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Summarry of Thesis (EN)

Designing a multimodal urban public transportation for increasing the services' resiliency

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Chapter 1 of the thesis establishes the conceptual, methodological and empirical foundation for investigating resilience in urban metro systems, with particular emphasis on multimodal integration and disruption management. The chapter begins by situating public transportation as a critical component of urban mobility systems, emphasizing its high daily utilization and systemic exposure to disruptions arising from both internal factors (e.g., equipment failures, infrastructure aging) and external conditions (e.g., weather, passenger incidents). These disruptions are classified into minor delays, slow-moving disturbances, and major incidents leading to partial or complete service suspension. The discussion highlights that such events generate cascading impacts, including increased travel time, service unreliability, economic losses, and safety concerns, thereby motivating the need for a rigorous analytical framework to understand both degradation and recovery dynamics in transit systems. The chapter further introduces the dual concepts of vulnerability and resilience, where vulnerability characterizes system exposure to disruptions, while resilience captures the system's ability to absorb shocks and restore functionality within a defined temporal horizon .

Building on this context, the chapter identifies critical limitations in the existing body of literature. A central issue lies in the predominant focus on single-mode analysis, particularly metro-only systems, which neglects the interdependencies inherent in multimodal transport networks. Additionally, passenger behavioral responses to disruptions are often simplified, reducing the realism of resilience assessments. The discussion underscores that contemporary urban growth intensifies these challenges, as infrastructure expansion lags behind demand, necessitating interim solutions such as bus-based connectivity to complement metro systems. This motivates the integration of multimodal planning approaches, especially under disruption scenarios, where coordinated responses become essential for maintaining accessibility and service continuity .

The research gap is then systematically articulated through both narrative discussion and a structured synthesis presented in Table 1. This table categorizes gaps across multiple dimensions, including system resilience phases, network perspective, performance measurement, geographical coverage, operational practice, scenario design, data availability, and comparative scope.

Analytically, the table reveals that existing studies inadequately address post-disruption recovery processes, rely heavily on cost and delay metrics rather than resilience indicators, and are geographically biased toward Asian megacities, with limited attention to European contexts such as Bucharest. Furthermore, operational practices like bus bridging are shown to be largely heuristic rather than systematically optimized, and the lack of high-resolution operational data (e.g., AVL/APC datasets) constrains empirical validation. The table thus functions as a conceptual map that justifies the thesis by linking identified deficiencies to specific research needs, particularly the integration of multimodal dynamics and resilience-oriented metrics.

Table 1: Categorized Research Gaps

Gap Category (Context)	Subject	Gap Description
System Resilience Phases	Post-disruption recovery & adaptation	Insufficient research on recovery and adaptation after major disruptions
Network Perspective	Multimodal vs single-mode analysis	Literature predominantly analyzes modes in isolation despite multimodal resilience dependence
Performance Measurement	Resilience indicators	Performance assessed mainly via cost and delay rather than resilience metrics
Geographical Context	Regional coverage of studies	Research concentrated in Asian megacities; lack of studies in European/developing regions
Operational Practice	Disruption bridging strategies	Bridging operations are reactive and experience-based, not systematically designed
Scenario Design	Disruption severity coverage	Focus on worst-case scenarios omits smaller disruptions affecting continuity
Data Availability	Operational datasets	Fragmentary logs and lack of high-frequency AVL/APC data constrain calibration
Comparative Scope	Network structure comparison	Analysis limited to a single transit network structure

In response to these gaps, the chapter formulates a clear research objective: to quantify metro system resilience under disrupted conditions through multimodal integration, with a specific focus on bus bridging strategies. This objective is operationalized through a set of research questions that progressively structure the investigation. These questions address the effectiveness of bus bridging in enhancing resilience, the development of quantitative resilience metrics based on operational indicators, the identification of critical thresholds separating resilient from non-resilient system states, the influence of bridging configurations on recovery trajectories, and the role of coordinated multimodal operations in mitigating cascading failures. Conceptually, these questions reflect a transition from descriptive analysis toward predictive and evaluative modeling of system behavior under disruption, emphasizing both performance degradation and recovery mechanisms .

The chapter then outlines the principal contributions of the thesis, which are methodological, analytical, and application-oriented. Methodologically, the work advances a quantitative framework that integrates graph-theoretic network analysis with operational performance indicators to assess resilience. Analytically, it introduces an empirical characterization of disruption patterns based on multi-year incident data, enabling the identification of recurring failure modes and temporal variations in system performance. The research further contributes by evaluating resilience across different spatial and temporal scales, including lines, stations, and peak/off-peak periods, thereby revealing heterogeneity in system behavior. A significant innovation lies in extending resilience analysis beyond metro-centric approaches to incorporate multimodal structures, particularly the role of intermodal connectivity and redundancy.

