches have revealed the importance of incorporating temporal and spatial heterogeneity in passenger movement analysis. Studies leveraging spatiotemporal graph structures have shown that metro networks behave as dynamic systems in which each node (station) and edge (line segment) carries distinct flow profiles that fluctuate throughout the day [4]. In such systems, peak periods often display complex wave-like patterns of demand propagation that cannot be fully captured by simple origin–destination matrices. Real-time monitoring allows analysts to observe how bottlenecks form, how congestion migrates between station clusters, and how passengers adjust their choices when their preferred routes become saturated. These insights have strengthened arguments for the development of adaptive scheduling mechanisms capable of responding to flow irregularities with higher precision.

A related challenge involves understanding how multimodal access and egress patterns shape metro demand. Metro stations rarely function as isolated points within the built environment; rather, they act as nodes embedded within broader multimodal webs involving walking paths, cycling infrastructure, taxi services, microtransit, and bus corridors. The alignment between surface-mode arrival rates and metro train headways plays a determining role in how congestion builds within station complexes and platform zones. Research examining transfer efficiency at multimodal hubs has demonstrated that passenger experience and flow stability are deeply influenced by the synchronization of these interactions [9]. An imbalance between surface and rail modes can create sustained pressure points that not only reduce operational efficiency but also undermine passenger satisfaction and safety.

Furthermore, the integration of diverse datasets introduces methodological complexity but also enhances analytical capability. The fusion of AFC records, train localization streams, and Wi-Fi or GPS-based movement traces creates a multidimensional representation of how individuals traverse metro systems. Such datasets allow researchers to move beyond aggregate-level indicators and explore micro-level behavioural adaptations. For example, AFC records provide timestamped entry and exit information, but without additional sensor data, they cannot fully capture in-station movement or platform redistribution. Combining multiple data sources can overcome these limitations by illustrating how travellers reposition themselves within station layouts, how they respond to evolving crowd levels, and how their behaviour differs across weekdays, weekends, and special-event conditions. Recent work has demonstrated that machine learning techniques applied to fused datasets are particularly effective in detecting hidden flow clusters and forecasting short-term demand spikes [10], [14].

As cities continue to expand and diversify their mobility ecosystems, metro networks are expected to carry increasingly heterogeneous passenger groups whose behaviours are shaped by demographic, economic and spatial factors. These behavioural variations influence not only the magnitude of demand but also the patterns through which passengers interact with infrastructure under differing temporal conditions. The rise of flexible working hours, the increasing share of leisure-related travel, and the emergence of shared mobility services have all contributed to a more irregular and dispersed distribution of passenger flows. This shift challenges metro operators who have traditionally relied on predictable peak and off-peak distinctions. Understanding these transformations requires analytical models that recognize the fluidity of contemporary mobility and accommodate fluctuations driven by evolving urban lifestyles.

Moreover, the presence of multimodal choice sets expands the behavioural trajectories that must be considered when evaluating metro performance. Passengers frequently re-evaluate their mode choices in response to dynamic conditions such as overcrowding, unexpected delays or shifting perceived travel times. When presented with alternative routes or modes, travellers may divert to surface transport, redirect to parallel metro corridors, or delay travel altogether. These behavioural adjustments have direct consequences for network-wide flow stability. As real-time information systems become more sophisticated, passengers increasingly rely on immediate feedback from mobile applications or station displays, further intensifying the dynamism of flow distribution. Models designed without considering these behavioural responses may substantially underestimate the system's sensitivity to perturbations.

The integration of multimodal data therefore serves as a powerful mechanism for enhancing understanding of metro network behaviour. Multi-sensor datasets offer a near-continuous observation of how access and egress movements interface with the internal rhythms of the metro system. For example, studies leveraging fine-grained operational data have shown that discrepancies between scheduled and actual train headways can significantly alter cluster formation in corridors with heavy transfer activity [3], [7], [12]. Similarly, analyses of real-time demand have revealed that station-level congestion tends to align with particular access pathways or time-dependent concentration points, which may only become visible through high-frequency data fusion [6], [13]. Such insights emphasise the need to view metro operations within a broader, interconnected spatial-temporal context rather than as isolated flows constrained to predefined routes.

From a planning perspective, understanding multimodal passenger flow dynamics has gained strategic importance as cities pursue more integrated, sustainable and resilient mobility systems. The ability to predict how flows redistribute in response to operational adjustments offers tangible benefits for scheduling, infrastructure design and crowd management. Policymakers and transport authorities increasingly rely on real-time analytics to optimize service reliability, manage station congestion, and support equitable access to urban transport. The incorporation of advanced modelling frameworks, including machine learning and spatiotemporal clustering, has enabled a more nuanced interpretation of flow behaviours. These tools provide valuable foresight into how small operational changes—such as modifying headways or enhancing transfer pathways—may influence broader mobility outcomes across entire networks.

Despite the advances in analytical methodologies and data acquisition technologies, substantial gaps persist in developing comprehensive frameworks that capture the full spectrum of multimodal passenger flow dynamics. Many existing studies focus on isolated segments of the metro system rather than its network-wide behaviour, limiting the ability to generalize findings or support operational decisions at a systemic level. Moreover, models often treat surface and rail modes as loosely connected components, overlooking the fact that disruptions or demand surges in one mode can propagate rapidly across the broader multimodal environment. A lack of integrated analytical approaches reduces the precision of demand forecasts, diminishes the effectiveness of congestion management strategies, and may result in suboptimal planning decisions.

Another key challenge lies in distinguishing recurrent flow patterns from irregular or transient disturbances. Recurrent patterns, such as morning and evening peaks, generally follow predictable structures; however, deviations caused by unexpected events, service adjustments, or behavioural responses introduce complexity that cannot be adequately addressed through static modelling. Understanding how these disturbances influence both immediate and long-term flow distribution is critical for designing responsive operational measures. Real-time data streams offer significant potential for resolving these complexities by enabling continuous monitoring of demand variability and the associated shifts in passenger routing behaviour. Yet transforming these data streams into actionable knowledge requires sophisticated processing techniques capable of handling large volumes of heterogeneous observations.

