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Headway-Based Multimodal Resilience Assessment of Metro Systems under Disruption: A Service-Level Case Study from Bucharest, Romania

Roozbeh EBRAHIMI GOLSHANABADI*[1]

** Corresponding author*

[1] National University of Science and Technology "Politehnica", Doctoral School of Transport, Bucharest, ROMANIA

✉ roozbeh.ebrahimi@stud.trans.upb.ro 0000-0002-9391-7269

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A B S T R A C T

Metro disruptions affect passengers primarily through headway inflation, headway dispersion and temporary losses of spatial coverage. This paper proposes a headway-native, service-level resilience framework that directly links operational disruption responses to passenger-visible performance. Three complementary indicators are formalized: Mean Headway Deviation (MHD) for service regularity, Service Availability Ratio (SAR) for spatial–temporal coverage, and a System Redundancy Index (SRI) capturing alternative-mode provisioning and operational reserves. These indicators are integrated into a time-varying composite resilience function, summarized over the disruption horizon using a normalized area-under-the-curve metric. The framework is demonstrated on a conceptual Bucharest metro corridor under three response strategies: (A) metro-only short-turn operation, (B) standard segment bus bridging, and (C) integrated extended/parallel/customized bridging. Scenario C delivers consistently superior performance, reducing mean headway deviation from +4.0 min to +1.5 min (−63%), restoring availability from 0.82 to 0.95 (+16%), and increasing redundancy from 0.46 to 0.63 (+37%). The composite resilience score improves from 0.54 to 0.78. Sensitivity analysis confirms dominance invariance under all admissible policy weightings, supporting robust planning use. These findings highlight how disruption-response strategies influence dynamic urban accessibility by preserving station catchments and maintaining corridor-level connectivity, thereby supporting more resilient settlement-level mobility planning.

1. INTRODUCTION

Metro systems are increasingly expected to sustain acceptable service levels under a broad spectrum of perturbations, ranging from routine operational delays to low-probability, high-consequence failures. In resilience research, this expectation is formalized using time-varying performance curves and the resilience-triangle interpretation, where the depth and duration of performance degradation and the speed of recovery jointly define system resilience (Ebrahimi Golshanabadi and Popa, 2024; Zhang et al., 2023). Within transport systems, resilience is not interpreted as the absence of failure, but as the ability to absorb disruptions, maintain partial functionality and restore service within bounded time horizons.

In metro operations, passenger-perceived performance degradation is governed less by static network topology than by headway behavior. Headway inflation directly increase waiting time, crowding and uncertainty, even when physical infrastructure remains connected (Raicu et al., 2024). Despite progress in metro vulnerability and robustness analysis, resilience assessments often rely on topological indicators or aggregate delay measures that only indirectly reflect passenger experience. In contrast, headway instability has been repeatedly identified as the dominant driver of unreliability in high-frequency urban transit services. Within this operational context, bus bridging emerges as the primary redundancy and continuity instrument during metro disruptions. The literature documents multiple families of bridging strategies, including standard segment replacement, extended bridging to diffuse terminal crowding and parallel services that create corridor-level overlays (Chen et al., 2024; Feng et al., 2024; Wen et al., 2024).

This paper proposes a headway-based resilience framework linking bus bridging to service performance, using three indicators and a time-varying function, validated on a Bucharest metro corridor across three scenarios. It is important to clarify that the Bucharest application is conceptual and serves as an analytical testbed rather than a fully calibrated empirical case study. The objective is not to reproduce exact operational conditions, but to evaluate how disruption-response strategies influence service-level resilience indicators under controlled and structurally consistent assumptions. This positioning ensures that the results are interpreted as framework validation rather than predictive system performance.

2. LITERATURE REVIEW

Bus bridging is a key mechanism for maintaining service continuity during urban transit disruptions. Research proposes optimization approaches, such as plan-based strategies, rolling-horizon dispatching, and passenger information systems to balance resource constraints under uncertain demand and bus travel times (Chen et al., 2024; Jin et al., 2016). Complementary studies address passenger flow control and multimodal substitution during disruptions, emphasizing the role of adaptive guidance and coordination in mitigating system-wide impacts (Li et al., 2024). The literature identifies three main bus-bridging strategies: standard segment replacement between adjacent terminals, extended bridging to redistribute demand, and parallel overlay services providing corridor-level alternatives with faster cycles (Feng et al., 2024; Wen et al., 2024).

Concepts such as resilience curves and the resilience triangle quantify resilience through the magnitude of performance loss, disruption duration and recovery speed (Ebrahimi Golshanabadi and Popa, 2024; Zhang et al., 2023). Many resilience models remain weakly linked to operational controls, with time-dependent indicators rarely tied to headway or spatial availability.

