Transport Network Resilience: Present and Future Challenges

Charis Chalkiadakis[0000-0002-5605-8784] and Eleni I. Vlahogianni[0000-0002-2423-5475]

National Technical University of Athens 24, Iroon Polytechniou st., 15773 Athens, Greece
xarisxalk@mail.ntua.gr

Abstract. Departing from its classical definition, resilience has been deemed as a key element for transportation network management as a proxy of the behavior of transportation networks under both disastrous events and non-recurrent system's conditions. In the present paper we provide a detailed taxonomy of resilience quantification and applications to modern transportation systems. The definitions of resilience found in literature are summarized, as well as methods, metrics, and models used in various studies are critically assessed. Moreover, we delve into the state-of-the art methods for the quantification of resilience. The analyses reveal specific challenges springing from the technological and communication advancements in the transportation sector that are critically discussed and future directions for integrating the concept of resilience in the context of smart cities via smart vehicles and infrastructures are identified.

Keywords: Resilience, Transportation Networks, Connected and Automated Transport, Simulation Methods

1 Introduction

Modern cities are changing rapidly leading to complex mobility patterns. On the other hand, transport infrastructure and processes still remain vulnerable to extreme Weather Events (EWEs), such as floods [1–4] and their impacts on a specific transportation-related infrastructure (e.g., ports) [5], road accidents or other types of incidents [6–8] or even disturbances connected to technological advancements [9–11]. Despite the existence of information and technological advancements, such as the recently introduced Cooperative, Connected, and Automated Mobility (CCAM), the ability of transportation networks to withstand and bounce back from disruptive phenomena remains a challenge for both researchers and practitioners.

Resilience is characterized by complexity, which may differentiate according to the point of view under which disturbances are examined [12–14]. It is highly acknowledged that all disturbances which may occur to a transportation network have impact on its performance and, thus, the resilience of a transportation network to any kind of event needs to be examined, as mentioned also in other studies such as [13]. Recently, resilience has been also coined as a feature of the transportation system and not as an outcome of a certain disturbance [15, 16]. This broader concept can be extremely valuable for monitoring and managing future mobility conditions in complex smart urban environments. Further examination of transportation-related resilience by studying the integration of new innovative technologies and their impacts in the resilience of transportation networks can be deemed as important.

In the present paper, a review on the concept and applications of resilience, both in terms of its definition and quantification with the aim of revealing emerging research topics concerning the integration of resilience in the process of designing and implementing advanced Traffic Management Strategies (TMS) is presented. The above is conducted in the framework of Information and Communication Technologies (ICT) advancements in connectivity and automation in the field of transportation. Specifically, the following research questions are raised and aimed to be addressed in the present research:

- What is resilience and why is important?
- How can resilience be quantified?
- Which are the main research questions concerning transportation resilience?

The remainder of the paper is structured as follows: In Section 2 various resilience definitions are provided, the resilience-related layers are discussed, and the main resilience-related metrics are introduced. Then, in Section 3 the main methods for quantifying resilience are presented and discussed. Special focus is given in simulation methods for resilience quantification. Next, in Section 4 the data sources used in resilience analysis are discussed. Furthermore, Section 5 includes challenges which are related to resilience, but they are also oriented towards the integration of the new technological advancements in the concept of resilience. Finally, Section 6 provides the conclusions and discussion of the present research.

2 Defining Resilience

Resilience, a concept that has garnered significant attention across various disciplines, including ecology, engineering, and social sciences, is increasingly recognized as a key element in the study of transportation networks. However, despite its widespread use, resilience lacks a universally accepted definition, largely due to its multifaceted and context-dependent nature [12, 17]. The interpretation of resilience varies across disciplines and is highly influenced by the specific system under consideration and the types of disruptions it faces. In the context of transportation, resilience is often broadly defined as the ability of a system to withstand, adapt to, and recover from disruptions, thereby maintaining a certain level of functionality or performance.

This broad definition, while useful as a starting point, requires further refinement to be effectively applied in the analysis and management of transportation networks. Key aspects that need to be considered include:

- The nature of disruptions: Transportation networks can be affected by a wide range of disruptions, including natural disasters (e.g., earthquakes, floods, hurricanes), technological failures (e.g., power outages, cyberattacks), and human-caused events (e.g., accidents, terrorist attacks). The characteristics of these disruptions, such as their magnitude, duration, and spatial extent, can significantly influence the system's response and recovery.

- The system's performance: The performance of a transportation network can be measured in various ways, including traffic flow, travel time, accessibility, and throughput. The definition of resilience should specify the performance metrics that are most relevant to the analysis and the acceptable levels of performance under disrupted conditions.
- The system's response: A resilient transportation network is not only able to withstand disruptions but also to adapt to changing conditions and recover quickly and efficiently. This may involve implementing alternative routes, adjusting traffic management strategies, and providing timely information to travelers.

Given the context-specificity of resilience, it is essential to categorize resilience studies based on the type of transportation network under consideration. Research has been conducted on various transport network types, including:

- Road transport networks: Studies in this area have focused on the impact of disruptions on traffic flow, congestion, and accessibility, and on strategies for enhancing network resilience through infrastructure design, traffic management, and emergency response [18–20, 20–25]
- Supply chain networks: Research in this area has examined the resilience of supply chains and the impact of disruptions on the movement of goods [26–29]
- Maritime and waterway transport networks: Studies have investigated the resilience of ports and shipping routes to disruptions such as storms and accidents [30–35]
- Air transport networks: Research has focused on the impact of disruptions on flight schedules, airport operations, and passenger travel [36, 37]
- Rail transport networks: Studies have examined the resilience of rail networks to disruptions such as accidents, weather events, and infrastructure failures [38–44]

Early definitions primarily share a common thread in defining resilience as the physical ability of infrastructure to absorb and recover from disruptions. More recent studies have expanded resilience definitions to include functional and behavioral dimensions, addressing adaptation strategies, redundancy, and operational adjustments. Infrastructure resilience focuses on physical durability, operational resilience addresses functionality under stress, ecological resilience introduces system adaptability, user-centric resilience considers human responses, and time-based resilience measures the speed of returning to pre-disruption performance. Table 1 illustrates the variability in how resilience is conceptualized, highlighting aspects such as recovery time, adaptability, and impact measurement.