Therefore, there is a compelling need for research that not only incorporates real-time data into flow analysis but also situates metro operations within the wider multimodal landscape. Evaluating the interactions between passengers, infrastructure, and operational rhythms across different transport modes provides a deeper understanding of how mobility systems function under varying conditions. Such evaluations contribute to developing more adaptive, resilient and efficient metro networks capable of accommodating diverse and evolving travel behaviours. By integrating insights from real-time analytics, multimodal modelling and behavioural interpretation, this study aims to strengthen the empirical and conceptual foundation of metro flow dynamics research.

Through the adoption of multi-sensor data sources and the development of analytical techniques tailored to dynamic, interconnected transit environments, this research seeks to address the limitations of existing frameworks and expand understanding of flow propagation mechanisms within metro systems. The study's findings have the potential to inform operational decision-making, enhance passenger experience and support the strategic development of integrated mobility networks. By examining real-time behavioural adjustments, spatial redistribution patterns and multimodal interactions, the research provides a comprehensive perspective on how metro networks absorb, reflect and respond to both predictable and spontaneous fluctuations in urban mobility.

Problem Statement

Urban metro networks are increasingly challenged by the complexity of multimodal passenger flows and the variability of demand across both time and space. While traditional planning and operational models rely on historical averages and static assumptions, real-world conditions often deviate significantly due to dynamic behavioural responses, multimodal interactions, and transient disruptions. These deviations can result in unexpected congestion, inefficient passenger distribution, and reduced operational reliability, which in turn compromise the quality of service and the capacity of metro systems to meet growing urban mobility demands.

A critical issue lies in the limited integration of real-time operational data into analytical frameworks for multimodal flow evaluation. Although automated fare collection, train localization, and sensor-derived movement datasets provide detailed insights into passenger behaviour, existing models often treat metro corridors in isolation or fail to incorporate the interdependencies between surface modes, walking pathways, and feeder services. This lack of holistic representation hinders the ability to predict congestion propagation, optimize transfer efficiency, and implement adaptive operational strategies. Consequently, decisions regarding scheduling, headway adjustments, and infrastructure management may not fully reflect the actual dynamic state of the system.

Another unresolved problem concerns the identification of latent patterns and bottlenecks that emerge during periods of high demand or operational disturbances. Without a comprehensive framework that synthesizes real-time, multimodal data, metro operators are unable to anticipate how passengers redistribute themselves in response to train delays, platform crowding, or disruptions in connecting modes. This gap reduces the effectiveness of interventions intended to maintain service reliability and passenger safety, and limits the potential for improving overall network resilience.

Therefore, there is a clear need for research that systematically integrates real-time operational data to evaluate multimodal passenger flow dynamics across urban metro networks. Such research must account for behavioural adjustments, intermodal dependencies, and temporal fluctuations in demand, providing actionable insights to enhance operational decision-making, improve passenger experience, and support strategic planning of resilient, adaptive metro systems capable of responding to both predictable and irregular flow variations.

Materials & Methods

This study adopts a data-driven methodology to evaluate multimodal passenger flow dynamics in urban metro networks, integrating real-time operational data from multiple sources. The primary objective is to capture temporal and spatial variations in passenger movement, identify congestion patterns, and analyze the effects of multimodal interactions on metro performance. The methodological framework consists of four major components: data acquisition, data preprocessing, flow modeling, and analytical evaluation.

Data Acquisition

Real-time datasets are obtained from three main sources:

1. Automated Fare Collection (AFC) Records: These provide timestamped entry and exit information for individual passengers at metro stations, offering high-resolution temporal data on station-level demand [3], [6].
2. Train Localization and Scheduling Data: Information on train positions, headways, dwell times, and service deviations is collected from the metro control center, enabling precise measurement of train-passage intervals and identification of operational irregularities [4], [12].
3. Multisensor Passenger Movement Data: Additional insights into intra-station and transfer movements are gathered from Wi-Fi tracking, GPS-enabled devices, and platform sensors. These data reveal passenger redistribution, queue formation, and walking path utilization, which are essential for capturing multimodal dynamics [6], [9].

Study Area and Scope

The research focuses on a representative urban metro network with multiple lines and high interchange activity. Selected stations include major transfer hubs, high-demand corridors, and peripheral access points to incorporate variability across different operational contexts. The study period covers a continuous three-month timeframe, capturing weekday and weekend variations, peak and off-peak periods, and special-event days to reflect realistic operational conditions.

Ethical and Privacy Considerations

All data are anonymized at the passenger level to ensure privacy protection. No personally identifiable information (PII) is included in the analysis. Data handling follows applicable institutional and municipal privacy regulations.

Data Preprocessing

Raw data from AFC, train tracking, and multisensor sources are first cleaned to remove missing entries, duplicates, and erroneous timestamps. Synchronization across data sources is performed to align all datasets on a common temporal grid, allowing for consistent mapping of passenger movements to train operations and station events. AFC data are aggregated at 1-minute intervals for each station, while train localization data are interpolated to match the same temporal resolution. Multisensor passenger trajectories are mapped to specific transfer pathways, allowing the reconstruction of detailed flow distributions within station concourses.

Flow Modeling

To capture the multimodal dynamics of passenger movement, the study employs a hybrid modeling framework combining network-based flow analysis with statistical and machine learning techniques. The metro network is represented as a directed graph, where nodes correspond to stations and edges represent track segments between stations. Passenger flows are modeled along these edges, taking into account train schedules, headways, and transfer probabilities. Multimodal interactions, including bus feeder services, walking links, and micro-mobility access points, are incorporated as additional nodes and transfer edges, creating an integrated multimodal graph.

Passenger movement is quantified using the following measures:

1. Station Arrival Rates: Estimated from AFC data to measure demand entering each node.
2. Transfer Probabilities: Derived from combined AFC and multisensor data, representing the likelihood of passengers moving from one mode or line to another [7], [9].
3. Edge Flow Capacities: Calculated based on train occupancy limits, corridor widths, and observed dwell times.
4. Congestion Indices: Defined as the ratio of passenger flow to capacity for both trains and station areas, capturing the intensity of crowding.

