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A New Approach to Assessing Transport Network Resilience

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Abstract: External events, as well as internal traffic flow conditions, can impact the performance of one or more infrastructure elements of a transportation network, potentially affecting the resilience of the system. This paper proposes an innovative approach to integrate key aspects of land use and infrastructure into the supply model of the road transportation system. Specifically, the concept of "augmented link" is introduced, which aims to include exogenous characteristics (e.g., referring to land use and/or infrastructure) into the transportation network model to assess network resilience and ensure optimal network performance, even under emergency conditions. The objective is to identify links that are most likely to experience critical failures within the road network by considering both external events and traffic flows affecting each link. The proposed approach was applied to a simulated test case. The obtained results are encouraging and showed the great potential of the proposed approach to identify a *priori* reliable routes under emergency conditions.

Keywords: augmented link; traffic flow; transport networks; transport resilience; urban planning

1. Introduction

Transportation systems are inherently complex and interact in a bi-directional way with the surrounding territorial systems, such as land use patterns. Specifically, transportation infrastructures—roads, bridges, and railways—are often situated within environments that include buildings, rivers, and natural features like hills. In urban areas, extreme events such as earthquakes can cause building collapses that damage nearby transportation infrastructure (e.g., roads, intersections, terminals). These damages can lead to network disruptions, as transportation links or nodes fail, severely limiting mobility in the affected area [1]. Similarly, events like river flooding or landslides can cause infrastructure failures, reducing or even halting transportation performance, further impeding mobility [2]. In all these scenarios, it is essential to design transportation networks that are resilient, ensuring continued connectivity between key locations within the impacted area.

Although the relationships between transport networks and territorial systems are not unknown to transportation and structural engineers, quantitative approaches for including relevant aspects of the territorial system into the transportation network have not yet been explored.

The goal of this paper is to propose a novel approach for including relevant aspects of both land use and transport infrastructure into the supply model of the transportation system in order to identify the risk failure of links in a given transportation network due to external events. This is relevant for assessing network resilience and guaranteeing good network performance in case of emergency conditions. In detail, this study introduces the

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concept of "augmented link", which aims to explicitly model the impacts of land use and infrastructure characteristics within the transportation network model. An "augmented link" is defined by its geometric and functional characteristics (endogenous features), along with land use and territorial attributes (exogenous variables) that refer to the link-surrounding areas. Additionally, the concept may incorporate infrastructure performance, which is influenced by the traffic levels utilizing the link in terms of resistance, fatigue damage, and failure [3–5].

Therefore, this paper proposes a novel framework for modeling transportation networks based on augmented links, which has a twofold goal:

1. identifying critical links based on both land use and transport infrastructure features in order to assess the network performances in case of disruptive events, both internal and external;
2. identifying paths for linking relevant origin/destination points with the lowest number of critical links, which is crucial in case of emergency conditions.

To test the potentialities of the proposed approach, a test case that is fully coherent with real-world cases has been simulated. Specifically, the considered external events refer to flooding cases, and the exogenous factors included in the link properties refer to territorial features.

In the following, Section 2 provides an overview of the related literature, mainly focused on transportation network resilience. Section 3 describes the extended transport supply model, which includes land use and infrastructure features. Section 4 reports a simulated test case, which is intended to explore the potentialities of the proposed approach. Finally, Section 5 discusses the obtained results, and some main conclusions are drawn together with further developments.

2. Related Work

Transportation networks can be described as integrated systems where infrastructure, vehicles, and services mutually interact to enable and facilitate the movement of people and goods from an origin to a destination.

The concept of infrastructure resilience is relatively new due to the growing prevalence of unpredictable stresses caused by climate change. As a result, the literature on transportation network resilience is relatively new and limited [6]. In such complex systems, the failure or disruption of one or more network elements may have important effects on the network operational conditions, leading to severe disruptions in extreme cases. To describe the ability of the system to resist, adapt to, and recover from disruptions or adverse conditions—both within and outside the system itself—the concept of resilience has been defined.

Generally speaking, a resilient transportation system can sustain essential operations or quickly return to acceptable performance levels following a disruptive event, such as infrastructure failure, natural disasters, or accidents, among others [7,8]. According to Wan et al. [9], although there are different definitions of resilience and various characteristics are used to describe resilience properties, four key points may summarize this concept: (i) resilience refers to an inherent ability in a system or network or a function that measures its performance against disturbances; (ii) the concept of resilience is commonly used to evaluate system performance under abnormal conditions caused by disruptions; (iii) various terms (e.g., resist, absorb, maintain) describe the performance of a disrupted system; and (iv) resilience is the ability to maintain stability or transition from one equilibrium state to another.

