Passenger Flow Control and Train Timetable Optimization in Urban Transit Systems: A Survey

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Abstract

Urban transit systems are vital for managing the increasing passenger demand and congestion in modern cities, especially in rapidly urbanizing regions. This survey paper examines a comprehensive range of optimization strategies and methodologies aimed at enhancing the efficiency, reliability, and passenger experience of urban metro systems. It emphasizes the critical importance of optimizing train timetables, managing passenger flow, and improving system resilience through collaborative optimization approaches. The paper highlights the significance of accurate passenger flow prediction and advanced forecasting techniques, such as the integration of Seasonal AutoRegressive Integrated Moving Average (SARIMA) models with Support Vector Machines (SVM) and the ResLSTM model, for real-time operational adjustments. It also explores energy-optimal timetabling strategies, including train trajectory optimization and the use of robust optimization models, to minimize energy consumption and enhance sustainability. The integration of transit components, synchronized timetables, and collaborative optimization strategies are discussed as essential for reducing passenger waiting times and enhancing system resilience. Case studies, such as the Tehran Metro, illustrate the practical applications of these optimization strategies. The survey concludes by highlighting the strategic imperative of optimizing urban transit systems to accommodate future growth, enhance resilience, and improve efficiency, while suggesting areas for future research, including the integration of synchronization models with vehicle scheduling and the development of comprehensive frameworks for evaluating urban transit systems' broader impacts.

1 Introduction

1.1 Importance of Efficient Urban Transit Systems

Efficient urban transit systems are essential for tackling the multifaceted challenges of contemporary urban settings, marked by increasing passenger demand and congestion [1, 2]. As cities grow, the complexity of metro networks escalates, necessitating effective strategies to ensure reliability and efficiency. These systems are crucial not only for managing urban expansion but also for alleviating congestion, particularly in rapidly urbanizing developing countries [1].

Optimizing urban transit systems is vital for operational efficiency, urban livability, and sustainability. Advanced algorithms are pivotal in resolving complex decision-making issues in transit environments characterized by high branching factors and real-time constraints [3]. Furthermore, integrating multiple transportation modes within urban mobility frameworks is crucial for a holistic understanding of transit dynamics, an aspect often neglected in planning studies [4].

In addition to operational efficiency, urban transit systems must address environmental impacts. Effective forecasting methods for rail transit passenger flow are critical for optimizing energy use and reducing carbon emissions, thereby promoting low-carbon urban development [5]. Moreover,

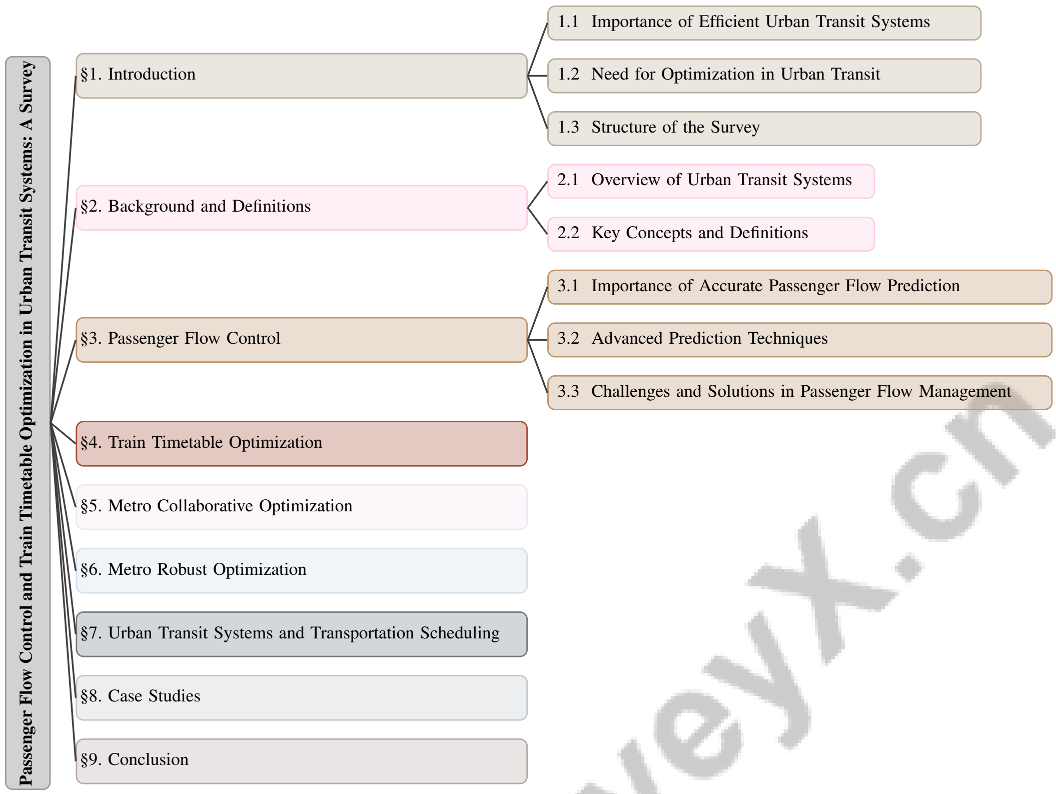


Figure 1: chapter structure

the resilience of these systems against environmental challenges, such as severe weather events, is essential, particularly for vulnerable underground stations [6].