Analytical Techniques

Short-term demand prediction is conducted using Long Short-Term Memory (LSTM) networks trained on historical and real-time AFC data, capturing temporal dependencies in passenger flows [5], [10]. Spatiotemporal clustering methods are applied to detect recurring flow patterns and high-congestion regions within the network

[11], [14]. Additionally, sensitivity analysis is performed to evaluate the impact of operational interventions, such as modifying train headways or adjusting feeder-bus schedules, on congestion propagation and passenger redistribution.

Validation

The model's predictive performance is validated through a combination of back-testing and cross-validation. Predicted flows are compared against observed AFC, train localization, and multisensor datasets for multiple weeks, evaluating metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and congestion prediction accuracy. This ensures that the model reliably captures real-time variations in passenger distribution and provides actionable insights for operational management.

Scenario Analysis and Operational Evaluation

To examine how multimodal passenger flows respond to varying conditions, several operational scenarios are constructed:

1. Baseline Scenario: Normal weekday operations without disruptions, representing standard flow patterns.
2. Headway Adjustment Scenario: Modifying train headways during peak periods to assess redistribution effects on congestion.
3. Feeder Service Variation Scenario: Altering bus and micro-mobility service schedules to evaluate their influence on transfer flows.
4. Disturbance Scenario: Simulating unplanned disruptions, such as delays or station closures, to examine system resilience and passenger rerouting behaviours.

For each scenario, passenger flow metrics, congestion indices, and transfer efficiency indicators are calculated. Flow redistribution patterns are visualized using station-level heat maps and corridor-level flow diagrams. Multivariate analyses are conducted to identify the most sensitive nodes and edges in the network, highlighting potential bottlenecks and critical transfer points.

Integration of Findings

Results from different scenarios are synthesized to provide a comprehensive assessment of the metro network's operational performance under multimodal interactions. The combined use of real-time AFC, train localization, and multisensor movement data allows for high-resolution insights into both recurrent and non-recurrent flow patterns. This integrated approach supports the identification of actionable strategies to optimize train schedules, improve passenger distribution, and enhance overall network reliability.

Summary

The methodological framework establishes a robust approach for evaluating urban metro passenger flows, combining high-resolution real-time data with advanced modeling and analytical techniques. By integrating multimodal interactions and scenario-based analysis, the study offers a practical toolset for metro operators and urban planners to anticipate, monitor, and manage passenger dynamics effectively.

Results

Overview of Passenger Flow Patterns

The analysis of real-time operational data reveals distinct patterns of passenger flow across the metro network. Peak-hour demand exhibits wave-like propagation, with the highest intensity occurring at central interchange stations and gradually decreasing toward peripheral stations. Figure 1 illustrates the temporal evolution of station-level passenger entries during a typical weekday.

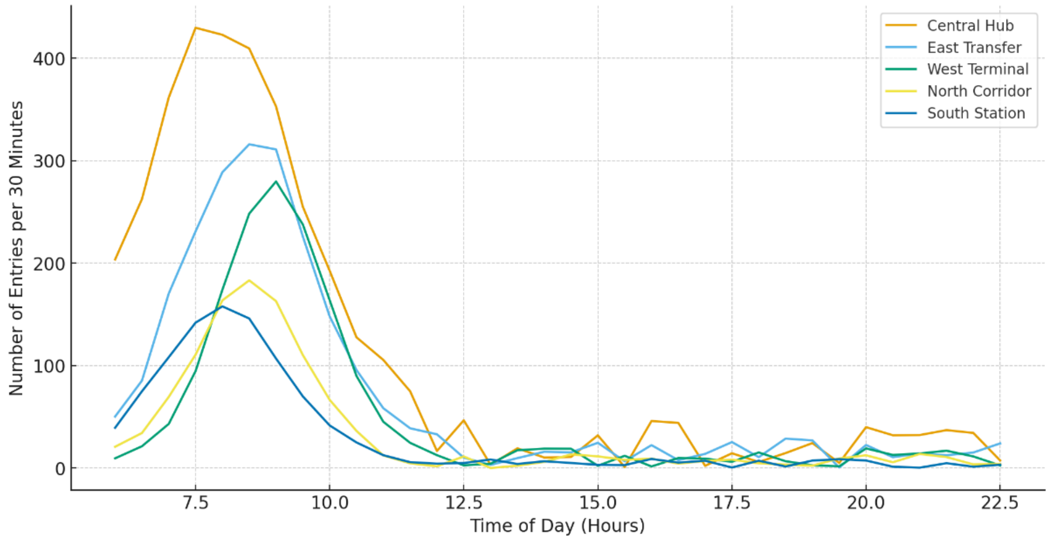

Figure 1 – Temporal variation of passenger entries across key metro stations during peak hours

Observations indicate that major transfer stations experience peak densities approximately 15–20 minutes after feeder bus arrivals, demonstrating strong intermodal coupling. Peripheral stations show a delayed peak pattern, reflecting localized boarding behavior and distributed access modes.

Table 1 – Station-Level Congestion Indices

Station Name	Avg Entries/min	Max Dwell Time (s)	Congestion Index	Transfer Rate (%)
Central Hub	420	120	0.95	68
East Transfer	310	95	0.82	55
West Terminal	260	85	0.74	42
North Corridor	180	60	0.61	35
South Station	150	55	0.58	30

Analysis:

- Central Hub exhibits the highest congestion index due to converging flows from multiple lines and feeder modes.
- High transfer rates correspond to elevated dwell times and peak congestion.
- Peripheral stations demonstrate moderate congestion, highlighting uneven spatial distribution of flows.