Table 1 summarizes key research on metro disruption management, passenger flow, and system resilience.

Table 1. Comparative review of metro disruption studies.

Study	Research focus	Methodology	Indicators / Metrics	Identified gap
Jin et al. (2016); Chen et al. (2024); Feng et al. (2024); Zhao et al. (2025)	Bus-bridging design for metro disruptions	Optimization and dispatch models	Passenger delay, fleet use, coverage	Weak link to service-level resilience
Li et al. (2024); Wen et al. (2024); Zhao et al. (2025)	Passenger flow control and multimodal substitution	Passenger assignment and flow modelling	Passenger flow, travel time	Limited resilience evaluation
Zhang et al. (2023); Du et al. (2022); Ebrahimi Golshanabadi and Popa (2024); Topal et al. (2026); Dong et al. (2022); Jaber et al. (2025); Amghar et al. (2025)	Transport resilience and disruption recovery	Resilience modelling and network analysis	Resilience curves, recovery time	Operational indicators rarely included
Batarce et al. (2016); Garrido-Valenzuela et al. (2022); Raicu et al. (2024); Mo et al. (2023)	Service reliability and operational performance	Empirical reliability analysis	Waiting time, crowding, bottlenecks	Mainly normal-operation analysis

The gaps in Table 1, especially the weak integration of service-level indicators, are addressed by linking disruption-response strategies to headway-based metrics and time-dependent resilience, enabling a more passenger-centered analysis. While prior studies have predominantly focused on empirically calibrated disruption scenarios or optimization-based implementations (Awan et al., 2025; Topal et al., 2026; Dong et al., 2022), the present study adopts a complementary conceptual approach. Specifically, it develops and tests a service-level resilience framework within a controlled analytical setting, allowing the isolated evaluation of operational mechanisms linking disruption response to passenger-visible performance. This positioning enables methodological clarity and avoids confounding effects associated with data-driven calibration.

3. METHODOLOGY

The methodological framework is structured as a deterministic, service-level analytical model that links disruption-response strategies to time-dependent resilience outcomes through a sequence of defined steps.

The system state at time t is represented by operational variables describing realized headway, metro frequency, bridging frequency, and effective service capacity (Garrido-Valenzuela et al., 2022). The framework consists of four stages: defining the disruption response (fleet, routing, frequency), translating conditions into service indicators, aggregating them into a time-dependent resilience measure, and evaluating performance and recovery over the disruption period (Batarce et al., 2016). This structure ensures that the analysis remains directly linked to operational conditions, while providing a clear and traceable evaluation of system resilience, avoiding purely descriptive assessment.

Figure 1 presents the methodological workflow of the proposed headway-based resilience framework, illustrating integration of bus-bridging design.