Chapter 2 develops the theoretical and methodological foundation for resilience analysis in public transportation systems by synthesizing existing literature on reliability, variability, disruption modeling, and resilience quantification. The chapter begins by situating resilience within the broader concept of service quality, emphasizing that traditional reliability measures such as punctuality and headway regularity serve not as direct resilience indicators but as baseline performance references against which disrupted system behavior can be evaluated. In this context, punctuality is defined as the degree of alignment between scheduled and actual departure times, reflecting the operational discipline of transit services. The average departure deviation across a line is formalized through an aggregate measure that compares actual and scheduled departure times over all vehicles and stops. Mathematically, this is expressed as a normalized summation of deviations:

$$P_l = \frac{1}{n_l n_{ij}} \sum_j \sum_i \left(\widehat{D}_{l,i,j}^{act} - D_{l,i,j}^{sched} \right) \quad (1)$$

where the indicator captures the relative frequency of departures falling within a predefined deviation band. This formulation establishes a quantitative benchmark for schedule adherence under normal operating conditions, which later supports the identification of performance degradation during disruptions .

The discussion then transitions to headway regularity, which is particularly relevant for high-frequency transit services where passengers arrive randomly rather than following schedules. Headway, defined as the time interval between consecutive vehicles, is a critical determinant of passenger waiting time and perceived service reliability. Variability in headways leads to phenomena such as vehicle bunching, which increases uncertainty and reduces service predictability. The chapter introduces two key metrics to quantify headway irregularity. The first is the coefficient of variation of actual headways:

$$COV(H_{l,j}^{act}) = \frac{\sigma(H_{l,j}^{act})}{\mathbb{E}[H_{l,j}^{act}]} \quad (2)$$

which measures dispersion relative to the mean headway. The second is the Percentage Regularity Deviation Mean (PRDM), defined as:

$$PRDM_{l,j} = \frac{1}{n_{l,j}} \sum_i \frac{H_{l,i}^{sched} - \widehat{H}_{l,i,j}^{act}}{H_{l,j}^{sched}} \quad (3)$$

This indicator captures the average deviation of actual headways from scheduled values. These formulations are analytically significant because they form the conceptual basis for the headway-based resilience indicators later introduced in the thesis, particularly those capturing service instability under disruption conditions .

Following the establishment of reliability metrics, the chapter examines the underlying causes of variability and unreliability in public transport systems. Drawing on Van Oort's classification, variability is decomposed into three primary components: driving time, dwell time, and stopping time. These components are influenced by both internal factors—such as schedule design, driver behavior, and infrastructure characteristics—and external factors, including weather conditions, traffic interactions, passenger demand fluctuations, and irregular loading patterns. The diagram presented on page 22 illustrates a complex causal network in which multiple internal and external variables interact to produce variability in departure times, trip durations, and service consistency. Analytically, this figure demonstrates that service unreliability is not the result of isolated factors but emerges from interconnected system dynamics, reinforcing the need for holistic modeling approaches that capture these interactions rather than treating disruptions as independent events.

The chapter then extends the discussion toward system performance under disruption, particularly focusing on short-term service suspensions. Resilience is conceptualized as the ability of a system to maintain or restore performance following disturbances, with emphasis placed on both system behavior during disruptions and recovery processes. Existing research in this domain is critically reviewed, particularly studies employing queuing theory to model passenger accumulation and service dynamics. Traditional bulk service queue models assume fixed service capacities and independent stations, assumptions that do not hold in real-world public transport systems where vehicle capacities vary and network interdependencies are significant. To address these limitations, the thesis proposes a modified bulk service framework that captures the dynamic interaction between vehicles and passengers, enabling the estimation of system stability, queue lengths, and waiting times under disrupted conditions. This methodological shift is important because it moves beyond static performance evaluation toward dynamic system behavior analysis.

In parallel, the chapter reviews literature on random service disruptions, focusing on queuing systems with server failures. Classical models, such as those developed by Madan and extended by subsequent researchers, consider systems with stochastic arrivals, exponential service times, and repair processes following breakdowns. These models introduce the concept of systems operating in alternating states of functionality and repair, allowing for probabilistic characterization of service interruptions. However, the chapter highlights that most of these models are based on single-service channels and do not adequately represent the complexity of public transport systems, where multiple vehicles operate simultaneously and disruptions propagate across network components. This critique reinforces the necessity of developing more sophisticated models that capture multi-channel dynamics and network-wide interactions.

The final section of the chapter addresses resilience quantification from a network perspective. A fundamental performance measure is introduced based on the proportion of active nodes in the network, defined as:

$$\theta(t) = \frac{1}{N}\sum_{i=1}^{N} s_i \qquad (4)$$

where $s_i$represents the operational state of node i, taking binary values between 0 and 1. This formulation provides a simplified yet effective representation of system functionality over time, enabling the derivation of key resilience characteristics such as the rate of performance degradation ($d\theta/dt$), total downtime, recovery duration, and maximum recovery level. Although this measure is abstract, it serves as a foundational concept for constructing more detailed resilience metrics in later chapters.