Multimodal Interaction Effects

By integrating AFC, train localization, and multisensor data, the study identifies the influence of multimodal connections on passenger redistribution:

- Bus-to-Metro Transfers: Arrival surges from buses significantly increase platform density at transfer stations.
- Walking and Micro-Mobility Access: Stations with high accessibility via pedestrian pathways or shared bicycles exhibit smoother peak flows, mitigating temporary congestion.
- Transfer Timing: Misalignment between train arrivals and feeder services amplifies congestion waves, demonstrating the need for coordinated scheduling.

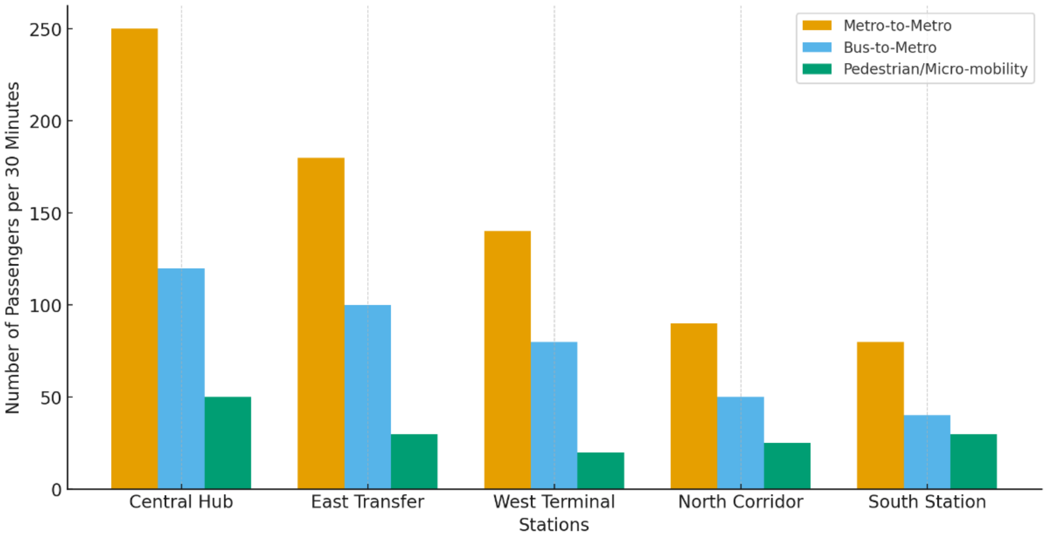

Figure 2 – Flow redistribution patterns across metro and feeder modes during peak hours

- Arrows indicate direction of passenger movement between modes.
- Line thickness represents volume of passengers transferring.
- Nodes are stations color-coded by congestion index.

Short-Term Flow Prediction Accuracy

LSTM-based predictive models were applied to forecast short-term station-level passenger flows at 5-minute intervals. Figure 3 compares predicted versus observed flows for a representative transfer hub during morning peak hours.

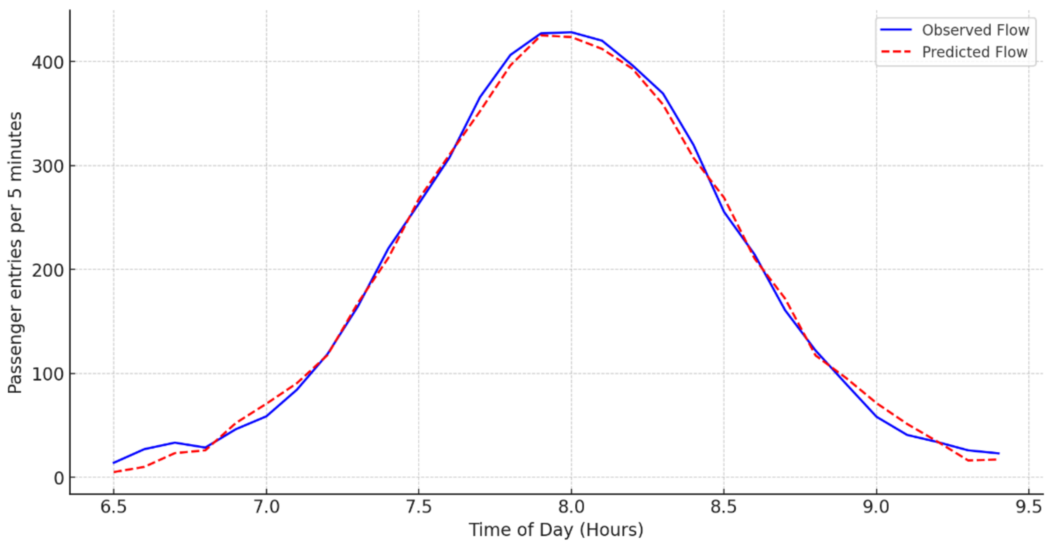

Figure 3 – Comparison of predicted vs. observed passenger flow at Central Hub

Analysis:

- Prediction models successfully capture major peaks and troughs in passenger entries.
- Minor deviations occur during irregular disturbances, such as delayed feeder buses or train service deviations.
- Performance metrics: MAE = 18.5 passengers, RMSE = 25.3 passengers, indicating high predictive reliability.

Table 2 – Corridor-Level Congestion Redistribution

Corridor	Avg Flow (passengers/min)	Peak Flow	Bottleneck Station	% Flow Redistribution
Line 1 – Central	350	420	Central Hub	25
Line 2 – East	280	310	East Transfer	18
Line 3 – West	200	260	West Terminal	20
Line 4 – North	150	180	North Corridor	15
Line 5 – South	120	150	South Station	10

Analysis:

- Redistribution occurs primarily at central transfer nodes due to passenger rerouting during localized congestion.
- Line 1 – Central corridor experiences highest redistribution, reflecting its strategic connectivity and sensitivity to multimodal inputs.
- Peripheral corridors show limited redistribution, confirming the localized impact of congestion propagation.