Urban transit systems also have significant implications for public health, as efficient planning can mitigate disease transmission within transit networks [7]. The rise of ride-hailing services exemplifies the evolving shared mobility landscape, necessitating seamless integration within urban transit frameworks [8]. Thus, optimizing urban transit systems is not simply a reactive measure but a strategic initiative aimed at fostering sustainable urban development.

1.2 Need for Optimization in Urban Transit

The optimization of urban transit systems is critical in response to rapid urbanization and the increasing demand for efficient public transportation services [9]. As urban populations grow, transit systems face heightened pressure to effectively manage passenger flow and minimize disruptions. Traditional methods reliant on static timetables and manual data collection inadequately address the dynamic complexities of modern urban transit environments [10]. Moreover, the lack of a systematic framework to assess the sustainability of urban rail transit systems impedes effective resource management and service delivery, highlighting the necessity for integrated optimization strategies [2].

The unpredictability of disturbances, such as delays or system failures, necessitates robust decision-making processes to ensure continuity and reliability [11]. This is particularly pertinent given the challenges of CO2 emissions, safety concerns, and the need for reliable data collection methods [10]. The complex interplay among various transport modes complicates optimization efforts, as previous studies often focus on single modes or aggregate multiple modes, leading to the loss of critical information regarding transfer and waiting times [4].

Additionally, the potential for public rapid transit systems to facilitate the spread of diseases, such as dengue, underscores the importance of optimizing passenger mobility and proximity to metro stations [12, 7]. The contact networks formed during metro travel significantly influence disease transmission dynamics, further emphasizing the need for optimized transit operations. The Integrated Last-Mile

AI-generated, for reference only.

Transportation Problem (ILMTP) addresses the necessity for optimizing last-mile transportation in conjunction with mass transit services to minimize overall transit time [8].

Optimizing metro timetables is crucial for reducing passenger travel time and congestion, particularly under time-dependent demand conditions [13]. This is especially relevant during peak hours when intercity train arrivals can lead to fluctuating passenger demand that regular timetables struggle to accommodate [14]. Advanced optimization strategies, such as maximizing the reuse of regenerative braking energy in electric rail systems, are essential for enhancing sustainability and efficiency in urban transit [15].

Furthermore, accurately forecasting passenger flow in rail transit systems is vital for facilitating low-carbon urban transportation planning [5]. The need for a more general formulation in optimal mass transport theory further underscores the necessity for comprehensive optimization in urban transit operations [6]. As new public transit infrastructure emerges, assessing welfare gains beyond mere travel time savings is critical for understanding the full impact of these systems [1]. These challenges and opportunities collectively highlight the strategic imperative of optimizing urban transit systems to accommodate future growth and enhance resilience and efficiency.

1.3 Structure of the Survey

This survey is systematically structured to provide a thorough examination of the strategies and methodologies employed in optimizing urban transit systems, particularly focusing on metro networks. The paper opens with an **Introduction**, emphasizing the critical role of efficient urban transit systems and the urgent need for optimization in light of escalating urbanization and demand. This is followed by a comprehensive **Background and Definitions** section, which outlines urban transit systems and clarifies key concepts such as passenger flow control and train timetable optimization.

The survey then explores specific optimization areas, beginning with **Passenger Flow Control**, which addresses the significance of accurate passenger flow prediction, advanced prediction techniques, and the challenges and solutions in managing passenger flow. The section on **Train Timetable Optimization** investigates models for energy-optimal timetabling, the benefits of synchronized timetables, and the effects of passenger demand variability.

Additionally, the survey covers **Metro Collaborative Optimization**, focusing on data-driven strategies and the integration of various transit components to enhance metro operations. The section on **Metro Robust Optimization** introduces robust optimization techniques that strengthen system resilience and reliability amid uncertainties.

The paper includes a section on **Urban Transit Systems and Transportation Scheduling**, which provides insights into the integration of passenger flow control and train timetable optimization in transit scheduling, with an emphasis on coordination between urban transit and intercity railway systems. To illustrate the practical application of these strategies, the survey presents **Case Studies** from various cities, including an analysis of the Tehran Metro System and the impact of the COVID-19 pandemic on urban rail transit.

The survey concludes with a comprehensive **Conclusion** that synthesizes the primary findings regarding the impact of optimization strategies on metro efficiency while examining the implications for overall service quality and passenger experience. Furthermore, it identifies critical areas for future research, particularly in enhancing robustness and adaptability in metro systems to meet varying passenger demands and operational challenges [16, 17, 18, 14, 11].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Overview of Urban Transit Systems

Urban transit systems are integral to metropolitan mobility, with metro systems efficiently managing high passenger volumes [9]. These systems comprise rolling stock, signaling, track infrastructure, and stations, each pivotal for operational efficiency [19]. Optimizing train design and scheduling enhances passenger flow and network connectivity [20]. Given the complexity of urban networks, data-driven approaches are essential for precise passenger flow estimation, as traditional methods often fall short [21]. Addressing trip length distribution (TLD) and origin-destination (O-D) matrix estimation challenges demands innovative solutions [22]. The integration of artificial intelligence in traffic management exemplifies the evolution of urban transit systems [10].