Table 1. Resilience concepts

Perspective	Definition	Representative research
Infrastructure	Physical durability, capacity to withstand disruptions	[18, 21]
Operational	Functionality and service continuity under stress	[24, 45]
User-centric	Human responses to transport disruptions	[22, 46]
Time-based	Speed of network recovery post-disruption	[21, 47]

Except for the above, there is research which define resilience in a more generic way. In [31], resilience is defined in a stricter way, as a function which allows for quantification of the impacts an event may have in the performance of a system. In [48] resilience is defined as the ability of a transportation system to absorb the disruption caused by an event, for the system to be restored in its previous state. In [47] resilience is defined as the time-dependent ratio of recovery from a performance loss due to a disruptive event that already took place. In [49] resilience is defined as a capacity of each transportation system, a definition relevant to the one of [48].

All the studies mentioned define resilience as the system's ability to maintain acceptable performance despite disruptive events. However, this generic definition doesn't capture the specific conditions of each event. This research adopts definitions for general transportation networks, which focus on recovery timeframes and operational performance during disturbances.

While resilience generally means maintaining system performance during disruptions, the question that arise is the following: should definitions be tailored to specific disruption types or universal across scenarios? Current resilience studies mostly address specific disruptions like extreme weather events or infrastructure failures. Emerging risks like cybersecurity threats and socio-economic disturbances add complexity. Quantifying resilience varies widely by event type, leading to inconsistencies across studies.

To address this, a more standardized approach integrating systemic performance indicators and adaptive response mechanisms is needed. Real-time data, predictive analytics, and comprehensive risk assessments can provide robust, scalable frameworks for diverse transportation systems.

2.1 Resilience-related layers

Literature reveals various resilience-related layers exist. Table provides further insight regarding the key resilience-related layers and their definition.

Table 2. Resilience-related layers, definitions, and associated references

Layer	Definition	Applications	Representative references
Adaptability/ Flexibility	Capacity for dynamic operational adjustments	Intelligent Transport Systems (ITS), Real-Time Traffic Management	[50–55]
Recoverability	Efficiency of network recovery post-disruption	Emergency response, disaster recovery planning	[30, 56, 57]
Redundancy	Availability of alternative routes and modes	Multi-modal networks, Real-life urban road networks	[51, 58-63]
Robustness	Resistance to disruption	Bridge design, flood mitigation, infrastructure plans	[30, 64-68]

From a performance's point of view, and based on the relevant literature [15, 30, 38, 69-71], the impacts of a disturbance on transportation networks are illustrated through the resilience triangle. The resilience triangle, as in Fig**Fig.** 1, illustrates the variations in network performance across disruption phases, emphasizing adaptability, recoverability, redundancy, and robustness. The resilience triangle thus clarifies performance dynamics during disruptive events, quantifying the extent of functionality loss and recovery.

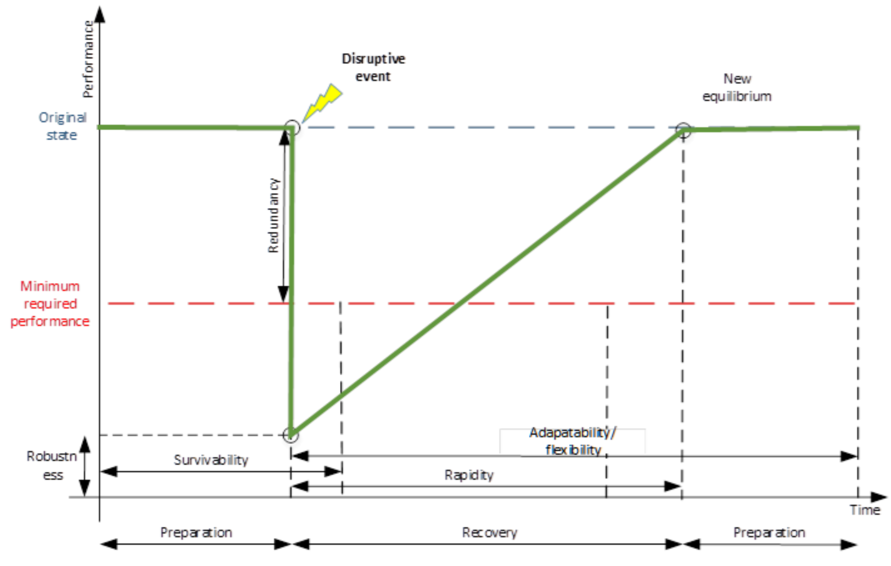

Fig. 1. The resilience triangle

Mathematically, the resilience triangle is expressed as:

$$R = \int_{t_0}^{t_r} (1 - \frac{P(t)}{P_0}) dt \tag{1}$$

where P_0 is the initial system performance, $P(t)$ is the system performance at time t, t_0 is the disruption onset, and t_r is the full recovery time. This integral quantifies the performance loss during a disruption, making the resilience triangle a widely used analytical tool.

It is also worth noting that the resilience triangle illustrates the three disaster management phases [72-75]: preparation, impact, and recovery. Integrating proactive traffic management strategies, especially in preparation and recovery phases, can significantly alter resilience outcomes. Examining how demand-side rebalancing solutions influence performance recovery is critical for comprehensive resilience planning and effective mitigation of network vulnerabilities.

It is to note that, in transportation related phenomena resilience must account for traffic demand, capacity, and flow for a thorough and complete assessment of resilience, yet this approach is complex and computationally demanding [14]. For example, one of the useful metrics is "shortest path", however shortest path because of a path assignment methodology, such as Frank-Wolfe assignment, cannot be thought of as a pure metric. The inclusion of other metrics, which are directly related to path assignment and shortest paths, is needed. Such metrics exist in the literature, and they namely are efficiency [76, 77] and criticality [78].