Building on this, the chapter introduces criticality assessment using graph-theoretic measures to identify structurally important nodes within the network. Two primary indicators are discussed: node degree and betweenness centrality. While node degree reflects the number of direct connections a node has, betweenness centrality quantifies the extent to which a node lies on shortest paths between other nodes. The latter is formally defined as:

$$BC(v_k) = \sum_{i \neq j \neq k} \frac{\sigma_{ij}(v_k)}{\sigma_{ij}} \qquad (5)$$

where σ_{ij}denotes the total number of shortest paths between nodes $i$and j, and $\sigma_{ij}(v_k)$represents those paths passing through node k. Nodes with high betweenness centrality are interpreted as critical transfer points whose failure can significantly disrupt network connectivity. This analytical framework establishes a direct link between network topology and system vulnerability, providing the basis for identifying critical infrastructure components.

Chapter 2 systematically bridges theoretical constructs and practical modeling approaches, laying the groundwork for the development of a comprehensive, headway-based and multimodal resilience assessment framework in the subsequent chapters.

Chapter 3 develops a structural robustness assessment framework for metro systems, using the Bucharest metro network as an empirical case study. The chapter begins by framing robustness as a system-level property reflecting the ability of a transport network to maintain functional integrity under disruptions. Unlike reliability, which focuses on adherence to schedules, or vulnerability, which captures exposure to risks, robustness is conceptualized as the capacity to withstand, absorb, and recover from disturbances. The discussion emphasizes that robustness is not merely a technical attribute but a determinant of user confidence and system attractiveness, particularly in urban contexts where public transport plays a central role in sustainable mobility. Early research approaches are reviewed, highlighting how metro systems have traditionally been represented as abstract graphs composed of nodes and links, with robustness inferred from topological metrics such as node degree, betweenness centrality, and network diameter. However, the chapter argues that such purely structural approaches are insufficient unless complemented by operational considerations such as passenger demand and capacity constraints, thereby motivating a hybrid analytical perspective that integrates topology and system performance .

The chapter proceeds by situating the concept of vulnerability within the robustness framework, tracing its origins to disaster studies and defining it as the susceptibility of a

transport network to events that degrade performance. Three principal categories of vulnerability are identified: link-based vulnerability, which examines the consequences of connection failures; capacity vulnerability, which addresses reductions in throughput; and accessibility vulnerability, which evaluates the impact of disruptions on users' ability to reach destinations. These categories are not independent but reflect different mechanisms through which disruptions propagate across the network. The discussion highlights the methodological evolution from qualitative assessments toward quantitative modeling, including probabilistic and behavioral approaches based on stochastic user equilibrium. In such models, link importance is inferred from route choice probabilities, allowing the simulation of performance degradation when critical links are removed. The chapter further introduces system dynamics as a complementary modeling paradigm capable of capturing feedback loops and temporal dependencies, thereby overcoming the limitations of static, linear representations. This theoretical grounding establishes a comprehensive analytical framework for identifying critical network components and assessing their role in system-wide disruptions.

Building on these conceptual foundations, the chapter introduces the methodological representation of the metro system as a graph structure. In this abstraction, stations are modeled as nodes and track segments as edges, with transfer stations functioning as high-importance nodes due to their role in maintaining connectivity across multiple lines. The robustness of the network is evaluated using several quantitative indicators, including a robustness index r_T, which reflects the availability of alternative paths, and the effective graph conductance CG, which measures the ease of connectivity between nodes. Additionally, two critical thresholds, $f_{90\%}$and f_C, are defined to represent the proportion of node removals required to induce substantial performance degradation or complete network fragmentation. These indicators provide a systematic means of evaluating how the network responds to progressive failures, enabling the identification of tipping points at which the system transitions from a functional to a degraded state .

The empirical component of the chapter focuses on the Bucharest metro network, which consists of five operational lines (M1–M5), approximately 64 stations, and a total network length of around 78 km. The system accommodates nearly 88 million passenger trips annually, underscoring its importance within the urban mobility system. The spatial structure of the network is characterized by a combination of topological forms, including ring, radial, loop, and branch configurations. As illustrated in Figure 1, Line M1 forms a circular ring around the city center, providing lateral connectivity, while Line M2 follows a radial alignment connecting northern and southern areas. Line M3 introduces a loop structure linking branches of M1, thereby enhancing redundancy, whereas Line M4 exhibits a branch topology with limited alternative connections. Planned extensions, such as Lines M5 and M6, further contribute to the network's structural complexity. This coexistence of multiple topologies results in a heterogeneous network, where different segments exhibit varying levels of redundancy and susceptibility to disruption. The figure analytically demonstrates how network geometry influences robustness, with ring and loop structures offering greater resilience compared to branch configurations that depend on single connections.