Metro systems face challenges, including disease transmission among commuters, necessitating strategies to mitigate risks related to passenger proximity [7]. The 'Risk Associated with Metro Passengers Presence' (RAMPP) method quantifies these effects, especially during dengue outbreaks [12]. Resilience against environmental threats, such as rainstorms affecting underground stations, is critical [23]. Developing resilient systems is vital in rapidly urbanizing areas with increasing demand for reliable public transportation [24]. Integrating ride-hailing services with mass transit is crucial for seamless multimodal transportation, enhancing efficiency [8]. Utilizing multiplex networks for transportation analysis provides nuanced system insights, facilitating improved planning and optimization [4]. Coordinated efforts are necessary to optimize performance and enhance resilience.

2.2 Key Concepts and Definitions

Key concepts are essential for operational efficiency and resilience in urban transit systems. Passenger flow control focuses on managing movements to optimize service delivery and reduce congestion [9]. Traditional models often overlook individual travel behaviors by treating flow as time series data, limiting effectiveness [25]. Advanced forecasting techniques refine station-level ridership predictions, addressing these limitations [21].

Train timetable optimization emphasizes synchronizing schedules to improve transfer coordination and passenger satisfaction, accommodating demand variability while ensuring resource efficiency [9]. Integrating dynamic models, such as Monte Carlo Tree Search (MCTS), enhances performance by adapting to real-time constraints [3]. Optimal mass transport, with flow-rate constraints, significantly improves resource allocation across networks [6]. Understanding commuter market access (CMA) and welfare gains from transit infrastructure is crucial for evaluating broader economic and social impacts [1].

Identifying vulnerability factors in urban rail systems is essential for assessing robustness and resilience, encompassing potential disruptions and their impact on service continuity [26]. A fuzzy sustainability index, incorporating environmental, economic, financial, and social indicators, offers a comprehensive framework for evaluating performance [2]. The limitations of traditional demand forecasting highlight the need for sophisticated approaches that consider energy consumption and carbon emissions, supporting low-carbon urban transportation planning [5]. These concepts collectively provide a foundation for optimizing urban transit operations, ensuring systems can effectively respond to growing demand and potential disruptions.

In contemporary urban rail transit systems, the efficient management of passenger flow is critical to operational success. Figure 2 illustrates the hierarchical structure of passenger flow control, emphasizing the significance of accurate prediction and the utilization of advanced prediction techniques. This figure categorizes essential components that contribute to operational efficiency, sustainability, and the overall passenger experience. Furthermore, it delineates the challenges faced in these areas and proposes innovative solutions aimed at enhancing prediction accuracy and refining management strategies. By integrating these insights, we can better understand the complexities of urban transit systems and the pivotal role that effective passenger flow control plays in their success.

3 Passenger Flow Control

3.1 Importance of Accurate Passenger Flow Prediction

Accurate passenger flow prediction is essential for managing urban rail transit systems effectively, particularly in metro networks where real-time decision-making is critical [27]. The sporadic arrival of intercity trains causes significant fluctuations in passenger numbers at metro stations, necessitating sophisticated models for operational efficiency [14]. Integrating bi-level programming with multimodal allocation models enhances sustainability by optimizing passenger flow and reducing carbon emissions [5]. Multiplex network theory offers a comprehensive perspective by accounting for multiple connectivity layers, crucial for understanding urban transportation dynamics [4]. Predictable travel and waiting times are vital for effective passenger flow management, improving the passenger experience [8]. Identifying transfer paths and ride information for passengers sharing the same OD pairs is crucial for optimal resource allocation and service delivery [20]. Advanced forecasting