2.2 Resilience-related metrics

There are three main categories of resilience-based metrics for transportation systems: topological metrics, attribute-based metrics and performance metrics. Topological metrics focus only on the structure of the transportation system, while ignoring its dynamic features. The effect of this fact is that said metrics do not manage to capture and incorporate in their concept the dynamic nature of resilience. Examples of topological metrics are the network diameter, centrality, and redundancy [79–83]. Attribute-based metrics usually focus only on one of the several layers/ aspects of resilience. Attribute-based metrics are of importance as they manage to clearly examine one resilience layer, hence they do not have the ability to describe the complexity and multi-variable dependency of resilience fully and clearly. Examples of attributes-based metrics are adaptability, safety, and recovery time [18, 38, 56, 84–86]. Finally, performance metrics are designed to examine the overall transportation system's performance over the whole period it is affected by disruptive events. Performance metrics provide a more integrated approach towards investigating the resilience of a transportation network, as they capture the dynamic nature of resilience, and they manage to examine more complex and more generic variables as the ones of attribute-based metrics. Examples of performance metrics are degradation of system quality over time [87], time-dependent ratio of recovery to loss [47], and expected fraction of demand satisfied in post-disaster network using specific recovery costs [28].

Evidently, a closer look at the above metrics shows that the resilience of a given transportation network is usually defined under a specific point-of-view. This fact leads to an inherent difficulty in studying resilience in its entirety. But do we need to investigate multiple objectives when studying resilience? If yes, is there the need to design and develop new evaluation frameworks which will manage to investigate resilience in a more complex and more integrated way? [71] mentioned the need to introduce a generic Resilience Index which will be able to examine the resilience of a transportation network through the consideration of topological, attribute-based, and performance metrics. Additionally, [88] indicates the need for the introduction and definition of a resilience reference metric which needs to be based on extensive comparative assessments.

3 Methods for Quantifying Resilience

In the relevant literature multiple ways of quantifying resilience emerge, spanning from the approach used towards resilience quantification to the scope of the analysis and the tools used to quantify resilience. This is illustrated in Fig. 2 and discussed below.

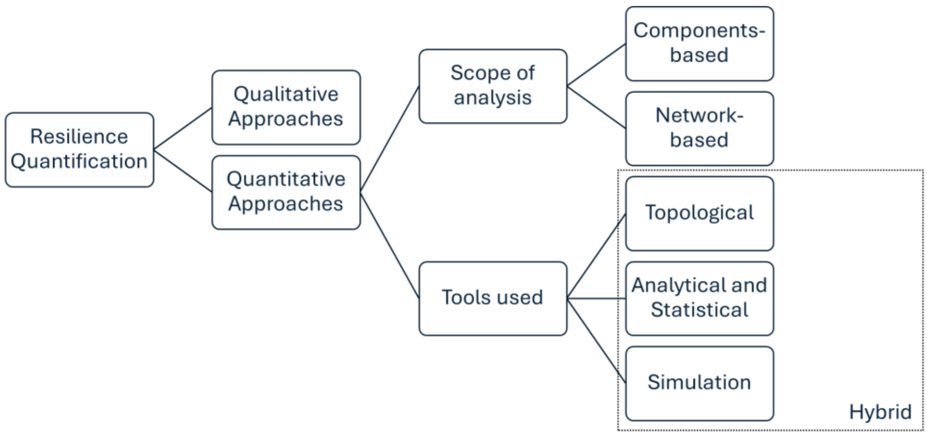

Fig. 2. Resilience quantification methods as identified in the relevant literature

Traditional resilience assessments primarily focused on network redundancy and robustness, evaluating connectivity under stressful conditions. To this end, previous research categorizes resilience analysis in two (2) types: qualitative approaches, which mostly are policy-driven assessments and conceptual resilience planning, and quantitative approaches which are numerical assessments using graph-theoretic models, performance metrics, and simulation-driven analytics. It shall be noted that the majority of previous research consist of quantitative studies [12–14, 89–91].

Qualitative approaches emphasize policy-driven frameworks, governance structures, and stakeholder collaboration, which shape resilience conceptualization and implementation. Such methods aim to assess the transportation networks in qualitative terms like high, medium, and low [89–91] and are frequently employed by urban planners and policymakers to establish benchmarks and regulatory strategies. Stakeholder-driven risk analyses, involving transport officials, city planners, and local authorities, are widely applied for vulnerability assessments and resilience objectives definition [92]. It is worth noting that qualitative methods, although insightful, lack empirical rigor and quantitative validation [93]. Thus, their effectiveness significantly improves when integrated with quantitative frameworks and real-time predictive models [10].

Departing from the traditional qualitative approaches for resilience assessment, quantitative approaches can be distinguished either based on the scope of the analysis or the tools used to quantify resilience. From the perspective of the scope of the analysis, the system is studied either through its components (component-based analysis) or as an entity (network-based analysis). Component-based analysis focuses on certain components of the transportation network (e.g., ports or corridors), but the resilience of the entire transportation system is not considered as a study object [27, 69, 94]. In contrast, network-based analysis considers the network with all its discrete components as a single object of study [16, 18, 78, 80]. In Table 3 and Table 4 more information concerning component-based and network-based methods of resilience analysis respectively can be found.