Passenger demand patterns are then analyzed to complement the structural assessment. The network accommodates approximately half a million daily passenger trips, with demand unevenly distributed across lines. As shown in Figure 2 , Lines M1 and M2 carry the highest passenger volumes, reflecting their central role in the network.



Figure 1: Location and topology of the Bucharest metro network

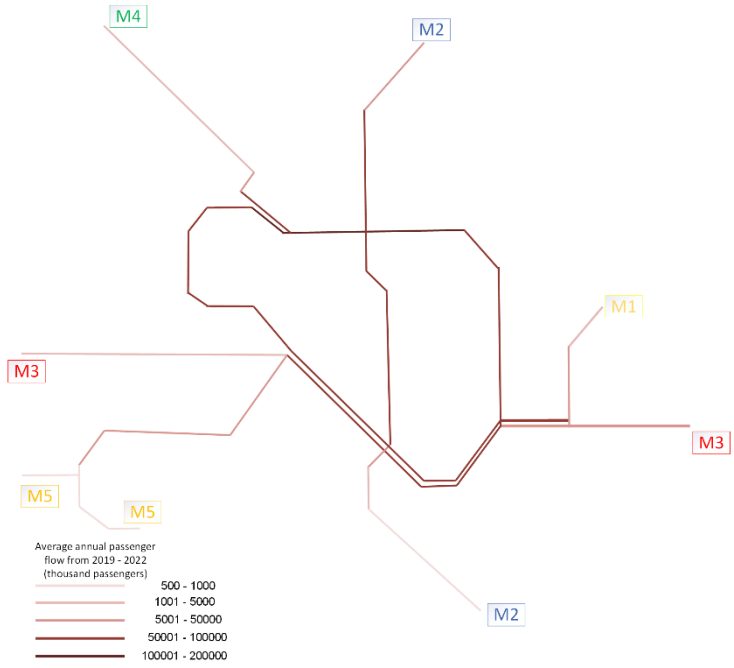


Figure 2: The Annual Distribution of the Metro Network's Passenger Flows in Bucharest

Temporal variations are also significant, with peak demand occurring during morning (07:00–09:00) and evening (16:00–18:00) commuting periods. These peak intervals represent conditions of maximum operational stress, during which the system's robustness is most critically tested. The figure illustrates the spatial distribution of passenger flows, highlighting high-demand corridors that are more vulnerable to disruption due to their load intensity. This integration of demand data with network topology provides a more comprehensive understanding of robustness, as it captures not only structural connectivity but also functional usage patterns.

The chapter further incorporates an empirical analysis of disruption events recorded between 2019 and 2022. A total of 348 incidents were identified, with annual variation ranging from 61 events in 2019 to 105 events in 2021, indicating a non-uniform temporal distribution of disruptions. Table 2 categorizes these incidents by cause, revealing that technical failures, train failures, and passenger emergencies constitute the most frequent disruption sources.

Table 2: Number of Incidents in The Bucharest Metro Network Based on Cause of Disruption Between 2019 and 2022

Cause of Disruptions	2019	2020	2021	2022	Grand Total
Technical Failure	10	21	20	10	61
Train Failure	8	13	21	17	59
Passenger Emergency	10	11	19	11	51
Power Outage	11	12	14	12	49
Signal Failure	8	18	14	8	48
Fire Alarm	5	10	11	10	36
Strike	6	3	1	12	22
Water Leak	2	2	2	5	11
Bomb threat			3	6	9
Flight return	1				1
Snowstorm				1	1
Grand Total	61	90	105	92	348

Strikes, although less frequent, represent system-wide events with potentially large impacts. The table provides a quantitative breakdown of disruption types, demonstrating that operational and human-related factors jointly shape the disruption profile of the network. This empirical evidence supports the argument that robustness assessment must account for both frequent localized disruptions and less frequent but more severe system-wide events.

A further analytical distinction is made between node-based and link-based disruptions, as summarized in Table 3 .

Table 3: Number of Incidents in The Bucharest Metro Network Grouped by Node and Link-Based Between 2019 and 2022

Node-Based		Link-Based	
Cause of disruption	count	Cause of disruption	count
Passenger Emergency	51	Technical Failure	61
Power Outage	49	Train Failure	59
Fire Alarm	36	Signal Failure	48
Strike	22	Snowstorm	1
Water Leak	11		
Bomb Threat	9		
Flight Return	1		
Total	179	Total	169

Node-based disruptions primarily affect stations, while link-based disruptions impact track segments and line continuity. The analysis reveals that these two categories occur with comparable frequency, indicating that both must be considered in robustness evaluations. Importantly, localized disruptions such as train failures occur more frequently than network-wide events, emphasizing the need to incorporate high-frequency, small-scale disturbances into resilience modeling. This finding challenges approaches that focus exclusively on worst-case scenarios, highlighting instead the cumulative impact of recurrent minor disruptions on overall system performance.