Significant issues can occur when transport network elements, like roads, bridges, or tunnels, are disrupted by unexpected events, resulting in failure to meet expected performance levels such as travel time, crash risk, and service quality. In these situations, the network topology, along with land use and population density, plays a key role in determining the impact [10]. Network topology has received great attention, and many studies have discussed how network topology, such as grid and hub-and-spoke, impact transportation network resilience to disruptions. These studies included implications for both disaster preparedness and recovery strategies, revealing that redundancies in the network would increase the resilience level [10]. In other words, less-redundant connections lead to networks that are more vulnerable and less resilient to disaster. In detail, well-connected networks with more alternative paths tend to be more resilient than those with simpler or less-interconnected topologies, as they can diversify flows and reduce the impact of a single failure. An improved network structure promises greater resilience, regardless of changes in demand [11]. In addition, networks with redundant paths (i.e., alternate paths for traffic) are more robust [12]. Redundancy makes it possible to compensate for the loss of a node or arc, improving resilience and reducing service interruption time. Route diversity and spare capacity dimensions have been used together to provide an integrative measure for the selection of redundancy enhancement schemes, with the final aim to identify critical links [13]. As for this latter point, transport network resilience depends on network-critical elements, which are those whose loss has the greatest impact on the system [14–16]. Critical links may be identified by using variables such as travel demand, travel time, and network flow [17]. Furthermore, the criticality rankings of individual links have also been identified based on failure scenarios by using the distribution of criticality scores for each link, which in turn is based on traffic assignment for each failure scenario [18].

Network resilience can be evaluated based on various indicators, such as recovery time, adaptive capacity, and efficiency of alternative paths. However, the minimum amount of local topological information that each node must possess in order to guarantee the self-healing of the network when nodes fail with a given probability is one of the most interesting options for assessing network resilience. The knowledge of the neighbor topology of each node in the network within a minimum distance or number of hops is of utmost importance to ensure the full recovery of the network [19]. Finally, there is a trade-off between robustness and efficiency. While a highly resilient network may have a higher cost in terms of design and management, a network over-optimized for efficiency may be vulnerable to disruptions [20].

A topology optimization plan for a case study has also been proposed [21], which develops optimal recovery sequences for various failure scenarios, emphasizing that recovery should prioritize node vulnerability over degree. The findings highlight that while post-failure recovery is important, pre-failure topology optimization is more critical for enhancing resilience.

The relationships between resilience, sustainability, and key resilience-related principles and criteria were studied in [22], which provided a comprehensive set of criteria from the literature on resilience and urban sustainability. These form the basis for a conceptual framework that categorizes resilience criteria into environmental, economic, social, and institutional dimensions, with specific sub-criteria addressing areas such as land use, infrastructure, and health. Based on the concept that urban resilience based on a single system is insufficient, as cities are complex, interconnected systems involving economy, society, environment, and technology, swarm optimization algorithms have been used to enhance a back-propagation neural network for evaluating resilience—also towards natural disasters—across different subsystems (e.g., economy, society, environment, and science and technology) in order to guide better policy development strategies.

While the resilience of individual transportation systems has been well assessed, interactions between multiple systems can affect the accuracy of these assessments due to increased complexity and interconnection. Passengers are typically distributed across interconnected network structures, which are geographically interdependent. When one mode is disrupted, others can offer alternative options to accommodate delayed passengers. Recent research on urban transportation has focused on disruption management in systems concerning metro networks and bus services [23–25], while some other research has focused on the analysis of extra-urban intermodal transport networks under disrupted conditions [26–28].

Focusing on integrating complex urban systems to better identify critical nodes in urban-directed networks, an analysis based on 26 cities in the Yangtze River Delta Urban Agglomeration has led to the definition of an evaluation index system for urban resilience, covering pre-absorption, in-process adaptation, and post-recovery abilities for public health emergencies [29]. Meanwhile, in [30], a large number of random network structures was generated, and their corresponding resilience values were computed to assesses the impact of topological structure on resilience under different scenarios. Similarly, a framework for the comparative assessment of resilience in transportation systems was proposed in [31].

Other studies have explored the performance of critical network elements under various degrading conditions [32,33]. For example, when transport infrastructure fails due to external events, traffic flow will vary significantly on the affected links [34], and the local economic system may be also affected to varying degrees, the severity of which depends on the significance of the failure [35].

To summarize, external events as well as internal traffic flow conditions could impact on the performances of one or more infrastructural elements of the transportation network, which might have effects on transportation system resilience.