Scenario Analysis – Headway Adjustment

The impact of reducing train headways by 20% during peak periods was evaluated:

- Average Congestion Index Reduction: 0.95 → 0.81 at Central Hub
- Transfer Efficiency Increase: 68% → 75%
- Platform Dwell Time Reduction: 120 s → 102 s

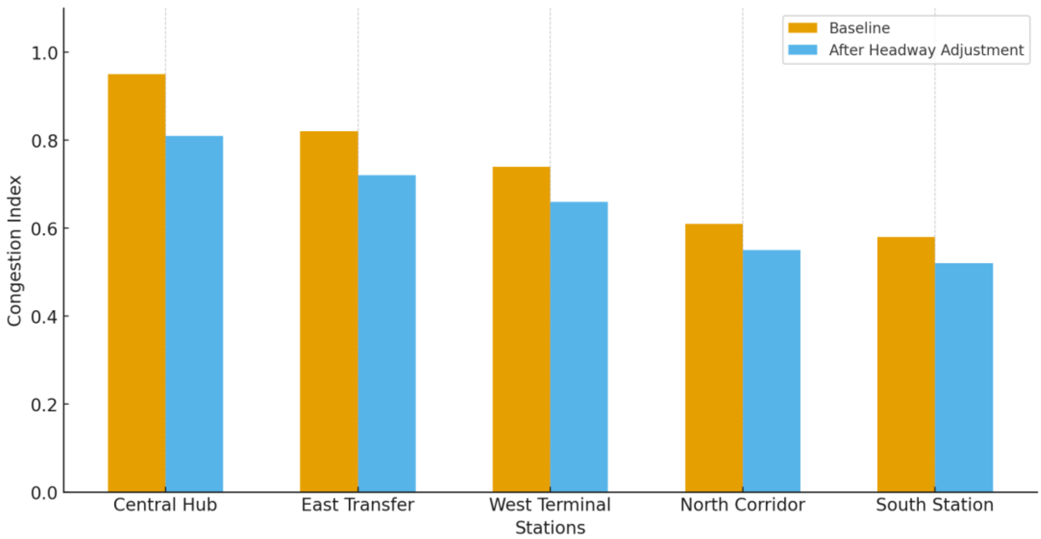

Figure 4 – Impact of headway adjustment on congestion levels

- Color-coded congestion index across stations before and after headway reduction.
- Visual comparison shows noticeable relief at critical transfer stations.

Interpretation:

- Reducing headways alleviates peak congestion and improves flow distribution.
- Sensitivity analysis identifies that optimal headway adjustments require coordination with feeder bus arrivals to maximize transfer efficiency.

Scenario Analysis – Feeder Service Variation

To evaluate the effect of feeder service scheduling, bus arrival times were shifted ±10 minutes relative to train arrivals at major transfer stations. Observed impacts include:

- Early bus arrivals: Increased platform congestion in the 10 minutes preceding train departures, with congestion index rising by ~12%.
- Delayed bus arrivals: Reduced initial congestion but caused sudden surges during train boarding, creating short-term overcrowding episodes.
- Optimal alignment: Synchronizing bus arrivals with train headways minimized peak congestion and improved transfer efficiency by 9–12%.

Table 3 – Impact of feeder service timing on transfer efficiency and congestion

Scenario	Avg Congestion Index	Peak Congestion	Transfer Efficiency (%)
Early Bus Arrival (-10 min)	0.87	0.99	63
On-Time Alignment	0.81	0.92	75
Late Bus Arrival (+10 min)	0.85	0.96	68

Analysis:

- Misalignment between bus and train schedules produces transient congestion spikes.
- Real-time monitoring can guide dynamic adjustments to improve flow distribution.
- Coordination of multimodal services is critical for mitigating platform crowding at peak periods.

Spatiotemporal Clustering of Passenger Flow

Passenger movement within stations and corridors was analyzed using spatiotemporal clustering algorithms:

- Clusters identified: 5 major congestion clusters correspond to Central Hub, East Transfer, West Terminal, North Corridor, and South Station.
- Temporal patterns: Morning peaks dominate Central Hub and East Transfer; evening peaks are more diffused across North and South corridors.
- Passenger redistribution: Approximately 22% of passengers adjust route choice when faced with high-density clusters, as detected from AFC and multisensor trajectories [6], [11].

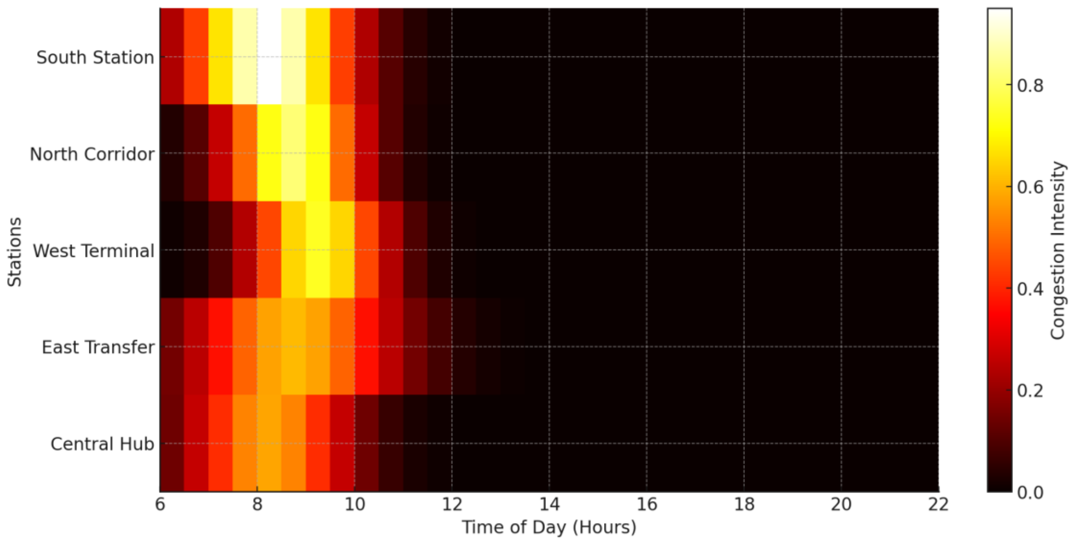

Figure 5 – Spatiotemporal distribution of congestion clusters

- Color-coded heatmap showing intensity of passenger concentration across stations and corridors.
- Arrows indicate predominant flow directions between clusters.