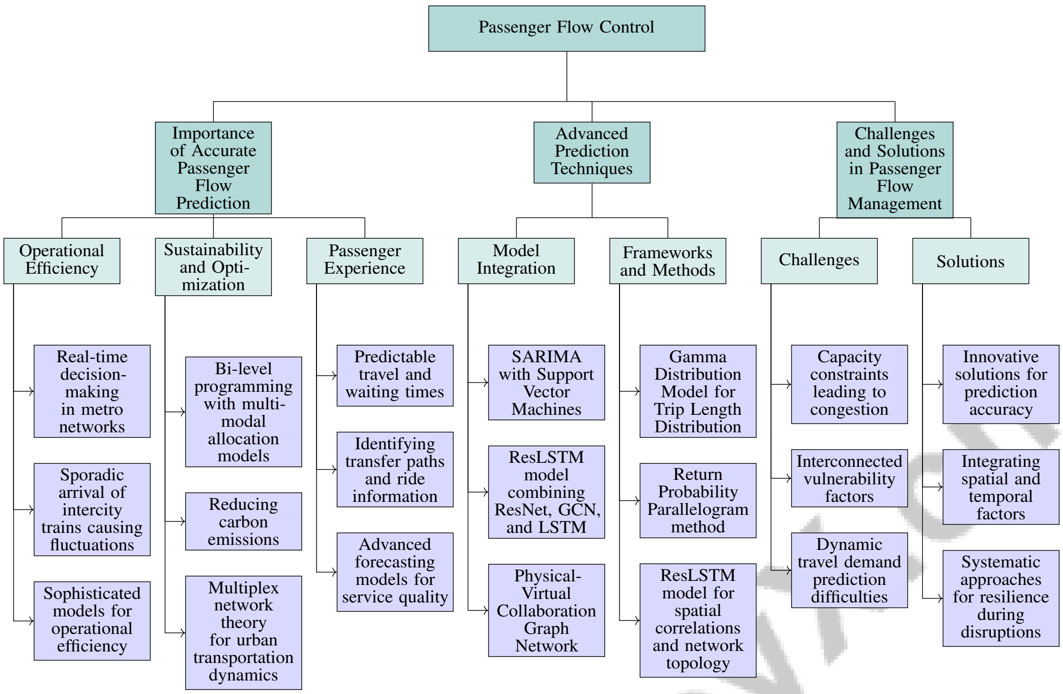


Figure 2: This figure illustrates the hierarchical structure of passenger flow control in urban rail transit systems, highlighting the importance of accurate prediction, advanced prediction techniques, and challenges with corresponding solutions. The diagram categorizes key aspects of operational efficiency, sustainability, and passenger experience, alongside advanced models and frameworks, and addresses challenges with innovative solutions to enhance prediction accuracy and management strategies.

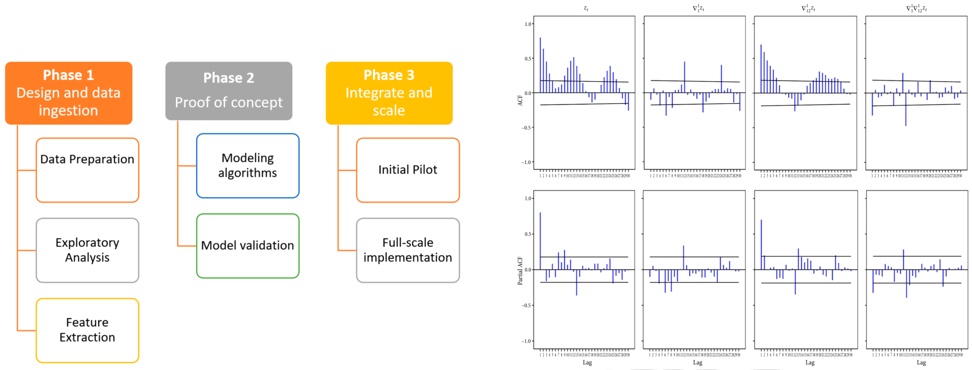
Method Name	Prediction Accuracy	Model Integration	Operational Efficiency
CAS-CNN[27]	Prediction Accuracy	Model Integration	Resource Allocation
MTO[14]	Exceeds 90BLPM[5]	Improved Accuracy	Model Integration
Operational Efficiency			
DD-BP[8]	Solution Quality	Multiplex Network Theory	Optimal Resource Allocation
PFPA[20]	High Accuracy	Model Combination	Improving Computational Efficiency
FTSI[2]	-	Model Integration	Optimal Resource Allocation

Table 1: Comparison of various methods for passenger flow prediction in urban rail transit systems, focusing on prediction accuracy, model integration, and operational efficiency. Each method is evaluated based on its ability to predict passenger flow accurately, integrate with existing models, and enhance operational efficiency through resource allocation and scheduling optimization.

models are paramount for managing passenger flow, enabling transit systems to adapt to fluctuating demand while maintaining high service quality, addressing ambiguities in performance indicators [2]. Table 1 presents a comparative analysis of different predictive models used in urban rail transit systems, highlighting their effectiveness in improving passenger flow prediction, model integration, and operational efficiency.

3.2 Advanced Prediction Techniques

Advanced prediction techniques significantly enhance passenger flow forecast accuracy in urban rail transit systems. The integration of the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model with Support Vector Machines (SVM) captures linear and nonlinear data characteristics, improving prediction accuracy [28]. The ResLSTM model, combining Residual Networks (ResNet), Graph Convolutional Networks (GCN), and attention-based Long Short-Term Memory (LSTM), enhances short-term forecasting by capturing spatial and temporal correlations among subway stations and incorporating external factors like weather and air quality. This model demonstrates superior predictive performance across various time granularities in the Beijing subway, optimizing operational efficiency and demand management [29, 30, 31, 25]. The Physical-Virtual Collaboration Graph Network (PVCGN) employs physical and virtual graphs to improve ridership dynamics understanding and prediction precision [21]. The Gamma Distribution Model for Trip Length Distribution (GDTLD) provides a robust framework for predicting passenger movements [22]. The Return Probability Parallelogram (RPP) method enhances prediction accuracy by incorporating returning flow from previous trips as a covariate, improving OD flow inference [25, 27]. The ResLSTM model's comprehensive framework captures spatial correlations, analyzes network topology, and incorporates external factors, marking the first instance of quantifying air quality's impact on forecasting accuracy, with robust applications in the Beijing subway [30, 31]. Such advanced techniques support more efficient and responsive transit operations.