In conclusion, Chapter 3 establishes a rigorous framework for assessing structural robustness in metro networks by integrating graph-theoretic analysis with empirical data on demand and disruptions. It demonstrates that robustness is a multidimensional property shaped by network topology, passenger flow distribution, and disruption dynamics. Through the Bucharest case study, the chapter illustrates how heterogeneous network structures exhibit varying resilience characteristics, with critical nodes and links playing a disproportionate role in maintaining system functionality. The combination of theoretical modeling and empirical validation provides a solid foundation for subsequent chapters, which extend the analysis toward operational resilience and multimodal integration strategies.

Chapter 4 examines the interaction between urban transport modes, focusing on the balance between competition and complementarity within multimodal systems. It argues that metro and bus services should not be analyzed independently, as their performance is interdependent. Depending on network design and service characteristics, these modes may either compete for passengers when they offer similar routes and travel times or complement each other by enhancing accessibility, providing feeder connections, and supporting service continuity during disruptions .

The chapter develops a theoretical framework combining utility maximization, network theory, and coopetition concepts. Passenger behavior is modeled through generalized cost,

incorporating travel time, waiting time, and transfer penalties, while network theory emphasizes the role of connectivity and intermodal hubs. Coopetition theory captures the dual nature of modal interactions, where modes simultaneously cooperate and compete. Using the Bucharest metro as a case study, the analysis estimates system utility, operational costs, and mode choice probabilities, allowing the evaluation of different interaction scenarios between metro and bus services.

Results show that uncoordinated parallel services tend to create competition and inefficiencies, whereas integrated configurations such as feeder services or coordinated operations enhance system performance by improving accessibility and redundancy. These effects are reflected in improved efficiency, more equitable service distribution, and increased sustainability through better resource use. Overall, the chapter demonstrates that multimodal coordination is essential for improving system resilience, as complementary metro–bus interactions can mitigate disruption impacts and maintain service continuity.

Chapter 5 develops a quantitative framework for evaluating metro system resilience through the formulation and application of a Modified Resilience Index (MRI), with a specific focus on the Bucharest metro network. The chapter begins by redefining resilience from a purely infrastructure-based concept toward an operational perspective, emphasizing the system's ability to maintain service continuity under disruptions and to recover acceptable performance levels. It argues that resilience must account for interdependencies between infrastructure, operations, and external support systems such as power and communication networks. This conceptual shift is particularly relevant in the Bucharest context, where aging infrastructure and increasing demand amplify vulnerability, necessitating an empirically grounded and operationally sensitive assessment approach.

The methodological framework is constructed on the integration of multi-source data and network-based analysis. Operational data from Metrorex annual reports (2019–2024) are combined with historical disruption records to capture both normal performance and disturbance conditions. Key variables are extracted systematically, including disruption severity, spatial extent, duration, and passenger impact. The metro system is represented as a weighted and directed graph, enabling the identification of bottlenecks through spatiotemporal analysis at fine temporal resolution (15-minute intervals). This approach reveals congestion patterns and critical nodes whose disruption would disproportionately affect system performance. The analytical framework thus links passenger flow dynamics with structural network properties, allowing resilience to be interpreted as an emergent property of both demand distribution and network topology.

Central to the chapter is the formal definition of the Modified Resilience Index, which aggregates system performance under disruption conditions. The MRI is expressed as a normalized function of demand and service provision:

$$MRI = \frac{\sum_i Q_{\mathrm{req},i}\left(H_{\mathrm{ava},i} - H_{\mathrm{req},i}\right)}{\sum_i Q_{\mathrm{req},i} H_{\mathrm{req},i}} \qquad (6)$$

where $Q_{\text{req},i}$denotes passenger demand at station i, $H_{\text{ava},i}$represents available service capacity, and $H_{\text{req},i}$denotes the required service level during disruptions. This formulation captures the gap between available and required operational capacity, weighted by passenger demand, thereby reflecting both supply-side constraints and demand-side pressures. In addition to this network-level formulation, the chapter introduces a complementary statistical model in which resilience is conceptualized as a composite function of four key components: disruption intensity I(proxied by a Train Vulnerability Factor), affected area A(share of ridership impacted), event duration TE, and consequences C(approximated through passenger delay effects). These components are integrated in a reliability-inspired functional structure, implying that resilience emerges from the interaction of multiple interdependent factors rather than any single variable.

The empirical results reveal significant heterogeneity in resilience across metro lines, time periods, and operational conditions. Table-based results indicate that resilience values vary between peak and off-peak periods, with higher stability generally observed during weekends due to lower and more predictable demand. Line-specific analysis shows that Line M1 exhibits relatively strong and improving resilience over time, particularly after 2020, suggesting effective adaptation and recovery mechanisms. In contrast, Lines M2 and M4 display greater variability, indicating sensitivity to demand fluctuations and operational stress. The temporal evolution of resilience also reflects external influences, including pandemic-related demand shifts and network expansion, with the integration of Line M5 contributing positively to overall system resilience. These findings demonstrate that resilience is not static but evolves in response to both internal system changes and external shocks.