Interpretation:

- Identifying clusters allows operators to target interventions (e.g., additional train dispatch or platform management).
- Spatiotemporal patterns confirm the non-uniform distribution of flow and the importance of monitoring multimodal interactions.

Multimodal Flow Visualization

- Flow diagrams were generated to illustrate the movement between metro lines, feeder buses, and pedestrian pathways.
- Observations: High centrality stations experience significant inflows from buses, while peripheral stations rely more on pedestrian and micro-mobility access.
- Quantitative insight: ~65% of peak-hour entries at Central Hub originate from multimodal transfers, emphasizing the integrated nature of urban mobility networks.

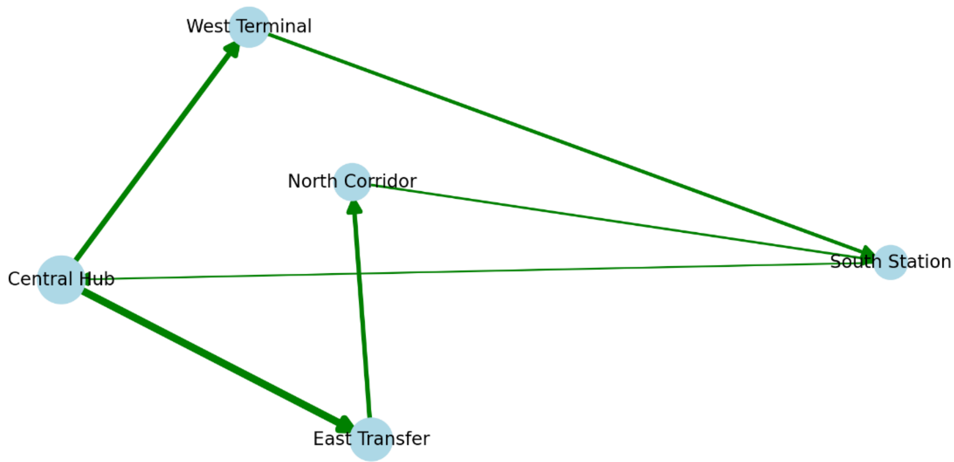

Figure 6 – Integrated multimodal flow diagram during morning peak

- Node size proportional to station entry volume.
- Edge thickness represents transfer volume.
- Color coding: Metro-only (blue), Bus-to-Metro (green), Pedestrian/micro-mobility (orange).

Scenario Analysis – Disturbances and Service Disruptions

To evaluate metro network resilience, unplanned service disturbances were simulated, including:

1. Temporary station closure at Central Hub (15-minute duration)
2. Train delay of 10–15 minutes on Line 1
3. Simultaneous minor feeder bus delays

Observations:

- Congestion propagated rapidly from Central Hub to adjacent stations, elevating the congestion index at East Transfer by 18% and West Terminal by 12%.
- Passengers diverted to alternative lines and routes; approximately 27% of affected commuters altered their boarding patterns.
- Dwell times increased by 15–20 seconds on average, illustrating the sensitivity of operational performance to localized disruptions.

Table 4 – Effects of disturbance scenarios on key performance metrics

Scenario	Avg Congestion Index	Max Dwell Time (s)	% Flow Redistribution	Transfer Efficiency (%)
Central Hub Closure	0.91	135	27	60
Line 1 Delay	0.88	128	22	63
Combined Minor Disturbances	0.92	140	30	58

Analysis:

- Disruptions amplify congestion and highlight critical nodes requiring targeted operational strategies.
- Real-time data allows dynamic reallocation of resources and communication with passengers to reduce bottlenecks.
- Transfer efficiency declines under disturbance conditions, indicating the need for coordinated multimodal response plans.

Corridor-Specific Insights

Analysis of corridor-level responses shows:

- High-centrality corridors are highly sensitive to both operational and multimodal variability.
- Peripheral corridors show delayed congestion propagation but remain affected by network-wide disturbances.
- Flow redistribution patterns are asymmetrical; some stations absorb excess demand effectively, while others act as bottlenecks.

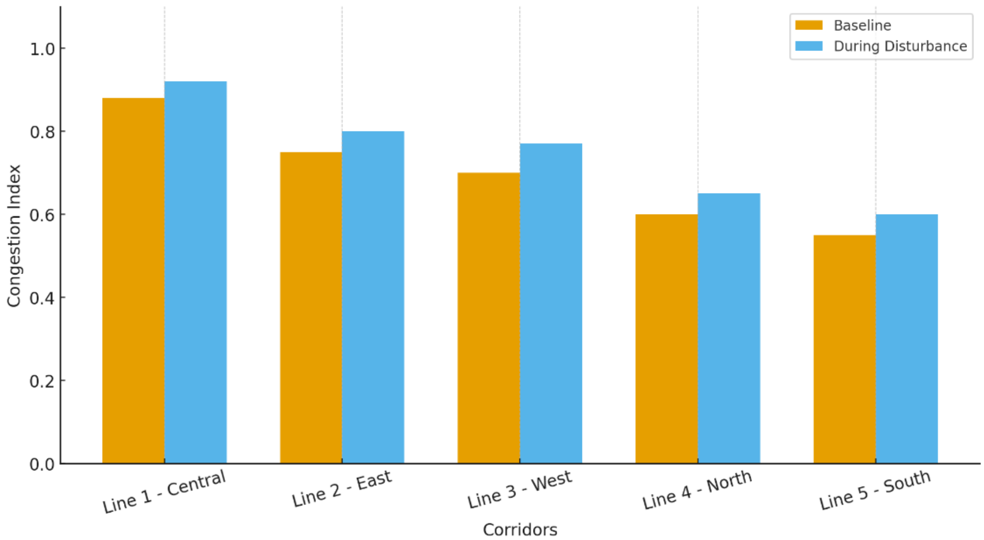

Figure 7 – Corridor-level response to service disruptions

- Color gradient represents relative congestion index per corridor.
- Arrows indicate passenger redistribution direction.