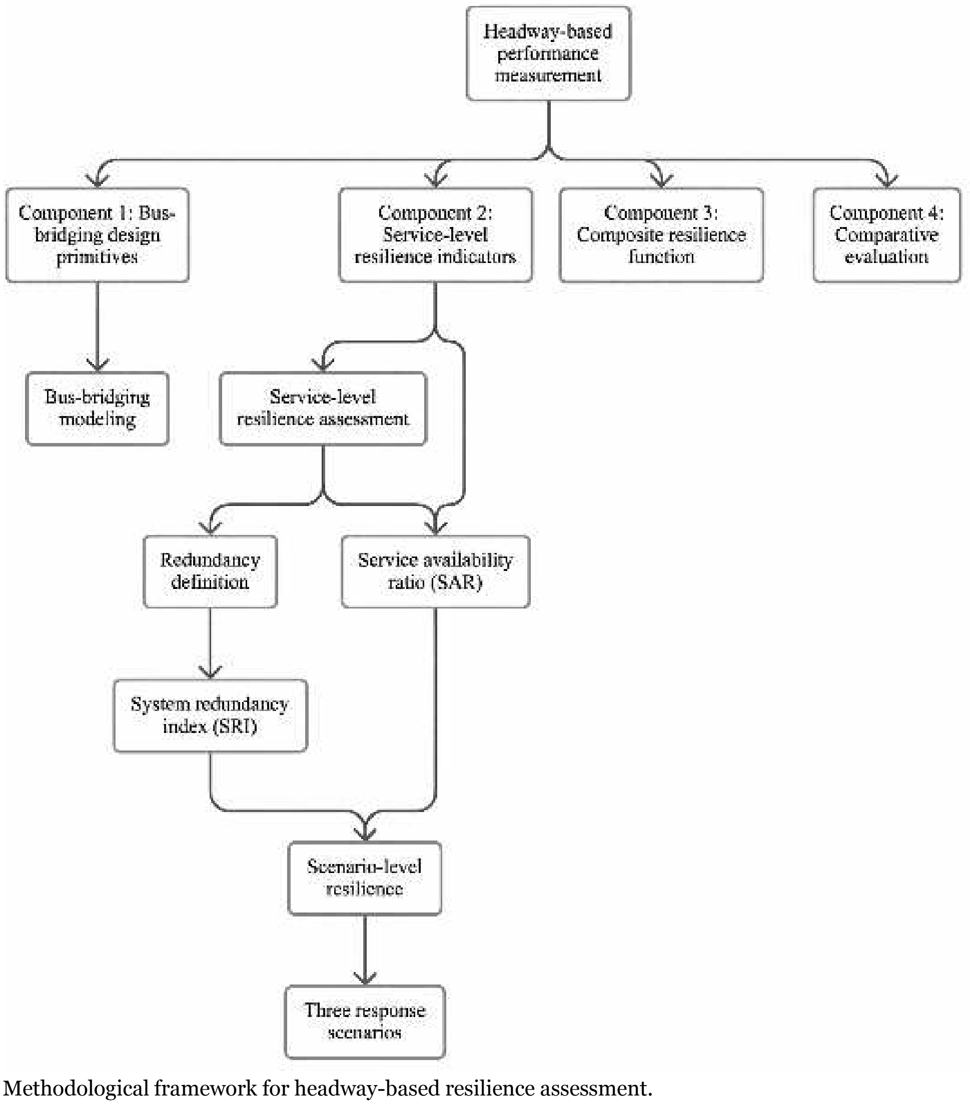

Fig. 1. Methodological framework for headway-based resilience assessment.

3.1. Bus-bridging design primitives

Bus bridging is modeled as an operational redundancy mechanism whose effectiveness depends on routing geometry, fleet allocation, dispatch frequency and passenger assignment, consistent with prior disruption-response and bus-bridging literature (Chen et al., 2024; Du et al., 2022; Jia et al., 2025; Wen et al., 2024). For a bridging line l, the minimum bus dispatch frequency required f_r (veh/h), to absorb disrupted passenger demand is derived from capacity equilibrium:

$$f_r \geq \frac{D_r}{\alpha_{cap}} \qquad (1)$$

where:

D_r - disrupted passenger demand (passengers/ hour);

α - acceptable load factor ($0 < \alpha < 1$);

cap - passenger capacity per bus (passengers/vehicle). Fleet required:

$$B_r = f_r \times T_r \tag{2}$$

where:

B_r - be total available buses (vehicles) and T_r round-trip cycle time (minutes). Passenger waiting time under headway-based control can be approximated by a headway-variability form:

$$E[W] \approx \frac{\sigma_{H_b}^2}{2H_b} + \frac{H_b}{2} (irregularheadways) \tag{3}$$

where:

mean headway H is expressed in minutes (minutes). Integrating rail and bus implies the perceived composite headway $\hat{H}$ satisfying:

$$\frac{1}{\hat{H}} = \frac{1}{H_m} + \frac{1}{H_b} \tag{4}$$

where:

H_m - metro headway (minutes);

H_b - bus headway (minutes). The composite headway reflects the combined effect of metro and bus services in minutes (min).

3.2. Service-level resilience indicators

In high-frequency transit, resilience is evaluated at the service level, where disruptions appear as headway changes. The framework therefore uses service-based indicators from schedules and substitute capacity to capture degradation and redundancy. If H_o denotes the scheduled headway (min) and H_i the realized (disrupted) headway (min), mean headway deviation is:

$$MHD = \frac{1}{n}\sum_{i=1}^{n} |H_i - H_0| \tag{5}$$

To normalize stability into a unit interval, a Headway Stability Ratio (HSR) is defined:

$$HSR = 1 - \frac{MHD}{H_0} \tag{6}$$

Service continuity is quantified through the Service Availability Ratio (SAR), defined as:

$$SAR = \frac{S_{eff}}{S_o} \tag{7}$$

where: S_{eff} epresents frequency-equivalent service capacity delivered within acceptable access and waiting-time envelopes under disruption and is the scheduled frequency-equivalent service capacity offered by the reference system (Wen et al., 2024).

Operationally, the Service Availability Ratio (SAR) measures the proportion of baseline service capacity that remains accessible to passengers during disruption conditions. The effective service capacity S_{eff} includes both the remaining metro frequency and the frequency-equivalent capacity provided by substitute bus-bridging services within the disrupted corridor. For substitute services, frequency-equivalent capacity is derived from the dispatch frequency and passenger capacity of the deployed bus fleet relative to the reference metro capacity. The indicator therefore captures the degree to which multimodal substitution restores spatial–temporal service availability compared to normal system operation.