Table 3. Components-based methods of resilience analysis

Metrics	Approach	Indicative references
Average ratio of throughput achieved and total demand	Quantification of vulnerability as result of inherent reliability and short-term recovery activities for ports and other intermodal components in freight systems	[27]
Global and local resilience	Assessment of instantaneous resilience of human machine system in trains/ tramways	[69]
Aggregate delay and relocation rate	Analysis of aggregate delay and relocation rate of passengers	[94]

Table 4. Network-based methods of resilience analysis

Metrics	Approach	Indicative references
Connectivity and serviceability	Risk assessment method for emergency response planning and management	[80]
Congestion index	Fuzzy inference for analysis of road segments’ congestion	[95]
Adaptability and recoverability	Resilience for system optimum and user equilibrium traffic assignment	[18, 96]
Incident impact factor	Identification of vulnerable links in road network due to incidents	[97]
Direct and Indirect costs – Economic impacts	Assessment of economic impacts	[59, 98, 99]

Travel time resilience	Model with equilibrium constraints to measure and maximize travel time resilience	[59, 100]
Environmental resilience	Framework to facilitate decision making process	[59, 101]
Time-dependent network resilience	Assessment of resilience, at system level, with a time-dependent resilience index	[48, 102–104]
Vulnerability and Criticality	Identification of vulnerable and critical links, in qualitative and quantitative terms	[16, 78, 80, 105–108]
Network resilience	Network resilience quantification for disaster scenarios	[29, 109–111]
Accessibility	Identification of vulnerable road segments	[112]
Post-event resilience level	Quantification of network resilience and identification of post-event activities	[28]
Total recovery time	Post-event scheduling optimization for bridge network	[113]
Redundancy	Optimization of network models to evaluate network redundancy	[51, 58–63]
Delay, cost, distance, and emissions	Supply chain modal shift by assessing the resilience of static intermodal and dynamic synchromodal solutions	[114]
Overall resilience and vulnerability	Public transport assessment, by using Fuzzy Logic techniques, at city and country wide level	[115, 116]
Utilization rate	Service utilization from queueing theory to extract insights regarding a supply chain's resilience.	[117]
Efficiency	Inverse of average shortest path length	[16, 76, 77]
Macroscopic Fundamental Diagrams (MFDs) Throughput Loss	Area between baseline and disrupted MFD curves	[118]
Recovery Time	Time taken to restore baseline conditions	[66, 119, 120]

Focusing on the tools used to quantify resilience, diverse methodologies are involved ranging from empirical data evaluations to advanced computational modeling techniques. Recent methods integrate machine learning, agent-based modeling, and optimization algorithms to provide scalable, real-time resilience assessments. The methods for quantifying resilience can be categorized in three (3) main categories: topological methods, analytical methods, and simulation methods. In the present research, special focus is given on simulation methods, as the majority of the literature falls into this category.

3.1 Topological Methods

Topological methods are based on the topology of the network and express resilience by examining the networks' characteristics. These models have explicit expressions mostly relying on the calculation of shortest path and some of them are determined by node degree distribution [3, 78, 80, 93, 121–123].

3.2 Analytical and Data driven Methods

Analytical methods make use of logical models like event and fault tree analysis [124, 125], Bayesian analysis [15, 126], Data Envelopment Analysis [127], and Analytic Hierarchy Process (AHP) [128, 129] to analyze each condition under the prism of possible responses and failure states. Analytical methods are rather complicated, especially if large transportation networks' resilience is investigated. The complexity of analytical methods in the case of large transportation networks lies on the existence of various scenarios and decision-making options that can take place when large transport networks operation is disrupted.

Data-driven methods are increasingly pivotal in evaluating the resilience of transportation networks, especially in the context of dynamic, large-scale disruptions such as natural disasters, accidents, or system failures. Unlike model-driven simulation frameworks, data-driven methods do not simulate internal system mechanisms directly. Instead, they focus on analyzing historical or real-time performance metrics derived from empirical observations. This allows for the assessment of system behavior under varied disruption scenarios, offering powerful insights into resilience without requiring detailed physics-based modeling [130].

In the research of [131], a hybrid framework combining clustering algorithms and transformer neural networks to recognize network traffic states from large-scale AVI (Automatic Vehicle Identification) and sensor data is developed. The approach quantifies operational resilience by identifying the transition points between normal and disrupted traffic states, enabling real-time network management. Key performance metrics, including speed variance and trajectory entropy, are automatically extracted and classified to produce adaptive resilience indicators suited to incident response and urban mobility planning.

In [132], a Machine Learning-based assessment framework for the resilience of urban road networks during rain-induced disruptions is presented. By integrating large time-series datasets (traffic speed, flow, network connectivity) with neural predictive models, the authors forecast network degradation and recovery time. Their results demonstrate improved early warning accuracy and refined quantification of resilience through dynamic data analysis, providing actionable intelligence for traffic operators under adverse weather.

Additionally, the research of [133] proposes an empirical, data-driven workflow for dynamic resilience assessment, calibrating iterative traffic assignment models with observed flow and speed data. Researchers quantify resilience by simulating various network disruption scenarios (road closures, accidents), tracking volume-delay functions and recovery timelines. The validated framework enables urban planners to assess response strategies and prioritize infrastructure investments using real-world data.

Furthermore, in [87] a deep reinforcement learning framework is utilized for traffic signal controls optimization and analysis of daily urban traffic dynamics from the perspective of resilience. Simulation experiments with convolutional neural networks reveal that adaptive controls improve throughput and reduce disruption recovery periods. The data-driven framework enhances the theoretical understanding of urban road network responses to sudden failures.

Finally, the research of [134] leverages anonymized crowdsourced traffic data from smartphones and vehicles to estimate network resilience at the community scale. By mapping travel delay, incident frequency, and adaptive route choices, the authors build resilience indices that facilitate rapid vulnerability assessment and guide targeted improvement strategies for urban planners.

3.3 Simulation Methods

Simulation methods are instrumental in assessing and enhancing the resilience of urban road networks. The complexity and dynamic nature of urban traffic flow, coupled with the potential for diverse disruptions, necessitate sophisticated simulation tools. Simulation approaches offer powerful means to evaluate how transportation systems perform under stress, enabling scenario testing, strategy validation, and risk-informed decision-making. These methods go beyond simple analytical assessments by modeling the temporal and spatial dynamics of disruptions. Therefore, opposingly to analytical methods, simulation methods for resilience analysis on large transportation networks go beyond simple calculations, building upon diverse mathematical fields like graph theory [79, 135, 136], game theory [19, 137], fuzzy logic [48, 89, 138–140], and optimization [27–29, 33, 141, 110, 55, 111, 119, 142, 143, 120, 144], and incorporating broader strategic approaches such as scenario analysis [18, 27, 107, 145, 146]. Table 5 below presents a comprehensive overview of the latter.