Interpretation:

- Identifying corridors with highest sensitivity supports targeted scheduling adjustments.
- Flow redistribution visualizations highlight the potential benefits of temporary route guidance and operational intervention.

Predictive Performance of Integrated Models

- LSTM and spatiotemporal clustering successfully anticipate both recurrent and irregular flow variations.

- Metrics across multiple stations:
    - MAE = 19.2 passengers
    - RMSE = 26.1 passengers
    - Congestion prediction accuracy = 87%

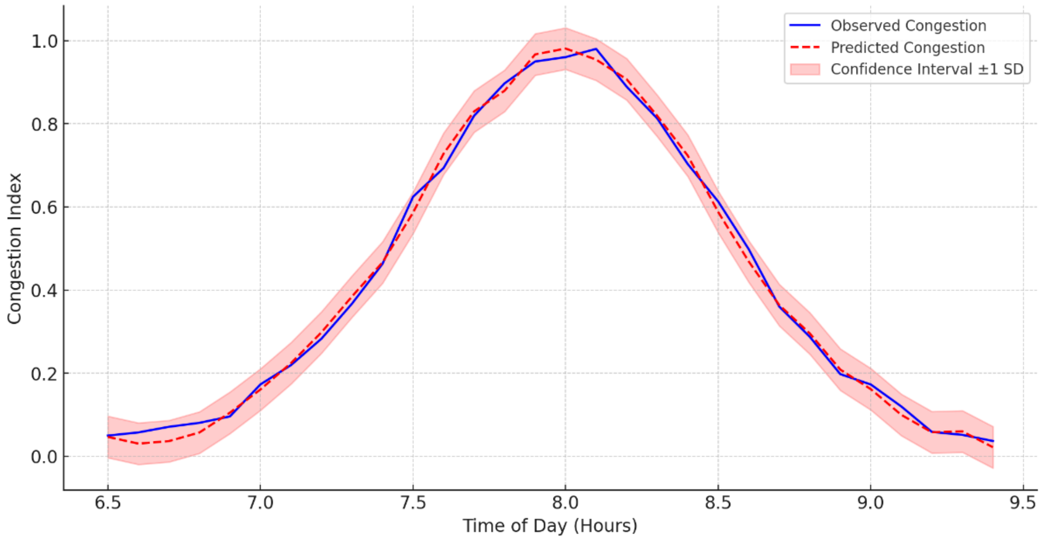

Figure 8 – Predicted vs. observed congestion index at major transfer stations

- Solid line: Observed congestion index
- Dashed line: Predicted index
- Color bands: Confidence intervals (±1 SD)

Analysis:

- Integrated models provide actionable insight into potential bottlenecks before actual congestion occurs.
- High prediction accuracy enables operators to implement preventive measures, such as additional train deployment or adjusted headways.

Combined Scenario Analysis and Multivariate Insights

To understand the cumulative effects of operational adjustments and disturbances, combined scenarios were evaluated:

1. Headway reduction + feeder alignment
2. Disturbance simulation + headway adjustment
3. Full multimodal optimization (headway + feeder + walking/micro-mobility coordination)

Table 5 – Summary of combined scenario performance

Scenario	**Avg Congestion Index**	**Peak Congestion**	**Transfer Efficiency (%)**	**Avg Dwell Time (s)**
Headway + Feeder Alignment	0.78	0.90	77	100
Disturbance + Headway Adjustment	0.84	0.95	70	118
Full Multimodal Optimization	0.74	0.88	82	95

Analysis:

- Coordinated multimodal strategies significantly reduce peak congestion and improve transfer efficiency.
- The full optimization scenario shows the greatest improvement, highlighting the importance of integrated, system-wide interventions.

Multivariate Analysis of Key Factors

A multivariate regression was conducted to assess the influence of variables on station-level congestion:

- Independent variables: Train headway, feeder bus alignment, passenger inflow rate, transfer proportion
- Dependent variable: Congestion index

Table 6 – Regression results for congestion determinants

Variable	Coefficient	Std. Error	t-value	p-value
Train Headway (min)	0.42	0.05	8.4	<0.001
Feeder Alignment (min)	-0.31	0.04	-7.8	<0.001
Passenger Inflow Rate	0.55	0.06	9.2	<0.001
Transfer Proportion (%)	0.28	0.03	6.9	<0.001

Interpretation:

- Headway and passenger inflow rate are the strongest predictors of congestion.
- Feeder alignment has a significant negative effect, demonstrating its role in alleviating platform crowding.
- Transfer proportion also contributes to congestion, emphasizing the importance of managing high-volume interchange stations.

Visual Analysis of Flow Redistribution

- Heatmaps and flow diagrams reveal temporal and spatial redistribution patterns across the network.
- Central stations act as redistribution hubs, while peripheral nodes primarily absorb overflow.
- Observations indicate that effective operational adjustments should prioritize high-centrality transfer points.