(a) The image represents a flowchart outlining three phases of a project: Design and Data Ingestion (Phase 1), Proof of Concept (Phase 2), and Integrate and Scale (Phase 3).[10]

(b) Partial Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plots for Various Variables[32]

Figure 3: Examples of Advanced Prediction Techniques

As shown in Figure 3, advanced prediction techniques are crucial for enhancing efficiency and optimizing operations in passenger flow control. The structured three-phase project model starts with Design and Data Ingestion, emphasizing meticulous data preparation, followed by the Proof of Concept phase, testing theoretical models' feasibility. The final phase, Integrate and Scale, focuses on implementing and expanding successful models into broader operational frameworks. Complementing this approach are Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) plots, providing a statistical basis for understanding relationships between variables over time. These plots serve as diagnostic tools to identify patterns in passenger flow data, informing more accurate predictions [10, 32].

3.3 Challenges and Solutions in Passenger Flow Management

Method Name	Dynamic Factors	Spatial Correlations	Predictive Accuracy
TOM[13]	Time-varying Demand	Different Locations Interactions	Accurate Demand Data
AHP-ISM[26]	Management Factors	Network Topology	Systematic Analysis
ResLSTM[30]	Weather Conditions	Network Topology Information	Improved Prediction Accuracy
SARIMA-SVM[28]	Periodic Trends	Different Locations	Enhance Prediction Accuracy
PFPA[20]	Time-varying Demands	Station Sequence Layer	High Accuracy
GDTLD[22]	Trip Length Distribution	Spatial Distribution Stops	Gamma Distribution Model
RPP[25]	Changing Travel Behavior	Different Locations Interactions	Improved Forecasting Accuracy

Table 2: Comparative Analysis of Methods for Passenger Flow Management in Urban Transit Systems: Examining the Role of Dynamic Factors, Spatial Correlations, and Predictive Accuracy. This table provides a detailed assessment of various methodologies, highlighting their unique approaches to addressing challenges in passenger flow management.

Managing passenger flow in urban transit systems presents challenges due to dynamic passenger demand and network operations. Capacity constraints on trains and platforms often lead to congestion and delays when demand exceeds capacity [13]. Interconnected vulnerability factors further complicate management [26]. Existing methods struggle to capture dynamic inter-station correlations and the combined impact of static and dynamic factors on passenger flow [30]. Reliance on dispatcher experience for forecasting leads to substantial errors due to the lack of adaptive quantitative models [28]. These models often neglect spatial correlations within subway station networks, resulting in inaccurate predictions and ineffective resource allocation [30]. The difficulty of accurately assigning passenger flow on a network scale is exacerbated by dynamic travel demand, which traditional methods struggle to predict [20]. Arbitrary data adjustments distort real data, leading to inaccuracies in trip length distribution [22]. This reflects a broader issue of neglecting causal relationships and long-range dependencies in passenger flow data, focusing primarily on aggregated time series data [25]. Innovative solutions enhance prediction accuracy and management strategies, integrating spatial and temporal factors to refine forecasts [30]. Systematic approaches to identify and analyze relationships affecting urban rail transit stations' resilience during disruptions are necessary. Developing a comprehensive understanding of these factors enables targeted strategies to enhance resilience and efficiency amidst growing demand and environmental challenges [24]. Table 2 presents an in-depth comparative analysis of different methods employed to tackle the complexities of passenger flow management in urban transit systems, emphasizing the integration of dynamic factors, spatial correlations, and predictive accuracy.

4 Train Timetable Optimization

4.1 Energy-Optimal Timetabling

Energy-optimal timetabling is vital for sustainable urban rail systems, requiring advanced optimization techniques for efficient train schedules. Train trajectory optimization, which adjusts speed profiles and dwell times, enhances energy efficiency by refining arrival and departure times [33]. Robust optimization models address uncertainties in transfer walking times, creating resilient timetables adaptable to dynamic conditions [34]. The Fuzzy Transport Sustainability Index (FTSI) balances user behavior and environmental impacts, ensuring energy-efficient timetabling aligns with sustainability goals by minimizing energy use and incorporating multimodal solutions [8, 33]. Mixed Integer Linear Programming (MILP) models optimize schedules to meet increased demand, maintaining energy efficiency through buffering time and demand variability [35, 18]. Genetic algorithms further refine timetables by adjusting departure, dwell, and running times, achieving energy savings of 4% to 34.5% [13, 15]. The decision diagram-based branch-and-price decomposition method optimizes last-mile scheduling, emphasizing comprehensive energy efficiency [8]. The Monge-Kantorovich Transport method optimizes mass transport with energy-efficient constraints, ensuring effective resource allocation [6]. Integrating user behavior and environmental impacts into planning is crucial for balancing energy efficiency and service quality [5]. Advanced optimization techniques, such as multi-train trajectory optimization and robust scheduling methods, are essential for developing energy-efficient schedules that dynamically respond to urban transit demands, enhancing stability and minimizing disruptions [18, 33].