In this study, redundancy is defined as an operational capability of the integrated metro-bus system to preserve feasible substitute paths and effective service capacity when rail segments are disrupted. Redundancy is therefore not considered as a purely topological attribute; instead, it reflects the combined contribution of inherent network reserves, global connectivity strength, and deployable alternative-mode supply under realistic operational constraints. Specifically, redundancy is reflected through three complementary components: (i) normalized structural robustness $\check{r}_T$, representing the metro network's intrinsic ability to sustain connectivity under failures; (ii) effective graph conductance C_G, capturing the ease with which flows can be redistributed across remaining links; and (iii) normalized bus-bridging intensity B, reflecting the extent to which substitute bus services can be deployed with sufficient frequency.

In this framework, redundancy reflects the metro-bus system's ability to sustain passenger paths and capacity during disruptions, defined as a multidimensional operational concept combining network structure and alternative-mode capacity. Accordingly, the System Redundancy Index (SRI) is expressed as a convex aggregation of three normalized components, capturing structural robustness, network connectivity efficiency, and substitute transport supply (Ebrahimi Golshanabadi and Popa, 2024):

$$SRI = \alpha\bar{R} + \beta\bar{G} + \gamma\bar{B}$$
$$\alpha + \beta + \gamma = 1, \quad \alpha, \beta, \gamma \ge 0 \tag{8}$$

where:

$\check{R}$ - normalized structural robustness of the metro network, expressing the ability of the rail topology to preserve connectivity under node or link removal;

$\check{G}$ - normalized effective graph conductance, which measures the efficiency with which passenger flows can be redistributed across the remaining network following a disruption;

B - normalized bus-bridging intensity, capturing the substitute service capacity that can be deployed through bridging operations during rail disruptions.

Each component is normalized to the unit interval [0, 1] using min-max normalization:

$$\tilde{X} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \qquad (9)$$

where: *X* denotes the raw value of the corresponding indicator.

The bus-bridging intensity *B* is calculated as the ratio between deployable substitute bus capacity and the disrupted rail capacity:

$$B = \frac{f_b C_b}{f_r C_r} \qquad (10)$$

where:

f_b - dispatch frequency of bridging buses (vehicles per hour);

C_b - passenger capacity per bus;

f_r - scheduled metro frequency on the disrupted segment (trains per hour);

C_r - passenger capacity per metro train. This formulation links redundancy directly to operational response parameters.

In the absence of predefined policy priorities among the three redundancy dimensions, equal weights are assigned to the components ($\alpha = \beta = \gamma = 1/3$), ensuring balanced representation of structural and operational redundancy within the composite indicator. Operationally, SRI increases when substitute bus services extend coverage beyond the disrupted segment, overlay parallel corridors, or target high-demand origin–destination pairs, thereby expanding the set of feasible, headway-bounded paths available to passengers during disruption and recovery (Lei et al., 2024; Xiong et al., 2024).

Scenario-level resilience is operationalized as a convex aggregation of the three service-level indicators capturing stability, continuity, and redundancy:

$$R(t) = w_1 \times HSR + w_2 \times SAR + w_3 \times SRI$$
$$w_1 + w_2 + w_3 = 1, \quad w_k \geq 0 \qquad (11)$$

In the baseline evaluation of this study, equal weights are adopted ($w_1 = w_2 = w_3 = 1/3$). Consequently, the composite resilience index for each scenario is computed as:

$$R = (HSR + SAR + SRI)/3 \qquad (10)$$

The formulation yields a bounded and interpretable resilience metric that preserves the operational meaning of each component. Its convex structure prevents dominance by any single dimension unless explicitly weighted, ensuring robustness to extreme values. Time-dependent resilience R(t) is summarized via a normalized area-under-the-curve (AUC), capturing both degradation depth and recovery speed in a single scalar while retaining temporal dynamics for cross-scenario comparison.

3.3. Bucharest corridor test and scenarios

The demonstration uses a corridor-level conceptual test on the Bucharest Metro, focusing on a high-demand segment with limited interchange and rerouting options.

Figure 2 shows a schematic, topological (non-geographic) network representation for 2019–2024, based on publicly available data and excluding future extensions.

Fig. 2. Schematic representation of the Bucharest Metro network *(source: author)*.

Three disruption-response scenarios are evaluated: (A) metro-only short-turn operations, (B) standard segment bus bridging, and (C) an enhanced multimodal strategy with extended, parallel, and customized services. Table 2 summarizes the operational assumptions, headways, substitute capacity, spatial coverage and redundancy, providing a consistent basis for comparative resilience assessment across scenarios.