The statistical modeling component further refines these insights by enabling predictive analysis of resilience behavior. The model is calibrated using regression techniques to estimate parameters governing the influence of intensity, affected area, duration, and consequences on resilience outcomes. The consequence component is explicitly formulated as

$$C = \text{Ridership} \times \text{Duration} \times \text{Number of Events} \quad (7)$$

linking disruption frequency and severity to passenger impact. Sensitivity analysis demonstrates that the weighting scheme applied to vulnerability factors remains robust under moderate parameter variation, indicating stability of the model structure. However, the calibration is acknowledged as internal to the constructed index rather than externally validated, highlighting a methodological limitation related to the absence of independent resilience benchmarks.

In discussion, the chapter emphasizes that resilience assessment must incorporate both spatial and temporal dimensions of system performance. The integration of bottleneck identification with resilience modeling allows the identification of critical thresholds beyond which the system transitions from stable to unstable operation. The results underscore the importance of operational factors such as service frequency, rolling stock reliability, and passenger distribution in shaping resilience outcomes, complementing traditional structural analyses.

Furthermore, the observed differences between weekday and weekend performance highlight the role of demand variability as a key driver of resilience degradation.

The chapter concludes by establishing the MRI as a practical and interpretable tool for quantifying metro system resilience under disrupted conditions. It demonstrates that resilience can be systematically measured using operational data, enabling comparison across lines, time periods, and disruption scenarios. At the same time, the findings suggest that improving resilience requires targeted interventions addressing both infrastructure reliability and operational management, particularly in high-demand corridors and critical network nodes. Overall, Chapter 5 provides a rigorous analytical foundation for subsequent chapters by linking empirical data, network analysis, and statistical modeling into a coherent framework for resilience quantification.

Chapter 6 develops a comprehensive analytical framework for identifying and modeling bottlenecks in metro systems, with a particular emphasis on passenger behavior under disruption conditions and its implications for system performance. The chapter begins by conceptualizing service interruptions not merely as operational anomalies but as triggers of dynamic system responses involving both infrastructure constraints and passenger decision-making. It establishes that resilience degradation is strongly mediated by how passengers adapt to disruptions, making behavioral modeling an essential component of bottleneck analysis. The chapter thus extends traditional capacity-based approaches by integrating behavioral and system-performance perspectives into a unified framework.

The methodological foundation is structured around two interconnected analytical layers. The first is a behavioral layer grounded in discrete choice theory, which models how passengers select alternative travel options during disruptions. The second is a system-performance layer, which translates these behavioral responses into network-level effects such as congestion, flow redistribution, and recovery dynamics. This dual-layer structure enables the analysis to capture both the immediate impact of disruptions on passenger decisions and the subsequent propagation of these effects throughout the network. By linking individual-level choices to aggregate system performance, the framework provides a more realistic representation of how bottlenecks emerge and evolve.

Empirically, the chapter utilizes a dataset of 348 disruption events recorded in the Bucharest metro system between 2019 and 2022. These disruptions are classified by cause, revealing a concentration in a limited number of dominant categories, including technical failures (17.5%), train failures (16.95%), and passenger emergencies (14.65%). This distribution indicates that operational and human-related factors jointly contribute to system instability. In addition to frequency analysis, the chapter examines recovery duration patterns, showing that approximately 80% of disruptions are resolved within one hour, while the remaining 20% persist longer and exert disproportionately large impacts on system performance. This temporal distribution is critical, as longer disruptions are more likely to induce cascading congestion and sustained bottleneck conditions.

A central component of the chapter is the formalization of passenger choice under disruption using a multinomial logit (MNL) model. The modeling process begins with the construction of a generalized cost function for each alternative i, defined as

$$GC_i = VoT \cdot T_i + C_i \quad (8)$$

where VoTrepresents the value of time, $T_i$is travel time, and $C_i$is the monetary cost. This formulation converts heterogeneous travel attributes into a unified cost metric, enabling consistent comparison across alternatives. The generalized cost is then transformed into a utility function

$$V_i = -\beta \cdot GC_i \quad (9)$$

with $\beta = 1$assumed for normalization, reflecting a deterministic comparison framework rather than an empirically estimated behavioral model. Finally, choice probabilities are derived using the multinomial logit structure

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}}, \quad (10)$$

ensuring that probabilities are positive and sum to unity. This sequential formulation provides a transparent mapping from travel conditions to passenger behavior.