4.2 Synchronized Timetables

Synchronized train timetables are crucial for optimizing urban transit systems, enhancing service quality, and reducing waiting times [36]. Harmonizing schedules across lines and modes facilitates seamless transfers and minimizes delays, especially in complex networks where multiple lines intersect. This synchronization requires aligning arrivals and departures at transfer stations strategically, reducing waiting times and improving satisfaction [36]. Advanced data-driven methods, including real-time estimation, are employed to understand passenger flow dynamics and predict demand variability accurately. Synchronized timetables reduce transfer times, enhance travel experiences, and promote public transit as an alternative to private transportation, supporting sustainable urban mobility [8]. They also optimize resources by adjusting train frequency and capacity in response to real-time demand, crucial for managing peak-hour congestion [20, 13]. Furthermore, synchronized timetables enhance system resilience by enabling operational flexibility and rapid adjustments to disruptions [34]. Robust optimization techniques that account for uncertainties in demand and operations are integral to developing adaptable timetables [35].

4.3 Passenger Demand Variability and Elasticity

Passenger demand variability and elasticity pose significant challenges for optimizing train timetables. Accurate demand prediction is crucial for creating schedules that accommodate fluctuations and ensure efficient service [20]. Urban transit networks, characterized by dynamic origin-destination flows, require sophisticated modeling to capture demand variability and elasticity [27]. Advanced methods like the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model, combined with Support Vector Machines (SVM), enhance predictive accuracy by capturing both linear and nonlinear patterns [28]. The Dual Attention Graph Neural Network (DAGNN) offers a novel approach to managing urban rail complexities, considering spatial and temporal correlations to improve timetable optimization [30]. Case studies, such as the Guangzhou Metro, demonstrate optimized timetables' effectiveness in reducing waiting times by 28.47%, showcasing their potential to enhance passenger experiences [14]. Multi-modal allocation models, validated with real-time data, emphasize the importance of considering demand variability in optimization [20]. By incorporating advanced prediction techniques and robust optimization strategies, transit systems can adapt to dynamic demand, ensuring efficient and reliable operations that meet urban commuters' evolving needs.

5 Metro Collaborative Optimization

5.1 Data-Driven Approaches in Collaborative Optimization

Data-driven methodologies are pivotal in enhancing metro operations' efficiency and passenger experience [19]. These approaches leverage advanced computational models and analytics to optimize train timetabling and passenger flow management. The multi-marginal optimization problem, which addresses transport scheduling and flow-rate constraints, exemplifies the role of data-driven techniques in optimizing metro systems [6].

The Metro Contact Network-Graph Model (MCN-GM) uses smart card data to simulate contact networks, capturing individual interactions and expected contact durations to provide insights into passenger flow dynamics [21]. This understanding facilitates service delivery optimization and congestion reduction. Decision diagrams further coordinate passenger flow between mass transit and last-mile services, identifying optimal routes and schedules to minimize travel and waiting times [8].

Moreover, the multi-marginal optimization problem aids in transport scheduling and flow-rate management, ensuring effective resource allocation across the network [6]. This is vital in urban transit, where complex passenger flow dynamics demand sophisticated optimization methods for operational efficiency.

Data-driven approaches also identify system vulnerabilities and develop risk mitigation strategies by analyzing extensive datasets, revealing patterns that inform the design of resilient transit systems [19]. The use of decision diagrams enhances scheduling efficiency between mass transit and last-mile services [8].

A comprehensive framework evaluates urban transit systems' impacts, encompassing direct and indirect economic effects [1]. This framework underscores the importance of data-driven approaches in understanding urban transit systems' broader economic and social implications.

Integrating data-driven methodologies into metro collaborative optimization is crucial for addressing urban transit systems' complex challenges. These approaches enhance understanding of passenger flow patterns, improve network performance, and enable real-time forecasting, contributing to metro networks' efficiency, reliability, and adaptability [9, 37, 16, 25]. Leveraging advanced computational models and data analytics, metro operations can become more efficient and resilient, adapting effectively to contemporary urban environments' dynamic demands.

5.2 Integration of Transit Components

Integrating transit components is crucial for optimizing metro systems' efficiency and passenger experience. Effective coordination among train schedules, passenger flow management, and infrastructure utilization is vital [36]. A significant challenge is "bunching," where simultaneous train arrivals cause congestion and delays, necessitating timetable constraints for even train distribution [36].

Collaborative strategies integrating diverse transit components can enhance metro efficiency and passenger experience. Aligning train timetable optimization with energy-efficient practices, such as regenerative braking systems, reduces energy consumption and enhances sustainability [15]. Maximizing regenerative braking energy reuse achieves substantial energy savings while maintaining operational efficiency.

Real-time data and advanced computational models help develop synchronized timetables, essential for efficient transit operations [36]. These timetables strategically align train arrivals and departures at transfer stations, minimizing passenger wait times and enhancing travel experience [8]. Implementing synchronized timetables requires understanding passenger flow dynamics and sophisticated prediction models to anticipate demand fluctuations and optimize resource allocation.

Collaborative strategies using data-driven approaches, including decision diagrams and graph-based models, provide a nuanced understanding of urban transit systems and facilitate transit components' integration. Analyzing connectivity layers, encompassing physical and virtual interactions, enhances passenger flow prediction accuracy. This precision aids demand management, operational efficiency, and effective service delivery, leading to better transit experiences [29, 25, 8, 21, 9].