3.4. Data sources, assumptions, and conceptual scope of the Bucharest case study

The Bucharest case study serves as a conceptual testbed to demonstrate the headway-based resilience framework, rather than a fully calibrated simulation. Its aim is to assess the analytical behavior of resilience indicators and disruption-response strategies, not to reproduce exact operations. The network is represented using publicly available topology data, comprising five metro lines (M1–M5) and a limited set of interchange nodes structuring passenger flows. Due to limited high-resolution data, key parameters (headways, capacities, fleet, speeds) are set using typical metro and bus ranges to ensure realistic, comparable disruption scenarios.

Table 2. Scenario parameterization and indicator ranges.

Parameter	Symbol	Scenario A (Metro-only Baseline)	Scenario B (Standard Bus Bridging – S-BBS)	Scenario C (Parallel Bus Bridging)
Scheduled headway	H_0	6 min (peak) / 9 min (off-peak)	6 min metro + ~3.5 min effective composite	6 min metro + ~2.5 min effective composite
Disrupted Headway	H_d	10 min (avg under short-turns)	8 min (bridging stabilizes partly)	6-7 min (effective corridor regularity restored)
Mean Headway Deviation	MHD	≈ +4 min from schedule	≈ +2.5 min	≈ +1.5 min
Bus Average Speed	v_b	—	25 km/h (city average during incident)	28-30 km/h (optimized corridor / bus priority)
Fleet Available	x_l	—	10–12 buses (re-allocated STB fleet)	14-18 buses (total for parallel + feeders)
Effective Bus Headway	$\tilde{H}_b$	—	≈ 3.5 min	≈ 1.6 - 2.0 min
Line Non-linearity Coefficient	α	—	≤ 1.25	≤ 1.35 (extended loops allowed)
Coverage / Stations served	S/S_0	≈ 0.82 (closure loss)	≈ 0.90 (with segment bridging)	≈ 0.95 (with extended and parallel coverage)
System Redundancy Index	SRI	0.46 (baseline)	0.53	0.61 - 0.65
Resilience Index	R	≈ 0.54 (moderate)	≈ 0.67	≈ 0.78 (high)

The Bucharest Metro case study should therefore be seen as a conceptual demonstration rather than a fully calibrated simulation. In addition, key operational reference values used in the scenario design, such as disruption-duration thresholds and walkable access distances, are adopted as literature-informed planning assumptions rather than empirically calibrated parameters.

4. RESULTS

Table 3 compares disruption-management scenarios for the Bucharest Metro corridor.

Table 3. Scenario performance comparison.

Indicator	Scenario A (Metro-Only Baseline)	Scenario B (Standard Bus Bridging – S-BBS)	Scenario C (Extended / Parallel Bus Bridging – E/P-BBS)	% Change A→C
Mean Headway Deviation (MHD)	+4.0 min (+67 % vs schedule)	+2.5 min (+42 %)	+1.5 min (+25 %)	↓ 63 %
Headway Stability Ratio (HSR = 1 – MHD/H_0)	0.33	0.58	0.75	↑ 127 %
Service Availability Ratio (SAR)	0.82 (82 %)	0.90 (90 %)	0.95 (95 %)	↑ 16 %
System Redundancy Index (SRI)	0.46	0.53	0.63	↑ 37 %
Composite Resilience Index (R)	0.54 (moderate)	0.67 (intermediate)	0.78 (high)	↑ 57 %
Service Recovery Time ($T_{(rec)}$)	55 min	40 min	30 min	↓ 45 %
Functional Reliability R(f) (steady-state post-recovery)	0.90	0.93	0.96	↑ 7 %

The metro-only baseline (A) shows the largest degradation due to lack of substitute capacity. Standard bus bridging (B) improves stability and availability but is limited by terminal crowding and coverage. The extended/parallel configuration (C) performs best, reducing headway deviation and improving recovery and redundancy by distributing flows across multiple access points. Overall, a clear monotonic ordering (C > B > A) is observed across all indicators, confirming that the performance gains are structural rather than metric-dependent. The composite resilience values reported in Tables 2 and 3 are calculated using equal indicator weights (w_1=w_2=w_3=1/3), ensuring internal consistency between the indicator values (HSR, SAR, SRI) and the resulting resilience index. Scenario C substantially improves service performance relative to the baseline: mean headway deviation decreases from +4.0 to +1.5 min (–63%), headway stability rises from

0.33 to 0.75 (+127%), availability increases from 0.82 to 0.95 (+16%), and redundancy from 0.46 to 0.63 (+37%), raising composite resilience from 0.46 to 0.72. Recovery time declines from 55 to 30 min (−45%) while post-recovery reliability increases from 0.90 to 0.96 (+7%).

Figures 3 and 4 show that these resilience gains result from systematic operational improvements through enhanced bus-bridging strategies.