Table 5. Approaches utilized in simulation-based resilience analysis

Approach	Key feature	Applications	Key references
Scenario Analysis	Explores multiple what-if scenarios	Disaster planning, network stress-testing, proactive planning by evaluating network performance under hypothetical disruption scenarios	[21, 27, 47, 147]
Graph-Theoretical	Connectivity, redundancy, and critical node/link detection	Node/link failure analysis	[17, 135]
Game-Theoretic	Agent interactions and competition for network resources	Traffic behavior modeling, response dynamics	[19, 33]
Fuzzy Logic	Incorporates linguistic and vague data (e.g., qualitative terms like 'high risk', moderate congestion') through membership functions	Human behavior in emergencies; risk and uncertainty modeling	[138, 148]
Probabilistic Models	Simulates stochastic failure and system degradation scenarios	Seismic/flood impact modeling	[149]
Optimization	Identifies best interventions, routing, and recovery schemes	TMS design, resilience planning	[119, 142, 150]

Simulation models allow for the identification of both vulnerable components of the transportation networks and optimal TMS [147]. Simulation models can be a valuable tool for examining the resilience of transportation networks, considering the capabilities such methods and models have, as well as the latest technological advances (e.g., quantum computing) which allows for short computational times when large transportation networks are under examination [33, 151].

Additionally, in [77] a link-based approach to two transportation networks under two disruption strategies have been used, and, thus, global efficiency and relative size of giant component metric have been introduced. [152] implemented a new resilience metric, which considered the characteristics of network efficiency and displaced population under a disruptive event has been introduced.

Concerning the scope of the simulation analysis, and by having in mind the complementary roles of the simulation paradigms and the high degree of heterogeneity in urban transportation systems (including diverse vehicle types, varying driver behaviors, and complex traffic patterns), the integration of different model types (microscopic, mesoscopic, macroscopic, and agent-based) is advised since that offers a flexible modeling environment that can adapt to both detailed operational studies and strategic planning tasks [153]. Agent-based models (ABMs) and microscopic simulation models are particularly well-suited for this purpose [154–156]. Agent-based modeling further enhances hybrid methodologies by simulating individual user behaviors and interactions, providing deeper insights into behavioral responses, evacuation dynamics, and adaptive user behavior during disruptions [157, 158].

Particular attention should be paid to Macroscopic Fundamental Diagrams (MFDs), which serve as a macroscopic representation of traffic performance at the network level. Inspired by the foundations of Wardrop [159], where a generic relation between average speed and flow has been proposed, various research like [118, 160–165] are focused on MFDs and their existence in various networks and under various conditions. MFDs show the relationship between vehicle density and flow at an aggregate level and provide an intuitive way to evaluate both steady-state and dynamic behaviors of traffic systems during disruptions. The area between the baseline and disrupted MFD curves-termed throughput loss-serves as a robust metric of resilience degradation, as shown in [166].

Interestingly, there are few research attempts on the possibility to utilize MFDs towards evaluating the resilience of urban road networks. [167] made use of MFDs to assess the criticality of network links by proposing a network performance loss indicator. However, this research is limited to link-level disruptions for assessing the criticality, following the traditional path for criticality quantification [16, 78]. In the research of [168] the use of MFDs is associated with a resilience-oriented perimeter control methodology in a two-region network. This research is limited in the sense that a two-region network is used and the shape of MFDs is considered parabolic. This is also mentioned by the authors; there is the need for a multi-region network, which is closer to real-life networks, to be taken into consideration. In [169] MFDs are used to identify the most critical links of the network, however no statistically significant correlation was found, since analyses are based on non-realistic networks (e.g. Sioux-Falls, Anaheim, Tiergarten, Berlin, and Chicago). Another drawback of the methodology used in [169], as mentioned also by the authors, is the fact that the flow-density MFD is utilized, departing from the use of other travel disutility attributes, such as trip completion rate. Finally, in [170] MFDs-based resilience indicators are proposed and a regression model to describe the relationship between topological attributes of transportation networks and the traffic resilience of transportation systems is introduced.

Moreover, simulation outputs such as vehicle trajectories, average speeds, or density distributions can be used to generate real-time MFDs within Digital Twin frameworks, which support dynamic and adaptive resilience evaluation [171, 172].

Advanced simulation techniques for urban resilience include balancing model types. While microscopic and agent-based models receive significant attention due to their ability to represent heterogeneity, it's essential to acknowledge the role of macroscopic and mesoscopic models. Macroscopic models, as shown in [173], are particularly useful for large-scale network resilience analysis, offering a computationally efficient way to assess the impact of disruptions on overall network performance. Mesoscopic models, as outlined in [174], bridge the gap between microscopic and macroscopic simulation, allowing for a balance between detail and computational efficiency.

3.4 Hybrid Methods

As illustrated in Fig. 2, hybrid methods for resilience quantification are utilized as a superset which combines topological, analytical and statistical, and simulation methods for providing multifaceted resilience quantification.

In terms of relevant literature, [175] proposes a hybrid method combining network performance modeling with resilience assessment under flood disaster scenarios, integrating simulation-based degradation, recovery, and structural vulnerability analysis. [176] develops a hybrid simulation framework combining agent-based and system dynamics approaches for urban risk mitigation and resilience evaluation, capturing both traveler behavior and network effects. [177] integrates topological, functional, and human flow vulnerabilities in a hybrid framework assessing urban road network resilience to climate change impacts, leveraging multiple data and modeling techniques. [16] present a hybrid framework using topological analysis, simulation, and machine learning for urban road network criticality and vulnerability identification.