Although there is increasing literature dealing with transportation network resilience, as it emerges from the above review, most studies are based on simulation scenarios for identifying critical elements and measuring the resilience under several conditions. Particularly, the assessment of the network resilience is often obtained via the removal/degradation of one or more links, changing link features (e.g., reducing capacity, closing link, reducing lane width) and checking the consequences [18].

For a given transportation network, link features are usually modeled as dependent on endogenous (with respect to the transportation system) infrastructure and service features. In detail, link geometry (e.g., length, width, slope) refers to infrastructure features, while link performances (e.g., running time, waiting time at intersections or at bus stops, boarding time) refer to service characteristics [36]. Generally, infrastructure and service features are not independent; for example, link length or pavement conditions affect the link performance in terms of travel time, while curves affect safety [37]. Similarly, the type of intersection (controlled or uncontrolled) impacts waiting times [38].

However, link performances are also influenced by exogenous variables such as land use and spatial characteristics. As an example, rivers close to roads may cause infrastructure disruption in the event of flooding. Similarly, buildings along urban roads may render them unusable if they collapse during an earthquake. Therefore, exogenous and endogenous factors affect link features and network resilience, which is crucial, particularly in the case of extreme events such as earthquakes or flooding, when mobility and connections must be guaranteed for ensuring emergency services. To the authors' knowledge, the exogenous characteristics of network elements, particularly links, have not yet been embedded in the transport network properties.

Based on these considerations, this study proposes a new approach that allows for the identification of critical links with respect to both endogenous and exogenous features. More in detail, critical links in the supply transportation system are identified based on three criteria, *importance*, *relevance*, and *exposure*, which are defined for each link depending on both endogenous and exogenous features. As known, disruptions affecting critical links are crucial, as they might limit connections in the considered area. The introduction of endogenous and exogenous link features has two main advantages: *1*) it allows for the identification of critical links *a priori* by also considering the effects of exogenous features; *2*) it allows for the identification of, again *a priori*, alternative paths for ensuring connections, mainly for emergency services, in the event of adverse occurrences. Again, to the authors' knowledge, there are no similar approaches in the literature for identifying what was described in the two previous points *1*) and *2*).

In the following section, after a brief summary of network transportation models based on graph theory, the concept of augmented link and its implications are described.

3. Materials and Methods

A transport supply model represents the technical, infrastructural, and organizational characteristics of a transport system and simulates transport network performances depending on the link traffic flows that result from travel demand. As is better specified in the following sub-sections, a supply model is essentially composed of a graph, representing the topology of the connections allowed by the considered transport system, and the cost/performance functions associated with each link of the graph, which depend on the physical and functional link characteristics as well as the link traffic flows. Each link is then characterized by a quantitative feature (i.e., the link cost), which allows for the identification of paths between origin/destination points in the considered area based on the minimum cost criterion.

In the usual approach, the link cost functions depend only on the endogenous characteristics of the link itself. This standard model has been extended by including exogenous characteristics in the link cost functions in order to consider implicitly the effects of changes in the external system (like flooding or earthquakes) on the performance of the transport network. The proposed extension of the supply model (described in Section 3.2) enriches the characterization of each link in the network by combining endogenous characteristics (mainly expressed in terms of time and monetary cost) and relevant exogenous characteristics, such as settlement density, link structural resistance, and proximity to watercourses. Such link, defined by both endogenous and exogenous features, has been named "augmented link".

In the following, after a brief summary of the usual supply transport model (Section 3.1), the augmented link concept is introduced (Section 3.2) for a road transport system.

3.1. Transport Supply Modeling: A Short Overview

Let T be a road transportation network, defined by the set of nodes, links, and link travel costs as follows:

$$T = (N, L, TC)$$

where:

$N = \{i\}$, with $\;i = 1, \cdots, m$

$L = \{(i, j) : i, j \in N$, with $\;(i, j) \neq (j, i)\}$

$TC = \{c_{i,j} \;\; \forall (i, j) \in L\}$

N is the set of nodes i, where m is the number of nodes in N, and each node represents a travel activity (e.g., a junction or a transport terminal); L is the set of links connecting node i and node j if a relationship exists among them (e.g., a road linking two junctions; a transport line linking two terminals); and $c_{i,j}$ is the link travel cost defined for each link (i, j) belonging to L. The link cost reflects the average disutility experienced by users when performing the activity associated with the link [36]. In the following, link (i, j) will be simply referred to as link l unless the extended notation is needed for clarity. For each node

$i \in N$, let FS_i be its forward star, i.e., the set of final nodes of links exiting i, and let BS_i be its backward star, i.e., the set of first nodes of links entering i [39].