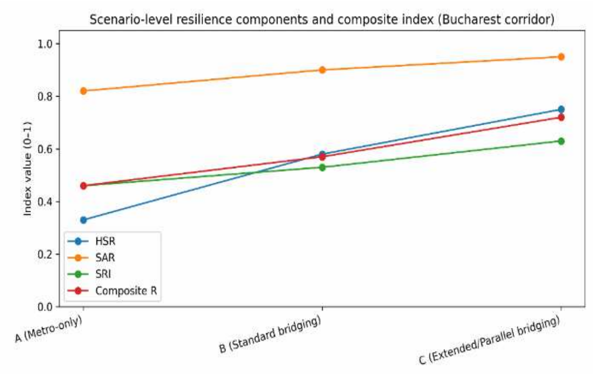

Fig. 3. Scenario-level resilience components and composite index (HSR, SAR, SRI, R).

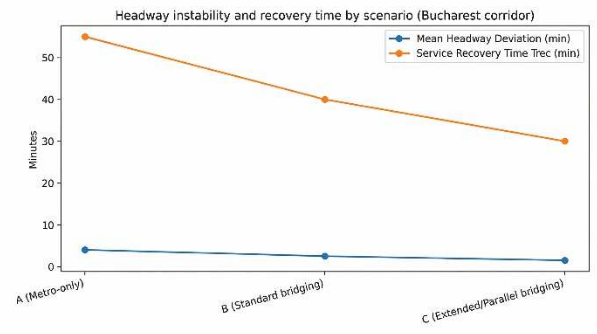

Fig. 4. Headway instability (MHD) and recovery time (T_{rec}) by scenario.

4.1. Sensitivity analysis

Because Scenario C dominates Scenarios B and A across all normalized indicators (HSR, SAR, SRI), the composite resilience ordering $R_C > R_B > R_A$ holds for any admissible weight vector. Under convex aggregation, component-wise dominance guarantees composite dominance.

Table 4. Component values used in the composite index.

Scenario	HSR	SAR	SRI
A: Metro-only baseline	0.33	0.82	0.46
B: Standard bridging (S-BBS)	0.58	0.90	0.53
C: Extended/Parallel bridging (E/P-BBS)	0.75	0.95	0.63

Table 5. Feasibility envelopes under any admissible weight choice.

Scenario	R_{min}	R_{max}
A	0.33	0.82
B	0.53	0.90
C	0.63	0.95

Table 6. Example policy weight profiles and resulting composite scores.

Weight profile	(w_1)	(w_2)	(w_3)	(R_A)	(R_B)	(R_C)
Equal emphasis	0.333	0.333	0.333	0.5367	0.6700	0.7767
Reliability-led	0.50	0.30	0.20	0.5030	0.6660	0.7860
Continuity-led	0.30	0.50	0.20	0.6010	0.7300	0.8260
Redundancy-led	0.30	0.30	0.40	0.5290	0.6560	0.7620

The sensitivity analysis tests resilience stability across feasible weight ranges, rather than changing scenario rankings. Tables 4 to 6 present indicator values, ranges, and representative weight configurations.

Figures 5 to 7 show one-way sensitivity curves: each weight varies from 0 to 1 while the remaining mass is split equally between the other two weights. Scenario C exhibits the tightest envelope, reflecting uniformly strong component performance.

The results highlight key thresholds: bus bridging is effective for disruptions over ~30 minutes, while shorter incidents can be managed internally. For longer events, rising passenger demand requires added capacity, but curb and berth limits constrain headways and increase dwell variability.

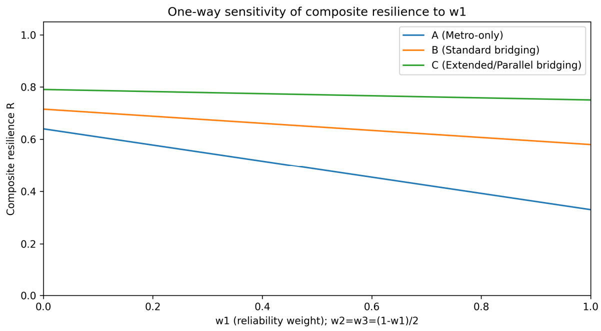

Fig. 5. One-way sensitivity of composite resilience to w_1 (reliability weight).

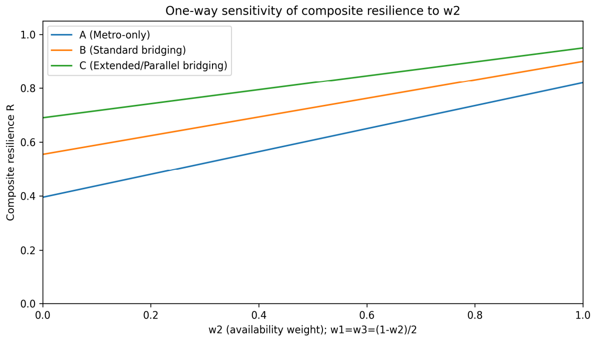

Fig. 6. One-way sensitivity of composite resilience to w_2 (availability/continuity weight).