Interestingly, the relevant literature provided is mostly focused on combining simulation models with other tools and techniques to properly quantify resilience. To this end, the potential of simulation models to be used as the backbone of hybrid methodologies for resilience analysis if further discussed. At first, the integration of GIS and big data analytics, with simulation methods, enables detailed spatial-temporal analyses of network vulnerabilities, facilitating accurate urban vulnerability mapping and real-time incident detection [178, 179].

Furthermore, simulation models can be integrated with real-time traffic management systems to evaluate the effectiveness of adaptive control strategies. This allows for the assessment of how traffic signals, ramp metering, and other control measures can be adjusted to mitigate the impact of disruptions [166, 173].

Considering disruptions, including traffic incidents, extreme weather events, and infrastructure failures, simulation models can be used to simulate these disruptions and assess their impact on traffic flow, travel time, and network accessibility [180, 181]. They also allow for evaluation of various resilience strategies, such as alternative routing [122], dynamic signal control [182], emergency response planning [29], and deployment of Connected, Cooperative, and Automated Mobility (CCAM) technologies [183, 184]. To evaluate these strategies, resilience metrics are required. These include efficiency (inverse average path length), giant component size (extent of connectivity), and travel time variance under stress. Other indicators include recovery time, accessibility loss, and the resilience triangle, which integrates performance degradation and recovery across time. Recent advances also include composite indices like mD-Resilience, which incorporates spatial, temporal, and equity factors [21, 127].

Additionally, data-driven simulation (a combination of data driven and simulation methods) is becoming increasingly important. Techniques such as machine learning and data assimilation can be used to calibrate and validate simulation models and also predict traffic conditions during disruptions. [185] demonstrate how GPS data can be used to characterize traffic flow, and this data can then be used to train machine learning models to improve simulation accuracy. Furthermore, social media data can be used to provide real-time information on disruptions [186]. [187] makes use of a theoretical model supported by Python-based simulations and multifaceted data (traffic flows, network topologies, infrastructure attributes). Said research evaluates resilience across interconnected urban transport and utility networks. The adaptive analysis captures complex interdependencies, enabling quantification of cascading failures and recovery in smart city environments. [188] adopts temporal network analysis and simulation-based traffic modeling to measure urban mobility resilience under various scenarios. The methodology leverages big data (observed network data and travel demand) to simulate flows, capture critical bottlenecks, and derive response indices. Findings reveal which areas of the network are most vulnerable, supporting smarter investment and maintenance strategies for city infrastructure.

Additionally, Digital Twins, which are digital replicas of real-world transportation networks, offer a powerful tool for resilience analysis. These frameworks integrate real-time data from sensors, connected vehicles, GPS, and control centers to simulate and adapt system responses on the fly [189]. Within resilience planning, digital twins are invaluable tools for evaluating disruption scenarios, managing adaptive responses, and optimizing recovery efforts.

4 Data Sources for Resilience Analysis and Quantification

Reliable and diverse data sources are foundational to urban road network resilience research. Data-driven resilience analyses significantly enhance understanding of network performance, environmental stressors, and predictive modeling for disruptions. The rapid advancement of artificial intelligence (AI), Internet of Things (IoT) sensors, and remote sensing technologies has substantially improved the precision and effectiveness of resilience studies [190–193]. Essential data for resilience analyses generally falls into three categories: i. Traffic flow and congestion data, ii. Infrastructure and environmental hazard data and iii. Socioeconomic and behavioral data.

Table 6 outlines key data sources for traffic operations, infrastructure and environmental hazard data, and socioeconomic and behavioral data, highlighting specific methodologies and their practical applications in resilience assessments. Each source provides unique insights into network performance, critical for timely and accurate resilience modeling and planning. It is worth noting that integrating machine learning techniques with these data enhances real-time predictive accuracy, supporting dynamic resilience assessments and proactive traffic management. Advanced sensor technologies, such as loop detectors, video cameras, and LiDAR, provide high-quality, detailed traffic data critical for resilience modeling [194]. However, limitations such as data quality variations, maintenance costs, and limited coverage necessitate complementary approaches, including crowdsourced data integration.

Accurate infrastructure and environmental hazard data provide insights into vulnerability and potential disruption severity. Key data sources include asset condition surveys, remote sensing imagery, and climate hazard assessments [103, 195]. Table 6 summarizes infrastructure and environmental data sources, describing their specific characteristics and highlighting their utility in identifying vulnerabilities and informing resilience planning and emergency preparedness strategies. While increasingly available, these data may still face challenges related to availability, resolution, interpretation complexity, and data handling capacity [195].

Socioeconomic and behavioral data are critical for understanding travel demand shifts, risk perception, and public responses to disruptions. Data collected through surveys, mobile analytics, and social media platforms contribute to comprehensive resilience modeling [196]. Table 6 highlights each source's strengths in capturing diverse aspects of human responses and behavior, essential for accurate and realistic modeling of resilience and crisis management strategies. Integrating socioeconomic data ensures resilience models accurately reflect human behavior, enhancing their real-world relevance and effectiveness. Nonetheless, inherent biases, privacy concerns, and inconsistencies pose significant challenges to data collection, necessitating robust privacy-preserving methods and representative sampling strategies [197].