Link costs can be expressed as a function of several performance variables associated with the link, e.g., travel time, monetary costs, discomfort, safety. Typical expressions are linear additive functions such as the following:

$$c_l = \sum_{k=1,\cdots,n_r} \beta_k \cdot p_{l,k} \tag{1}$$

where n_r is the number of performance variables, β_k are parameters weighting the different components $p_{l,k}$, and $p_{l,k}$ are performance variables that in turn depend on the characteristics of T:

$$p_{l,k} = f(\mathbf{X}_{l,k}), \quad \text{with } \mathbf{X}_{l,k} = \{x_{l,k}\} \tag{2}$$

For example, for $p_{l,k} = t_l$ (i.e., travel time on link l), variables $x_{l,k}$ belonging to $\mathbf{X}_{l,k}$ typically are link length, width, tortuosity, capacity, or operational intersection features (e.g., traffic lights *vs.* priority rules). Similarly, for $p_{l,k} = CM_l$ (i.e., monetary costs on link l), variables $x_{l,k}$ belonging to $\mathbf{X}_{l,k}$ are fuel consumption per km and parking cost (if parking along the link is permitted).

To complete this short overview, for each link l, the traffic flow volume is defined as v_l. It represents the number of users (i.e., vehicles if links refer to roads, as in the considered case) along the link l during the time reference period. Incoming and outgoing traffic flow vectors for each node i can be defined as follows:

$$\begin{aligned} I_i &= \{v_{j,i} \quad \forall j \in BS_i\} \\ O_i &= \{v_{i,j} \quad \forall j \in FS_i\} \end{aligned}$$

where $v_{j,i}$ and $v_{i,j}$ are the traffic flow volumes on link (j, i) and (i, j), respectively. For each node i, some conditions can be defined concerning the relationships (actual or expected) between the incoming and outgoing traffic flows. The conditions defined for each node may concern both feasibility conditions (e.g., flow conservation) and control strategies (e.g., reduction of incoming or outgoing traffic flow for a time sub-period, the conservation of traffic flow condition being verified anyway in the whole reference time unit). The conservation condition verifies that the difference between the sum of the incoming and outgoing flow at a given node is zero.

Finally, in the transport network T, paths may be identified between pairs of relevant nodes, which may correspond to aggregate demand origin/destination points or crucial poles in the territory, such as hospitals or Emergency Assembly Areas (EAAs).

3.2. Transport Supply Modeling: The "Augmented Link" Concept

Let T be a road transportation network, defined by the set of nodes, links, and link features, which includes both usual travel costs and land use/infrastructure features:

$$T = (N, L, AC)$$

with:

$N = \{i\}$, with $\; i = 1, \cdots, m$
$L = \{(i, j) : i, j \in N, \text{with } \; (i, j) \neq (j, i)\}$
$AC = \{c_{i,j} \;\; \forall (i, j) \in L, \quad q_{i,j} \;\; \forall (i, j) \in L\}$

where $q_{i,j}$ is the link land use characteristic defined for each link (i, j) belonging to L, and all the other variables have the same meanings as those defined in Section 3.1. Such characteristics refer to surrounding features (e.g., buildings, rivers) but may be extended to structural features (e.g., resistance capacity due to repetitive external loads, particularly for bridges). Again, link (i, j) will be referred to simply as link l unless the extended notation is needed for clarity. Finally, the augmented link l is a link where c_l and q_l are defined.

Both c_l and q_l depend on a set of variables. In addition to Equations (1) and (2), the following relationships are set:

$$q_l = \sum_{k=1,\cdots,n_s} \alpha_k \cdot s_{l,k} \tag{3}$$

where n_s is the number of relevant variables, α_k are parameters weighting the different components $s_{l,k}$, and $s_{l,k}$ summarizes the land use/infrastructure features of the link depending on the exogenous factors:

$$s_{l,k} = f(\mathbf{Y}_{l,k}), \quad \text{with } \mathbf{Y}_{l,k} = \{y_{l,k}\} \tag{4}$$

For example, in the case of flooding effects, for $s_{l,k} = RC$ (i.e., river closeness), suitable variables $y_{l,k}$ belonging to $\mathbf{Y}_{l,k}$ are river or canal distances from link l. Similarly, for $s_{l,k} = LC$ (i.e., land features), suitable variables $y_{l,k}$ belonging to $\mathbf{Y}_{l,k}$ are land slope and permeability of the land in the neighborhood of link l (i.e., at a suitable, prefixed distance). In the case of earthquake effects, for $s_{l,k} = LU$ (e.g., level of urbanization), suitable variables $y_{l,k}$ belonging to $\mathbf{Y}_{l,k}$ are building density along the road (i.e., link l) and building heights (Figure 1).