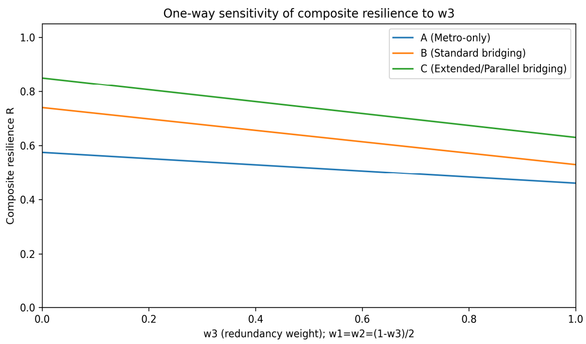

Fig. 7. One-way sensitivity of composite resilience to w_3 (redundancy weight).

This supports predefined bridging templates and interchange-first passenger guidance aligned with operational constraints (Feng et al., 2024; Halvorsen et al., 2020).

5. DISCUSSION

The superiority of Scenario C is not merely quantitative but reflects a structural shift in disruption-response dynamics. Specifically, resilience gains emerge from three interacting mechanisms: (i) spatial dispersion of boarding demand, which reduces terminal congestion and stabilizes headways; (ii) frequency augmentation through parallel services, which lowers effective waiting times; and (iii) expansion of feasible path sets, increasing redundancy under constrained network conditions.

These mechanisms jointly transform the system from a capacity-limited regime to a distributed service regime, where performance is governed by operational flexibility rather than infrastructure constraints. This finding can be generalized beyond the Bucharest case, suggesting that resilience in high-frequency metro systems is primarily determined by the ability to dynamically reconfigure service supply rather than by static network robustness.

The observed performance improvements under Scenario C are consistent with recent optimization bus-bridging studies, which demonstrate that disruption outcomes are highly sensitive to the spatial configuration and operational coordination of substitute services. For instance, Zhang (2023 showed that integrated routing and dispatching strategies significantly reduce passenger delays under disruption conditions, while Chen et al. (2024) demonstrated that extended bus-bridging configurations improve service continuity by redistributing passenger loads across adjacent stations. Similarly, Feng et al. (2024) highlighted that corridor-level coordination of bridging services enhances both operational efficiency and passenger accessibility.

In contrast to these optimization-focused approaches, this study reframes operational strategies through a service-level resilience perspective. While prior work has examined short-term service regularity and disruption recovery mechanisms (Jaber et al., 2025; Mo et al., 2023), it does not explicitly capture how these strategies influence service performance over time. Building on these insights, this study links operational strategies to dynamic resilience dimensions headway stability, service availability and redundancy.

Unlike prior studies that primarily evaluate bus-bridging performance using aggregate delay or cost-based indicators (Jin et al., 2016; Li et al., 2024), the present framework introduces a headway-based resilience formulation, in which disruption impacts are quantified through passenger-relevant service indicators. Specifically, Mean Headway Deviation (MHD) captures temporal instability, Service Availability Ratio (SAR) reflects spatial-temporal service continuity, and the System Redundancy Index (SRI) operationalizes the contribution of alternative-mode capacity.

This explicit linkage between operational control variables (e.g., dispatch frequency, fleet allocation) and resilience dynamics addresses a gap identified in recent reviews, where resilience metrics remain weakly connected to service-level operational mechanisms (Du et al., 2022).

The results suggest key operational implications. First, a disruption-duration threshold exists: bus bridging becomes advantageous mainly beyond ~30 minutes, while shorter events can be handled through internal metro recovery. This ≈30-

minute value is a literature informed, operationally plausible reference not an empirical estimate. Second, resilience is constrained by station curb and berth capacity, meaning added bus supply alone is insufficient if boarding interfaces create queuing and dwell variability. Third, resilience gains are highest when substitute services remain within walkable catchments (≈500 m) and require no more than one transfer. Similarly, the ≈500 m threshold reflects a widely adopted planning heuristic for pedestrian access to transit rather than a calibrated value derived from the model (El-Geneidy et al., 2014; Li et al., 2025). In this study, thresholds act as analytical benchmarks for comparing strategies not universal or empirical limits. The results also support translating resilience metrics into practical policy and planning decisions. From a service-reliability perspective, the emphasis on headway dynamics is supported by empirical studies demonstrating that passenger waiting time variability is primarily driven by headway irregularity rather than average frequency alone (Garrido-Valenzuela et al., 2022; Raicu et al., 2024). This reinforces the relevance of MHD and HSR as core resilience indicators in high-frequency metro systems.