The numerical results derived from this model illustrate how differences in generalized cost translate into sharply differentiated choice probabilities. For example, alternatives with moderate travel times and low costs dominate passenger preferences, while options with excessive travel time or inconvenience exhibit negligible selection probabilities. A reconstructed table of generalized costs (Table 4) shows that alternatives with total costs around €7–8 capture the majority of demand, whereas high-cost options (e.g., €16) are effectively ignored. These findings demonstrate that even small differences in travel cost can significantly influence passenger redistribution during disruptions, thereby shaping the formation and intensity of bottlenecks.

Table 4: Comparative Generalized Travel Costs Associated with Disruption-Induced Mode Choices

Alternative	Time cost (€)	Fare/expense (€)	Total Cost (€)
A1	41 min → €6.8	€1	€7.8
A2	36 min → €6.0	€1	€7.0
A3	55 min → €9.2	€1	€10.2
A4	25 min → €4.2	€4	€8.2
A5	96 min → €16.0	€0	€16.0

The chapter then transitions to a detailed bottleneck analysis grounded in passenger-flow modeling. The Bucharest metro network is examined as a case study, with particular focus on high-demand corridors such as the M1–M3 trunk and major transfer stations including Piața

Unirii and Gara de Nord. Bottlenecks are conceptualized as localized capacity constraints that can propagate delays across the network when demand approaches or exceeds available capacity. This condition is quantified using the capacity utilization ratio

$$CUR(t) = \frac{D(t)}{C} \qquad (11)$$

where $D(t)$is observed demand and $C$is design capacity. Values of CURapproaching unity indicate critical loading, while values exceeding one signify overload conditions and the onset of queue formation.

To capture spatial congestion effects, the analysis introduces passenger density as a key indicator, defined as

$$d(t) = \frac{N(t)}{A} \qquad (12)$$

where $N(t)$is the number of passengers and $A$is the available area. Empirical thresholds of 4–6 passengers per square meter are used to identify overcrowding conditions, beyond which service quality deteriorates rapidly. Additionally, the concept of time-over-threshold (ToT) is introduced to measure the duration for which system elements operate under critical conditions, thereby incorporating temporal persistence into bottleneck identification. This metric is particularly important in peak periods, where short but intense demand surges can trigger sustained congestion.

The results highlight that bottlenecks are not solely determined by link capacities but also by node-level interactions, especially at transfer stations where multiple flows converge. Even when individual links operate below capacity, nodes with high centrality and transfer activity can become critical points of failure. This finding underscores the importance of considering network topology and passenger flow convergence in bottleneck analysis. Furthermore, the interaction between passenger choice and network constraints is shown to amplify congestion effects, as rerouted passengers concentrate on a limited set of alternatives, increasing pressure on already critical segments.

In discussion, the chapter emphasizes that bottleneck formation is a dynamic and multi-dimensional phenomenon driven by the interplay between demand, capacity, and behavioral adaptation. The integration of discrete choice modeling with flow-based performance metrics provides a more comprehensive understanding of how disruptions propagate through the system. The framework also highlights the importance of identifying critical thresholds such as capacity utilization and density limits beyond which system performance degrades rapidly and recovery becomes more difficult.

The chapter concludes by demonstrating that effective resilience assessment must incorporate both infrastructural constraints and passenger behavior. Bottlenecks are shown to be key mechanisms through which localized disruptions evolve into system-wide performance degradation. By quantifying these mechanisms through analytical indicators and behavioral

models, the chapter provides a foundation for designing targeted interventions, such as capacity adjustments, passenger information strategies, and multimodal integration measures, to mitigate congestion and enhance overall system resilience.

Chapter 7 develops a headway-based resilience framework that explicitly integrates bus bridging as an operational mechanism for maintaining service continuity and accelerating recovery in disrupted metro systems. The chapter begins by reframing resilience from a structural or topology-driven concept toward a service-level perspective centered on headway regularity, availability, and passenger experience. It argues that structural robustness alone cannot guarantee functional performance, as passengers perceive resilience primarily through stable waiting times, continuous accessibility, and the presence of viable alternatives during disruptions. This conceptual shift establishes headway as the fundamental operational variable through which disruption impacts and recovery dynamics should be evaluated.

The methodological development proceeds by positioning bus bridging as a deliberate redundancy and continuity instrument rather than a reactive contingency measure. The framework identifies three principal mechanisms through which bridging contributes to resilience: stabilization of headways by compensating for lost rail capacity, preservation of service availability by maintaining connectivity between affected stations, and enhancement of recovery rapidity through additional operational flexibility. These mechanisms are operationalized through design variables including candidate route generation, fleet allocation, service frequency, and waiting time approximation, allowing bridging strategies to be systematically evaluated rather than heuristically deployed.

At the core of the framework is a set of quantitative indicators that collectively describe service-level resilience. The Mean Headway Deviation (MHD) measures the deviation of actual headways from scheduled values, capturing short-term instability in service delivery. The Service Availability Ratio (SAR) represents the proportion of the network that remains operational during disruption, reflecting continuity of service. The System Redundancy Index (SRI) quantifies the availability of alternative paths and multimodal connections, increasing when additional bus services create independent or parallel routes. These indicators are designed to capture complementary dimensions of resilience: temporal regularity, spatial coverage, and structural redundancy.