In the following, augmented links will be indicated as A-link for distinguishing them from the usual link representation that considers only endogenous link features.

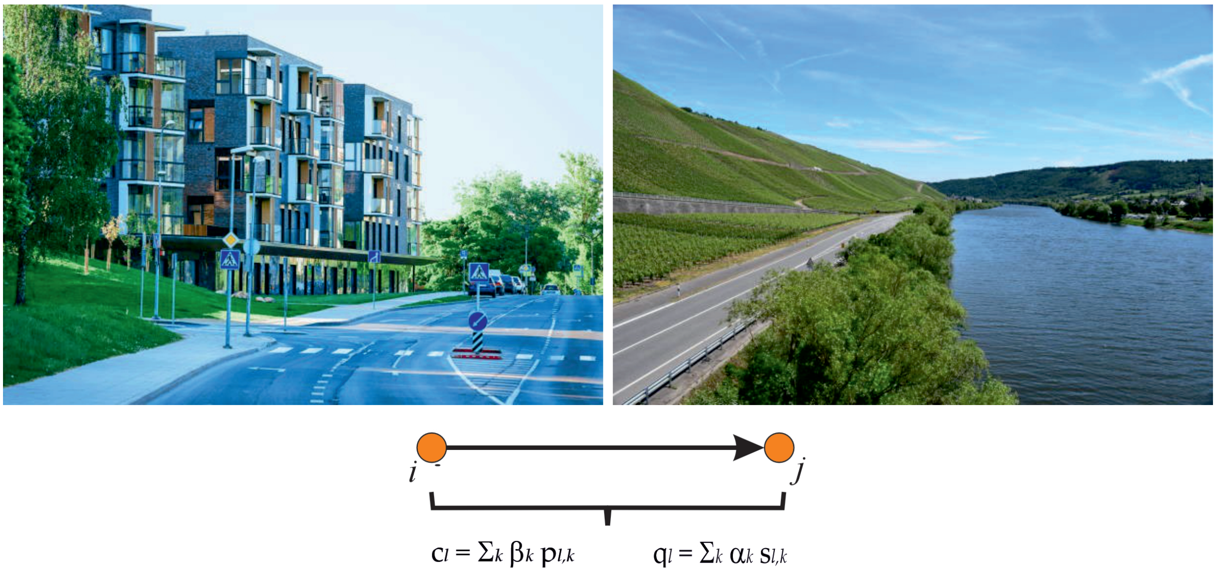

Figure 1. Real urban and extra-urban roads and their modeling by A-link road representation.

To identify critical A-links, some main properties are defined (see also Table 1):

- *Importance*: The A-link importance depends on the number of paths to which it belongs; in particular, its importance increases as the number of such paths increases;
- *Relevance*: The A-link is relevant if the A-link traffic flow in the considered time period exceeds a prefixed threshold, which depends on the A-link capacity (e.g., 80% of the A-link capacity);
- *Exposure*: The A-link exposure depends on its land use properties, which define the level of disruption it may suffer in the event of external extreme occurrences.

The first two properties depend on link-endogenous features, while the last one depends on exogenous features.

As for the indicators and related variables reported in Table 1, $a_{l,h}$ is a Boolean variable assuming a value of 1 if the A-link l belongs to path h and zero otherwise so that $\sum_h a_{l,h}$ represents the total number of paths to which l belongs. The variable cap_l is the A-link capacity, which is defined as the maximum number of vehicles that can use the A-link in a given time interval. Particularly, the relevance increases as v_l increases more than γcap_l, where γ is a percentage value. The exposure depends on the value of q_l. For simplicity, it has been assumed that exposure increases as q_l increases. For a given A-link, the disruption affects its capacity value. For example, an entirely flooded road cannot be used, and its capacity—the maximum number of vehicles that can use the road in the given time interval—is zero because no vehicles may use it. Similarly, debris from an earthquake could completely obstruct a road, and again, its capacity is zero.

Table 1. A-link characteristics and their indicators for identifying critical A-links.