Furthermore, recent resilience-oriented transport studies emphasize the need to integrate operational and behavioral dimensions, particularly under disruption conditions where passenger adaptation and service substitution jointly shape system performance (Amghar et al., 2024; Wen et al., 2024; Zhao et al., 2025). The present framework contributes to this direction by embedding substitute service capacity and accessibility into a unified resilience metric, thereby bridging the gap between operational control strategies and passenger-perceived service continuity.

5.1. Spatial planning and accessibility implications of disruption resilience

The findings have clear spatial planning implications for accessibility, station catchments, and corridor land-use interactions. Although operational, indicators like SAR and SRI act as proxies for dynamic accessibility under disruption. SAR captures how well station catchments are maintained: disruptions shrink them, while distributed bus bridging helps restore or expand access by adding boarding points along the corridor. In parallel, SRI captures the availability of alternative origin–destination paths within acceptable generalized costs, thus preserving connectivity between key urban functions. The superior performance of extended and parallel bridging can therefore be understood as a temporary spatial reconfiguration that redistributes access points and maintains a more continuous accessibility field, reducing localized accessibility loss. Overall, Resilience should be a planning criterion: low-redundancy corridors risk accessibility collapse, requiring multimodal redundancy, distributed access and flexible service overlays.

5.2. Practical implications for operations and emergency planning

The framework provides operational value by linking resilience to measurable service outcomes and passenger-visible performance. It supports pre-event planning by enabling evaluation of strategies (metro-only, segment bridging, extended bridging) based on stability, availability, and resources. In real time, it enables rapid comparison, showing metro-only is sufficient for short disruptions, while bus bridging becomes advantageous for longer events (≈30 minutes). It highlights key resource and infrastructure constraints, showing that adding substitute capacity alone is insufficient when curb space, berthing, and transfer handling become bottlenecks. This underscores the need for coordinated station-level operations. The framework also supports inter-agency coordination and corridor prioritization by providing a unified basis to align metro operations, bus deployment, and emergency planning, and to identify segments where targeted measures deliver the greatest resilience gains.

The framework directly informs transport policy and contingency planning by translating resilience into actionable decision rules. It identifies a disruption-duration threshold (≈30 min) that can serve as a trigger for escalating from metro-only control to multimodal intervention, supporting tiered emergency protocols. The System Redundancy Index (SRI) enables evidence-based fleet prepositioning by favoring distributed, corridor-specific standby allocation over centralized reserves. A unified resilience metric further facilitates inter-agency coordination by aligning metro, bus, and traffic management decisions on dispatching, priority measures (e.g., temporary bus lanes), and station operations. The results also emphasize the role of passenger-information strategies, showing that resilience improves when walkable access is preserved and transfers are minimized, thereby supporting real-time guidance and distributed boarding. Finally, the identification of curb and berth capacity as binding constraints highlights the need for station-area operational planning and temporary infrastructure measures alongside fleet policies. Collectively, these insights translate resilience assessment into implementable planning and response instruments.

6. CONCLUSIONS

This paper develops a headway-based, service-level framework for assessing metro system resilience under disruption, linking operational response strategies to passenger-visible performance through

Mean Headway Deviation (MHD), Service Availability Ratio (SAR), and a System Redundancy Index (SRI). The framework provides a structured way to represent degradation and recovery dynamics using interpretable operational indicators.

The Bucharest corridor application, used as a conceptual testbed, indicates that bus-bridging design significantly influences resilience outcomes. While standard segment replacement offers partial improvements over metro-only operation, more spatially diversified configurations (extended/parallel/customized bridging) consistently perform better across the evaluated indicators. These improvements are associated with enhanced passenger flow distribution, increased access redundancy, and more effective use of substitute capacity. Sensitivity analysis suggests that the relative ranking of scenarios is robust to alternative weighting assumptions.

The results also highlight several operational insights, including the existence of a disruption-duration threshold (≈30 minutes) beyond which bridging becomes beneficial, and the importance of station-side constraints such as curb and berth capacity. However, these findings should be interpreted with caution. The case study is intentionally conceptual and relies partly on representative parameter ranges rather than fully calibrated operational data; therefore, the reported magnitudes should be viewed as indicative rather than predictive, and context-specific validation is required before direct implementation.

The study proposes a transferable framework for evaluating disruption-response strategies in high-frequency metro systems, with future work focusing on AVL/APC calibration, stochastic travel-time variability, and real-time decision support. The indicators capture dynamic accessibility, showing how disruptions reshape system reach, while strategies that preserve multimodal access and distributed entry points help maintain station catchments, reduce inequalities, and support integration with land-use and transit-oriented development.

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