Table 6. Requirements for data availability for resilience research

Data source	Description	Applications
Traffic Operations		
Roadside sensors	Fixed-location monitoring of traffic flows	Congestion measurement, network performance
GPS, trajectories, and telematics	Vehicle movement and positioning data	Real-time traffic assessment, route optimization
Crowdsourced platforms	User-generated traffic incident reports	Immediate detection of disruptions, incident management
Infrastructure and Environment		
Asset surveys	Physical inspections of transport assets	Infrastructure resilience, maintenance planning
Remote sensing imagery	Satellite and aerial imagery	Disaster impact assessments, vulnerability mapping
Climate hazard models	Projections of weather-related risks	Climate adaptation strategies, emergency preparedness
Society, Economy and Behavior		
Travel surveys	Detailed travel patterns and mode choices	Modal shift analysis, evacuation modeling
Mobile phone analytics	Movement patterns and network usage behaviors	Real-time demand modeling, behavioral trends
Social media analysis	Public sentiment and rapid incident reporting	Crisis response optimization, communication strategies

5 Open Questions

5.1 Data, Methodologies and Methods to Support Network level Resilience Analysis

Despite significant advancements in integrating diverse data sources, challenges persist, particularly data scarcity in developing regions and urban contexts often overlooked in research. Limited availability and quality of high-resolution traffic and infrastructure data impede accurate modeling and robust resilience assessments [198, 199]. Emerging solutions, such as blockchain-based data sharing platforms and advanced IoT deployments, offer promising avenues to overcome these challenges, promoting transparency, security, and accessibility of the aforementioned data [200, 201]. International collaboration and public-private partnerships further enhance the breadth and depth of available data, creating extensive opportunities for resilience research advancements.

A general outcome of the literature review is that simulation remains the most importance tool for quantifying and assessing resilience in large scale transport applications. However, the accuracy and reliability of simulation models depend heavily on the availability of high-quality data. Data from loop detectors, GPS devices, video feeds, and even social media can be used to calibrate and validate models. [185] demonstrated how GPS probe data can accurately reconstruct real-time traffic conditions, while [181] applied simulation-based optimization using such real-world data to tune control strategies effectively. Hybrid modeling forms, jointly considering big data analytics, machine learning and simulation, may transform simulation tools into decision-support systems that inform both long-term infrastructure investment and short-term emergency management.

Despite the extensive adoption of simulation methods in resilience studies, several key challenges hinder their effectiveness and generalizability. First, model complexity and computational cost remain significant barriers, particularly when simulating large-scale urban networks with microscopic or agent-based models. These high-resolution models demand substantial computational power and time, making real-time scenario testing or multi-scenario comparisons difficult to scale [202, 203].

Another major challenge is the calibration and validation of simulation models. Accurate input data-such as traffic volumes, signal timings, driver behavior parameters, and disruption characteristics-are often incomplete or unavailable, especially in developing urban areas. The fidelity of simulation outcomes depends heavily on this data, and any discrepancy can propagate errors in resilience estimation [173, 185].

Simulation models also face difficulties in representing human behavioral responses during crises, such as panic-induced route choices or adaptive learning over time. Traditional traffic models often rely on equilibrium assumptions that do not hold under disruptive, highly dynamic conditions. Incorporating realistic behavioral heterogeneity remains an open research challenge [204, 205].

From a methodological standpoint, the lack of standardized resilience metrics within simulation environments complicates comparative evaluation. While concepts like travel time reliability, connectivity loss, and the resilience triangle are commonly used, their implementation varies widely across studies, hindering reproducibility and benchmarking [21].

Looking ahead, several research directions merit attention:

- Hybrid simulation architectures that combine agent-based, mesoscopic, and macroscopic components could offer scalable and behaviorally realistic frameworks for resilience testing
- Dynamic integration with real-time data feeds can transform simulations into responsive, adaptive tools, especially within Digital Twin systems

- AI-assisted model tuning, using reinforcement learning or genetic algorithms, could automate calibration and enhance predictive capability across disruption types
- Cross-domain interoperability with infrastructure, energy, and communication systems can provide a holistic view of urban resilience

In summary, while simulation remains a cornerstone of resilience analysis in transportation networks, evolving these tools toward higher realism, flexibility, and interoperability is essential for addressing the increasing complexity and uncertainty of urban systems.

5.2 Resilience as an integral part of Traffic Management

Traffic Management is considered important for the operation of transport networks, mostly in urban settings. Traffic Management, and the associated Strategies, allow for optimizing traffic flows or achieving more complex objectives like the cooperation between different areas of the network for optimizing the performance of the system. The current Traffic Management Strategies consist of four (4) main objectives: i. to reduce inflow in a certain area, ii. to increase outflow for a certain area, iii. to inform drivers about a situation, and iv. to reroute the flow. The choice of the necessary actions in each case is driven through the quantification of Key Performance Indicators (KPIs).

However, to what extent current Traffic Management Strategies integrate the concept of resilience in both their design and implementation? For this research question to be answered, the following need to be taken into consideration. At first, the quantification of resilience needs to be further clarified. At its current state, resilience consists of various metrics/ layers which reflect resilience under one specific perspective. However, there is the need for a generic and unified resilience metric. This metric should reflect the resilience of a network by incorporating in its definition and quantification a variety of the already-existed resilience related layers/ metrics. The latter may pose a significant modelling limitation, due to fact that the already existing resilience related layers/ metrics may examine different aspects of resilience which may not be directly correlated. In [88, 206], a Multi Criteria Analysis methodology for ranking of all resilience related layers/ metrics is proposed, with the aim to propose a resilience metric for assessing the overall resilience of a network through incorporating the resilience assessment frameworks of the critical infrastructures of the network. This process would allow for comparability of various resilience assessment methods by identifying conversion coefficients.

Another aspect that can be deemed as important is that of multimodality. Multimodality is a key aspect of future transportation scenarios, not only in its current form but in a broader concept which will include various new concepts such as Mobility as a Service and demand-responsive transport. Multimodality is included in the literature of resilience. As an example, [38, 111, 207] analyze resilience considering active modes and mode transfer. However, from a modelling perspective, the inclusion of multimodality in the concept of resilience increases the complexity of its quantification and thus its incorporation in Traffic Management Strategies. In order for multimodality to be sufficiently integrated in the concept of resilience, network complexity theory and multiplex technologies should be recruited. Current resilience-related layers/ metrics, mostly those associated with the topological features of the network, need to be revised. The revision is not necessarily in the change of the mathematical features that governs the topological metrics, but in the existing approach towards their examination.