6 Metro Robust Optimization

6.1 Introduction to Robust Optimization in Metro Systems

Robust optimization is crucial for improving the resilience and reliability of urban metro systems by effectively addressing uncertainties that affect operational efficiency and passenger satisfaction. Unlike traditional deterministic methods, robust optimization incorporates uncertainties into decision-making, enabling metro systems to manage variations in passenger demand, dwell times, and unexpected disruptions [26]. A significant application is in developing energy-efficient train timetables, where techniques like the recuperation of regenerative braking energy have shown potential for energy savings and operational efficiencies [15]. By optimizing train schedules to accommodate demand variations and operational uncertainties, these methods ensure high service quality with minimal energy consumption [5].

Robust optimization also addresses uncertainties related to passenger demand and operational conditions. Incorporating variability in dwell times allows metro systems to better respond to urban transit's dynamic nature, where passenger flow fluctuations and unforeseen events significantly impact performance [3]. Models such as the Monge-Kantorovich Transport with Flow-rate Constraints innovate in managing these uncertainties by using time-variable distributions to represent flow-rate constraints, facilitating effective resource allocation [6]. Beyond energy optimization, robust optimization can enhance fire resilience by assessing vulnerability and recovery capabilities [5]. Utilizing quantitative metrics to evaluate system resilience offers a structured methodology for improving decision-making in metro network management [19].

Future research should focus on developing robust predictive models capable of handling unexpected events, as emphasized by Abduljabbar et al. [10]. This is vital for ensuring metro systems can effectively respond to disruptions while maintaining high service quality. By integrating uncertainties into the optimization process, robust optimization provides a comprehensive approach to enhancing metro operations and adapting to contemporary urban challenges [3].

6.2 Handling Uncertainties in Passenger Demand

Managing uncertainties in passenger demand is critical for optimizing urban transit systems, as demand variability can disrupt service quality significantly. Effective strategies are essential to address these fluctuations [38]. A primary challenge is the inability of existing methods to capture dynamic inter-station correlations and the combined impact of static and dynamic factors on passenger flow [30]. Reliance on dispatcher experience for forecasting often results in substantial errors due to the lack of adaptive quantitative models [28].

Advanced probabilistic demand forecasting models consider passenger choices and competition, offering a nuanced understanding of flow dynamics [38]. These models utilize both historical and real-time data, enabling adaptation to sudden flow changes [39]. However, dependence on historical data poses limitations, as models like SARIMA may not capture abrupt shifts [32]. Integrating real-time data into predictive models is crucial for enhancing forecast accuracy. The Orthogonal Non-negative Matrix Factorization (ONMF) method exemplifies an approach that improves prediction precision by learning from historical and real-time data [28]. By refining data integration methods and enhancing model adaptability, transit systems can better manage demand uncertainties and maintain service quality [28].

Robust optimization techniques are essential for addressing demand variability and ensuring efficient service delivery. Methods proposed by Cacchiani et al. enable train schedules to adapt to fluctuating demand while maintaining operational efficiency [35]. Incorporating buffering time and demand variability into robust optimization strategies enhances resilience and reliability [18].

Future research should refine existing models, including real-time timetable adjustments based on live flow data and integrating additional factors affecting transfer times [34]. Enhancing the understanding of passenger behavior during unforeseen events allows transit authorities to implement targeted strategies to improve urban transit system resilience and efficiency [28].

7 Urban Transit Systems and Transportation Scheduling

7.1 Integration with Intercity Railway Stations

Optimizing transportation scheduling and enhancing urban mobility networks necessitates effective integration between urban transit systems and intercity railway stations. This integration is essential for facilitating seamless passenger transfers, minimizing waiting times, and improving overall travel experiences [36]. A significant challenge in achieving such integration is managing passenger demand variability, influenced by factors like intercity train arrivals at metro stations, which can lead to congestion and delays, especially during peak hours [14].

To address these challenges, advanced data-driven approaches and robust optimization techniques are utilized to synchronize train timetables and manage passenger flow across transit modes. Synchronized timetables are a key strategy, aligning schedules across different lines and modes to reduce passenger waiting times and enhance transfer efficiency at intermodal hubs [36]. Achieving this synchronization requires a comprehensive understanding of passenger flow dynamics, which can be achieved through integrating real-time data and employing advanced predictive models.

The use of decision diagrams in scheduling passenger flow between mass transit and last-mile services exemplifies the potential of data-driven approaches in optimizing transport scheduling and managing flow-rate constraints [8]. By leveraging these methodologies, urban transit systems can better anticipate demand fluctuations and allocate resources effectively, ensuring seamless connectivity between urban and intercity networks.

Integrating transit components, such as train timetables and passenger flow management, is crucial for enhancing the overall efficiency and resilience of urban transit systems [36]. Collaborative strategies that align train schedules with energy-efficient practices, including regenerative braking systems, further promote the sustainability of urban transit operations [15].

8 Case Studies

8.1 Tehran Metro System Challenges and Solutions

The Tehran Metro system contends with typical urban transit challenges, including traffic disruptions, scheduling inefficiencies, and infrastructure limitations, which impact operational efficiency and service quality. Addressing these issues requires robust optimization strategies to enhance train scheduling and bolster network resilience against fluctuating passenger demand and operational uncertainties [23, 18, 16]. Demand variability, driven by peak-hour congestion and intercity train arrivals, often results in overcrowding and delays, highlighting the necessity for effective service strategies.