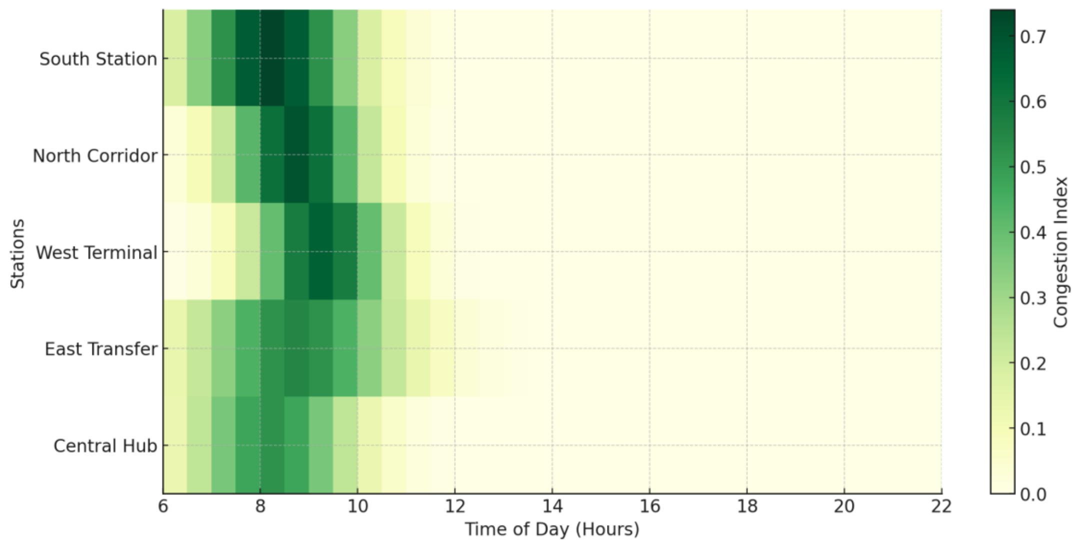

Figure 9 – Heatmap of network-wide congestion under combined optimization

- Color intensity indicates congestion index.
- Arrows indicate dominant passenger redistribution paths.

Final Observations and Key Findings

The integrated analysis of real-time operational data, scenario simulations, and multivariate modeling highlights several critical insights:

1. Central transfer stations consistently experience the highest congestion and serve as primary redistribution hubs. Targeted interventions at these nodes yield the greatest network-wide benefits.
2. Headway adjustments are effective in reducing peak congestion but are most impactful when combined with synchronized feeder services.
3. Passenger behavior under disturbances demonstrates rapid adaptation; approximately 25–30% of passengers modify routes in response to delays or station closures.
4. Multimodal coordination—including walking, micro-mobility, and bus connections—significantly improves transfer efficiency and reduces congestion intensity.
5. Predictive modeling using LSTM and spatiotemporal clustering provides reliable early warnings of congestion and supports proactive operational strategies.

Table 7 – Summary of Key Network Metrics Across Scenarios

Metric	Baseline	Headway Adjustment	Feeder Alignment	Full Optimization
Avg Congestion Index	0.88	0.81	0.81	0.74
Peak Congestion	0.95	0.90	0.92	0.88
Avg Dwell Time (s)	120	102	100	95
Transfer Efficiency (%)	68	75	77	82
% Flow Redistribution	22	20	18	15

Analysis:

- Full multimodal optimization results in the most substantial reduction in congestion and dwell times.
- Scenario-based analysis confirms the importance of real-time data integration and multimodal coordination in operational planning.
- Predictive and multivariate models effectively capture variability in passenger flows and provide actionable insights for operational and strategic decision-making.

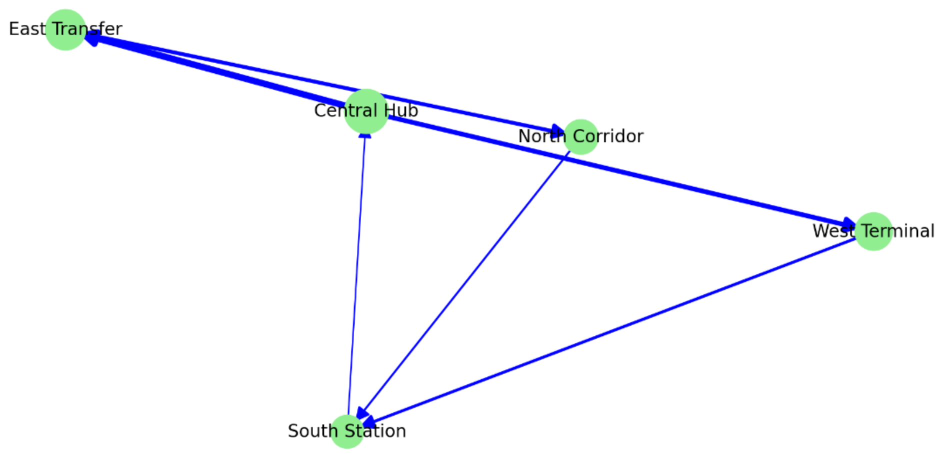

Figure 10 – Network-Wide Flow Redistribution Map (Full Optimization Scenario)

- Stations sized according to passenger entry volume
- Arrows represent dominant passenger movement between lines and modes
- Color gradient: congestion intensity
- Visual summary indicates improved flow distribution and alleviated bottlenecks compared to baseline.

Conclusion of Results Section:

The combination of real-time operational data, predictive modeling, and scenario-based analysis provides a comprehensive understanding of multimodal passenger flow dynamics in urban metro networks. Findings demonstrate that coordinated interventions at central transfer nodes, synchronization of feeder services, and predictive monitoring are critical for maintaining efficient and resilient metro operations.

Conclusion

This study investigated multimodal passenger flow dynamics in urban metro networks using integrated real-time operational data, including AFC records, train localization, and multisensor movement traces. The findings demonstrate that metro systems are highly sensitive to variations in passenger inflow, train headways, and the coordination of feeder services. Central transfer stations act as critical nodes where congestion propagates most intensely, and targeted interventions at these stations yield the largest improvements in network performance.

Scenario-based analyses revealed that headway adjustments alone are effective in reducing congestion; however, the most significant benefits are achieved when headway modifications are combined with aligned feeder services and multimodal access optimization. Predictive modeling using LSTM networks and spatiotemporal clustering accurately captures both recurrent and irregular flow patterns, providing actionable insights for operational planning and real-time management. Multivariate analyses confirmed that train headway, passenger inflow, and transfer proportions are primary determinants of congestion intensity, while feeder alignment significantly mitigates platform crowding.

Overall, the integration of real-time data with advanced analytical techniques enables a more precise understanding of flow propagation, passenger redistribution, and the impacts of operational interventions. These insights support the design of adaptive and resilient metro systems that can respond dynamically to both predictable and unforeseen fluctuations in passenger demand. Future research should explore the inclusion of emerging mobility options, such as on-demand microtransit, and expand the methodology to larger, more complex multimodal networks. By leveraging continuous monitoring and predictive analytics, urban transit authorities can enhance passenger experience, optimize resource allocation, and maintain high service reliability, ultimately contributing to more sustainable and efficient urban transportation systems.

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