Link Property	Description	Indicator
Importance	Number of paths to which the A-link belongs	$\sum_h a_{l,h}$
Relevance	Amount of A-link traffic flow	$v_l \geq \gamma \cdot cap_l$
Exposure	Level of disruption due to external events	$q_l = \sum_k \alpha_k \cdot s_{l,k}$

To combine these three properties in a unique measure of criticality, the known normalization method has been adopted. In detail, each indicator I has been normalized in $[0, 1]$ based on the following relationship:

$$I_{norm} = (I - min(I))/(max(I) - min(I)) \tag{5}$$

Therefore, the criticality associated with each A-link is defined as follows:

$$CR_l = \sum_j w_j \cdot I_{norm,j} \tag{6}$$

where w_j is the weight associated with $I_{norm,j}$ in a predefined scale if it is assumed that each indicator has a different significance. It is worthwhile to note that the use of weights is not compulsory because the different indicators $I_{norm,j}$ are normalized and then can be added. The use of weights to define the relative importance of the considered indicators might be useful for synthesizing and personalizing evaluation, but it must be used with caution. It is critical that the weights are defined in a transparent and justified manner, and that they are regularly revised to adapt to changes in context and priorities. A balanced approach that considers interactions among indicators and reduces subjectivity can maximize the effectiveness of this technique.

Finally, to identify $a_{l,h}$ and v_l, the following steps are required:

1. Modeling the transportation system in the considered area, including both the network T and the transportation demand between origin/destination pairs. This includes computing both c_l and q_l for each link l belonging to T based on $p_{l,k}$ and $s_{l,k}$;
2. Identifying the paths between origin/destination pairs (and/or relevant points of interest in the area) in order to compute $a_{l,h}$ for each link l belonging to T;
3. Assigning the transportation demand to the transportation network T in order to obtain the link traffic flow v_l for each link l belonging to T.

Note that, apart from the introduction of q_l and $s_{l,k}$, steps 1–3 are usually adopted for modeling transportation systems (more detail can be found in [36]). To conclude this section, Figure 2 summarizes the main steps of the proposed approach.

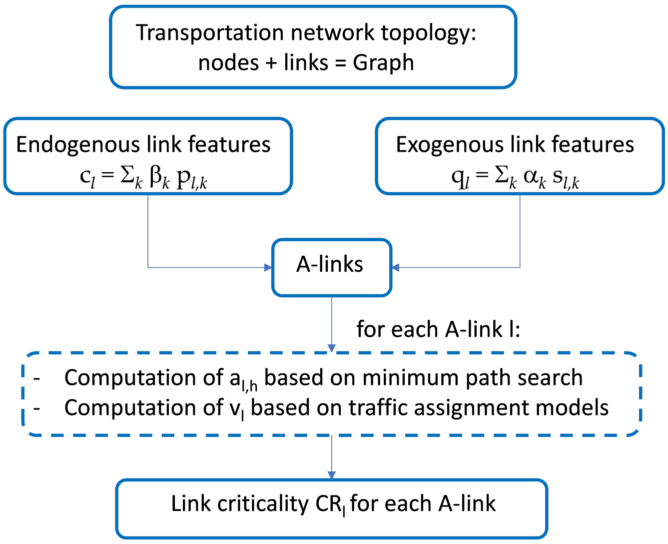

Figure 2. Overview of the proposed A-link approach.

4. Results

The approach based on A-links was tested in a simulated environment, considering flooding as an external event that might affect the transportation network. Particularly, a semi-automatic generated transportation network was implemented for an inter-municipality road system (Figure 3), which does not affect the generality of the obtained results. The simulated transportation network T consists of 100 nodes and 300 links, with 20 origin/destination nodes (including potential point of interests) for simulating transportation demand between origin/destination pairs. In addition, data have been generated for each A-link in T. The variables c_l and q_l for each link l belonging to T have been defined, together with $x_{l,k}$ and $y_{l,k}$ (see (2) and (4), respectively), as reported in Table 2. Such variables have been generated for each A-link l of the simulated transportation network T and are used to compute c_l and q_l. Particularly, in this experiment, the parameters β_k in (1) were chosen based on the corresponding literature (see again [36]), while for α_k, some hypotheses have been made. Note that parameters α_k must be calibrated, as generally, it happens for β_k. In this case, the goal is testing the approach, while the calibration of such parameters is not the focus of this paper. Furthermore, some of the variables, parameters, and formulae shown in Table 2 have been taken from the literature, but specific functions with related variables and parameters could also be set up for these.

It is worthwhile to note that for real case applications, data availability in usable and/or exportable format may be a key factor. Particularly, depending on the location of the transportation network (e.g., urban areas, extra urban regions) and the expected risky event, the nature of the data changes, as well as the amount of useful information. As an example, urban areas with high seismic risks require detailed knowledge of building features (e.g., height, distance from roads, density, and so on), population density, and road type (e.g., bridge or tunnel), among others. For areas with known flooding risks, information may concern mainly the distance of rivers from roads and territorial features (e.g., slope, land permeability).