To mitigate these challenges, the Tehran Metro has implemented solutions focused on optimizing train timetables and enhancing system resilience. Robust optimization models have been developed to accommodate demand variability and operational uncertainties, allowing for adaptive train schedules that respond to dynamic passenger flows [18]. These models incorporate buffering time and demand fluctuations to maintain service quality under adverse conditions [18].

The use of advanced data-driven approaches has further improved the Tehran Metro's ability to address operational challenges. By leveraging historical data and predictive models, the transit authority has enhanced passenger flow forecasts and optimized train schedules, leading to more efficient resource allocation and reduced waiting times [18]. Decision diagrams have been employed to optimize scheduling between mass transit and last-mile services, minimizing travel and waiting times and improving urban transit efficiency [8]. Additionally, energy-efficient practices, such as regenerative braking systems, have been pivotal in enhancing the sustainability of the Tehran Metro, achieving significant energy savings while maintaining operational efficiency [15].

8.2 Impact of COVID-19 on Urban Rail Transit

Benchmark	Size	Domain	Task Format	Metric
LTTO[17]	1,000	Urban Rail Scheduling	Timetable Optimization	Transfer Coordination, Passenger Satisfaction
NOP[16]	6	Metro Network Analysis	Performance Evaluation	Node Occupying Probability, Disabled Route Ratio

Table 3: This table presents a comparative analysis of two representative benchmarks in urban rail transit research, focusing on their respective sizes, domains, task formats, and performance metrics. The benchmarks, LTTO and NOP, are evaluated based on their applicability to urban rail scheduling and metro network analysis, respectively, providing insights into optimization and performance evaluation strategies.

The COVID-19 pandemic significantly affected urban rail transit (URT) systems, leading to a sharp decline in ridership due to lockdown measures, social distancing protocols, and a shift to remote work [40]. This decline resulted in substantial revenue losses and operational challenges for transit authorities worldwide. Research by Xin et al. [40] utilized the Synthetic Control Method to quantify the pandemic's impact on URT ridership, revealing a significant decline across various cities and offering insights into the challenges faced by transit authorities. Table 3 offers a comprehensive overview of benchmarks utilized in urban rail transit research, highlighting their characteristics and metrics relevant to the study of COVID-19 impacts on transit systems.

In response, urban rail transit systems implemented adaptations such as enhanced sanitation protocols, capacity limits, and contactless payment options to maintain operational continuity and safeguard passenger health amid declining ridership, which in some cities fell by up to 90

The pandemic accelerated the adoption of data-driven strategies in urban transit systems, with agencies increasingly using real-time data from smart card and GPS tracking systems to enhance service delivery, optimize bus scheduling, and manage passenger flow amid fluctuating ridership patterns. This shift has enabled transit authorities to better understand travel behavior, forecast demand, and adapt operations, ultimately improving the efficiency and quality of urban transportation services [40, 25, 7, 37, 9]. Dynamic and responsive transit operations have been instrumental in addressing pandemic-related challenges and ensuring the continued provision of essential urban rail services.

9 Conclusion

Optimizing urban transit systems, particularly metro networks, is pivotal for improving efficiency, reliability, and passenger satisfaction amidst rising urbanization and demand for public transportation. Effective passenger flow prediction plays a crucial role in transit management, enabling real-time operational adjustments and ensuring seamless connectivity. Techniques such as the integration of the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model with Support Vector Machines (SVM) and the ResLSTM model enhance forecast accuracy by capturing both linear and nonlinear data patterns.

Energy-optimal timetabling is a fundamental strategy in train timetable optimization, contributing to sustainable urban rail operations. Methods like train trajectory optimization and robust optimization models significantly reduce energy consumption while maintaining high service quality. The Fuzzy

Transport Sustainability Index (FTSI) provides a comprehensive framework for balancing user behavior and environmental impacts in transportation planning.

The synchronization of train timetables across different lines and modes is critical for minimizing passenger wait times and improving service quality. Synchronized timetables not only enhance passenger satisfaction but also optimize resource allocation, thereby boosting the overall sustainability and efficiency of urban transit systems.

Collaborative optimization strategies and data-driven methodologies are essential for enhancing metro efficiency and resilience. Approaches such as decision diagrams and graph-based models demonstrate the potential of data-driven methods in optimizing transport scheduling and managing flow-rate constraints. Robust optimization techniques further strengthen system resilience by incorporating uncertainties into decision-making, allowing urban transit systems to adapt to dynamic challenges.

Future research should focus on integrating synchronization models with vehicle scheduling and exploring additional constraints to minimize bunching events. Refining existing models to include more constraints and assessing their applicability across various railway networks will enhance the robustness and adaptability of optimization strategies. Developing comprehensive frameworks to evaluate the impacts of urban transit systems, considering both direct and indirect economic effects, is essential for understanding their broader implications on urban development.

This survey highlights the importance of integrated planning approaches to ensure robustness across all stages, recognizing that a singular metric of robustness may not suffice for diverse stakeholder needs. By employing advanced optimization techniques, data-driven strategies, and robust methodologies, transit authorities can effectively address the complex challenges posed by urbanization and fluctuating passenger demand, ultimately promoting the sustainability and resilience of urban transit networks.

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