These components are integrated into a composite resilience function that synthesizes the multidimensional nature of service performance under disruption. The resilience index is defined as

$$RI = w_1\left(1-\frac{MHD_S}{MHD_0}\right) + w_2\frac{SAR_S}{SAR_0} + w_3\frac{C_S}{C_0} \tag{13}$$

where $w_1 + w_2 + w_3 = 1$, and the ratios compare disrupted-state performance to baseline conditions. This formulation ensures that resilience increases when headway deviations decrease and when availability and connectivity improve. The inclusion of weighting parameters allows the model to reflect the relative importance of different performance

dimensions, while preserving interpretability and comparability across scenarios. In addition, a redundancy factor

$$R_f = 1 + \alpha(SRI - 1) \quad (14)$$

is introduced to capture the amplification effect of additional alternative routes, linking structural redundancy directly to functional resilience.

The framework further incorporates dynamic performance concepts such as recovery time, defined as the duration required for headway deviation to return below a predefined stability threshold. This temporal dimension is essential for distinguishing between systems that merely absorb disruptions and those that recover efficiently. By embedding these indicators within a unified analytical structure, the model enables the construction of resilience curves that describe system performance before, during, and after disruption events. These curves provide a graphical interpretation of degradation and recovery processes, highlighting how different bridging strategies alter both the depth and duration of performance loss.

The empirical application focuses on the Bucharest metro system, where the framework is used to evaluate alternative bus bridging configurations under corridor-level disruption scenarios. Three principal scenarios are analyzed: a metro-only baseline, a standard short-segment bus bridging strategy, and an extended or parallel bridging configuration with stronger multimodal integration. The results demonstrate clear performance improvements as bridging intensity increases. Specifically, the introduction of enhanced bridging reduces mean headway deviation from approximately +4.0 minutes to +1.5 minutes, increases service availability (SAR) from 0.82 to 0.95, and raises system redundancy (SRI) from 0.46 to 0.63. These improvements translate into a substantial increase in the composite resilience index from 0.46 (moderate resilience) to 0.72 (high resilience), accompanied by a reduction in recovery time from 55 minutes to 30 minutes.

The analysis also highlights the importance of design parameters in shaping resilience outcomes. Factors such as spatial service coverage, transfer penalties, and timetable coordination between metro and bus services significantly influence the effectiveness of bridging strategies. The study shows that bridging configurations that provide parallel or overlapping service corridors, rather than isolated substitutions, yield greater resilience gains by enhancing both redundancy and accessibility. Moreover, the integration of multimodal schedules under both normal and disrupted conditions contributes to reduced waiting times and improved passenger distribution, reinforcing the system's absorptive capacity.

In discussion, the chapter emphasizes that resilience is inherently a functional property emerging from the interaction between service regularity, network connectivity, and passenger behavior. The headway-based framework demonstrates that maintaining stable service intervals is as critical as preserving network topology, particularly in high-frequency metro systems where passengers rely on implicit scheduling. The results further indicate that localized disruptions can be effectively contained through well-designed bridging strategies, preventing the propagation of delays and mitigating cascading failures across the network.

Chapter 8 synthesizes the dissertation by integrating structural, operational, and multimodal perspectives on metro resilience, emphasizing that resilience is fundamentally an operational property rather than solely a structural one. While the Bucharest metro network exhibits moderate structural robustness maintaining high connectivity until approximately 15% node removal this does not ensure stable service performance during disruptions. Instead, resilience is experienced through headway stability, service availability, and recovery speed, highlighting the need to complement network topology analysis with operational indicators.

The chapter consolidates two main methodological contributions: the Modified Resilience Index (MRI), which quantifies resilience using disruption-related variables such as intensity, duration, and affected area, and the headway-based framework, which evaluates service-level performance through indicators like Mean Headway Deviation (MHD), Service Availability Ratio (SAR), and System Redundancy Index (SRI). The findings show that resilience declines sharply when disruptions spread spatially, indicating that system failure emerges from the combined effects of instability, reduced availability, and propagation across critical nodes.

A central conclusion is that bus bridging significantly enhances resilience by stabilizing service, maintaining connectivity, and accelerating recovery. Scenario analyses demonstrate that more extensive and coordinated bridging strategies lead to lower headway deviations, higher availability, and shorter recovery times. Moreover, multimodal coordination under normal conditions such as timetable synchronization also strengthens resilience by improving network flexibility.

Finally, the chapter acknowledges limitations related to data availability, simplified behavioral modeling, and the single-case-study scope. Future research is directed toward integrating high-resolution operational data, improving behavioral realism, and extending the framework to other urban networks.