Finally, although the data have been generated, they fully meet the actual conditions of real cases. In fact, the network model is a graph, which must be connected, directed, and weighted for representing a transportation network. The generated transportation network meets all of these requirements. As for the weights, the usual link "weights" are (generalized) travel costs, which are considered depending on endogenous features. In addition, the exogenous features have also been considered for each link, which provide the A-link's overall weight. Variables defining endogenous and exogenous features have been assumed based on the network structure in order to guarantee internal coherence. As for the other data, demand has been generated randomly, which is not an issue because it is common practice to generate demand data for simulated test cases.

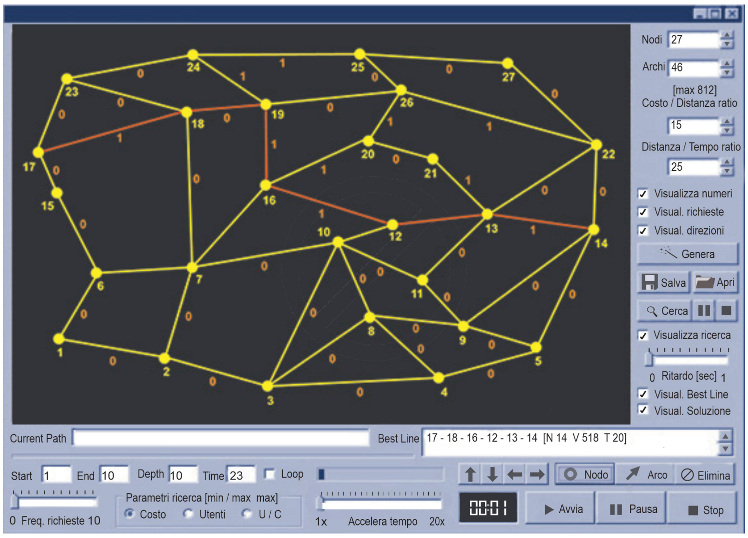

Figure 3. Representation of the simulated environment: extraction of the generated transportation network.

Table 2. Variables c_l and q_l together with the list of variables $x_{l,k}$ and $y_{l,k}$ for each A-link and corresponding functional form, including parameter values.

$p_{l,k}$	$x_{l,k}$	**Functional Form** $f(X_{l,k})$ *
Travel time tr, $\beta_{tr} = -1.6$ *	-Road length (L_l); -Road traffic flow (v_l); -Average free-flow speed (s_0); -Average speed when traffic flow is equal to capacity (s_c); -Road width (L_u); -Lateral distance from obstacles (L_0); -Average road slope (P); -Road tortuosity (T_o); -Disturbing coefficient (D); -$\delta = 1$ *; $\sigma = 3$ *	$tr_l(v_l) = L_l/s_0 + \delta(L_l/s_c - L_l/s_0)(v_l/cap_l)^{\sigma}$ with $s_0 = 56.6 + 3.2L_u + 4.5L_0 - 2.4P - 9.6T_o - 5.4D$
Monetary cost CM, $\beta_{CM} = -0.3$ *	-Average fuel cost per kilometer (mc_{fuel})	$CM = mc_{fuel} \cdot L_l$
$s_{l,k}$	$y_{l,k}$	**Functional Form** $f(Y_{l,k})$
River closeness RC, $\alpha_{RC} = -2$ **	-River distance (RD)	$RC = 1$ if $RD < 150$ mt, 0 otherwise
Land features LC, $\alpha_{LC} = -1$ **	-Land slope in %, i.e., elevation divided by the horizontal distance (LS); Permeability (LP)	$LC = 1.1LS + 1.8LP$ ***

* Ref. [36]. ** These values have been set based on interviewed experts' opinions. To apply the approach to real cases, these parameters must be calibrated using real data for the considered environment. *** In this experiment, this expression has been set using the generated data. For real case applications, the empirical relationship between LS and LP must be calibrated based on real data.

Based on the generated data and Table 2, the values of c_l and q_l were computed for each link l belonging to T. Then, the following steps were performed:

1. The transportation demand for the 20 origin/destination pairs was assigned to T by using a congested network assignment model [40] based only on c_l. Note that the assignment may be realized using the well-known PTV Visum software [41]. However, in this case, in-house software was used to consider the A-link features—both c_l and q_l—in a subsequent step;
2. The application of the assignment model provides the traffic flow v_l for each link and allows for the computation of the first three minimum cost paths (for example, [42]) for each origin/destination pair identified in T, the criterion being that each subsequent path must not exceed the minimum cost path by more than 10%. Note that if the generated paths do not meet the previous requirements, the total number of paths could be less than three;
3. Importance, relevance, and exposure were computed for each link (see Table 1). For the relevance, it was assumed that $\gamma = 80\%$;
4. The criticality CR_l expressed as in (6) was then computed, and critical links were identified for $CR_l \geq 0.7$. In this experiment, the weights w_j were assumed to be equal for all of the considered indicators;
5. A new assignment was made based on both c_l and q_l. Again, the first three minimum cost paths for each origin/destination pair in T were identified, the criterion being that each subsequent path must not exceed the minimum cost path by more than 10%. Again, note that if the generated paths do not meet the previous requirements, the total number of paths could be less than three;
6. The criticality CR_l was computed again by considering the results of the assignment that include A-link features.