Lastly, the concept of resilience that needs to be integrated in Traffic Management Strategies shall have a holistic approach. For that holistic approach to be achieved, the concept of resilience needs to be disengaged from EWEs. Most of the literature investigates resilience under the point-of-view of an extreme event; what if the event is not associated to a weather event but to a disturbance in general? The significance of such a differentiation in the approach of resilience is twofold. At first, the extent of the resilience-related layers/ metrics will not be geographically fenced in a certain area of interest (e.g., the area that an EWE took place), but they will be broader and thus able to examine larger areas. Then, if the concept of resilience departs from its conventional definitions and applications, the associated metrics and concepts will be future proofed in the sense that literature demonstrates the need for resilience in the era of smart cities. In the smart city context, resilience is vital, since intelligent systems are vulnerable to possible threats, such as jamming attacks, flooding attacks, and malware attacks [208] and, thus, such disturbances need to be integrated in the concept of resilience. It is important to note that the aforementioned do not appear to have an impact in the already-existing methods for quantifying resilience; the changes that need to be made can be characterized as conceptual.

5.3 Case-oriented vs case-agnostic resilience

The majority of previous research concerning resilience is characterized by having a case-oriented approach. Resilience of a transportation network used to be examined under a specific disturbance by using data representative of the state of the networks under the disturbance of interest. This, however, does not conform with the opinion that resilience needs to be generic and representative of the network and its structural components. For that reason, the concept of case-agnostic resilience should be introduced. At this point, a crucial question can be set: what is the difference of resilience under one scenario versus the general resilience of a transportation network? Resilience should be representative of the dynamics in the network like congestion, saturation of flow, and travel times. The traffic dynamics alter in the network based on the circumstances (e.g., peak hour or not, extreme event or not) and may differentiate among subareas of a network. Therefore, case-oriented resilience is representative of the state of the network under the impacts of a certain disturbance, while, on the other hand, case-agnostic resilience is representative of the state of the network under its occasional operation. But, what is most fitted type of resilience? Interestingly, both types of resilience are of importance.

What needs to be further clarified is the context under which resilience needs to be examined. From a Disaster Management and Emergency Logistics perspective, case-oriented resilience is important because specific disruptive events and their impacts are the primary concern. Explainability is critical here as well, enabling stakeholders to interpret the reasoning behind chosen response strategies, resource allocation, and lessons learned in the aftermath of disturbances. From a Traffic Management perspective, emphasis is placed on case-agnostic resilience, as ongoing changes in traffic dynamics are of interest. In this context, the operational performance of the network, its degradation over time due to any disturbance, and the implementation of appropriate Traffic Management Strategies to maintain functional levels are key objectives. Across both paradigms, the capacity to explain, justify, and communicate decisions enhances trust, supports transparent management, and ensures actionable insight for both acute events and routine operations. Thus, explainability forms a cornerstone of both case-oriented and case-agnostic resilience, integral to translating technical findings into effective action and policy.

Furthermore, in the context of investigating resilience, it is crucial to select the appropriate metrics that align with the specific research objectives and findings. For case-oriented resilience and given the fact that it is needed in the Disaster Management and Emergency Logistics topics, metrics such as resourcefulness, rapidity, preparedness, and recoverability can be deemed as important. On the other hand, metrics able to capture the dynamics of the network should be selected like criticality, efficiency, and vulnerability.

Concerning the Traffic Management perspective, the belief that the complexity of transportation applications, as well as the variability in conditions that may affect the resilience of transport system poses additional challenges to the quest of a universal resilience metric that cannot be tackled by linear or rank based approaches (such as the approach introduced in [88, 206]). A universal transport resilience metric should be disengaged from the type of application by allowing for complementary aspects of resilience to be taken into consideration. Methodologically, for such a universal metric to be introduced, a data-driven unsupervised framework should be considered. Said framework will depart from the classical definitions of resilience and will incorporate the investigation of various resilience-related metrics, in the strategic and the operational level, and by considering the technological advancements in the field of transportation.

6 Conclusions

Resilience emerges as an integral component in the management and strategic planning of transportation networks, particularly within the context of rapidly evolving urban systems and the development of smart cities. The literature review and synthesis presented illustrates the transition of resilience from its conventional, unidimensional definitions to multifaceted frameworks encompassing infrastructure durability, operational adaptability, and behavioral responses across a broad spectrum of disturbances ranging from extreme weather events to cyber-physical threats.

Interestingly, resilience quantification remains fragmented due to methodological heterogeneity and the lack of universally accepted metrics. Prevailing approaches in the literature comprise both qualitative and quantitative modes, with simulation-based methods gradually acquiring prominence owing to their capacity to model dynamic traffic scenarios and complex disturbance environments. The integration of advanced simulation paradigms, data-driven models, and real-time analytics has significantly contributed to the comprehensive evaluation of network robustness and adaptability.

A key observation is that the reliability and representativeness of resilience assessment are heavily dependent on data availability and methodological standardization. Challenges persist concerning the diversity and scarcity of high-resolution data streams, the absence of unified resilience metrics, and computational limitations, particularly for large-scale urban networks. These factors underscore the necessity for further methodological innovation and broad integration of emerging analytical frameworks.

From a forward-looking perspective, the research advocates for holistic and case-agnostic models which advance beyond event-specific analysis to encompass generic frameworks for traffic dynamics and system vulnerabilities in both typical and exceptional operational conditions. The inclusion of multimodal transport concepts and emerging paradigms such as Mobility as a Service necessitates the revision of conventional metrics and modeling approaches, leveraging network complexity theory and multiplex analysis. It is essential that resilience becomes a foundational principle within future urban transport strategy, traffic management, infrastructure investment, and emergency preparedness programs.

In conclusion, resilient transportation networks must be evaluated, planned, and upgraded through multidisciplinary approaches, robust data integration, and evolving assessment frameworks capable of addressing the complexity and uncertainty characterizing smart, interconnected urban environments.

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