Figure 4 reports the number of critical links per path for each origin/destination (*od*) pair resulting from the two assignments, i.e., without q_l (case A) and with q_l (case B). Figure 5 reports the number of paths per *od*, again for the two assignment cases (C and D, respectively), while Table 3 summarizes the average values.

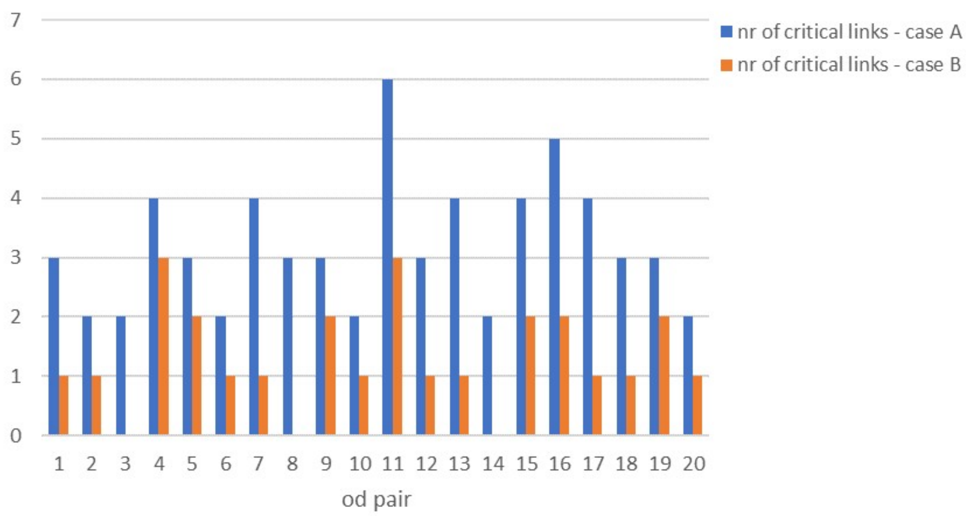

Figure 4. Comparison of the results: number of critical links per paths for each *od* (case A: assignment considering only c_l; case B: assignment considering the full features of the A-links).

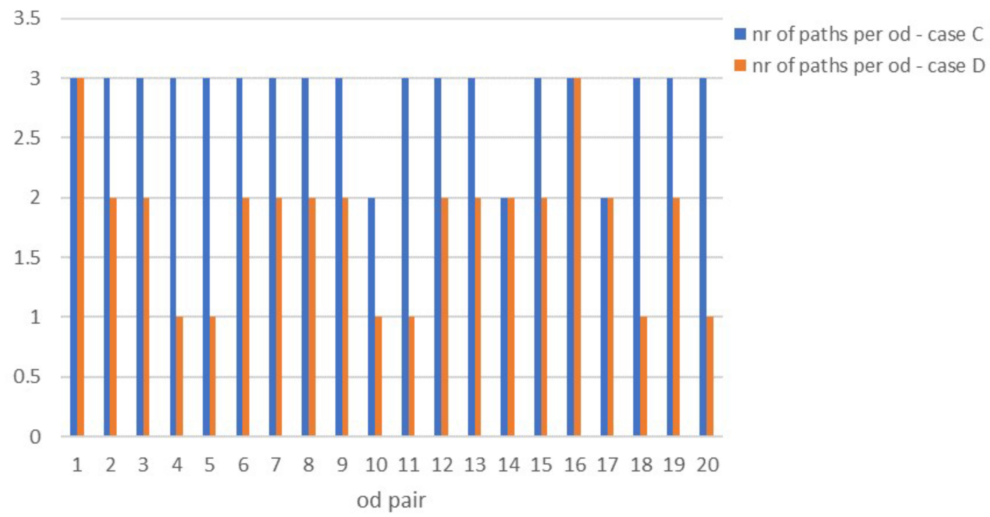

Figure 5. Comparison of the results: number of paths per *od* (case C: assignment considering only c_l; case D: assignment considering the full features of the A-links).

5. Discussion and Conclusions

The results in Table 3 are considered as an example of the potentialities offered by the A-link approach because they refer to a simulated environment. In addition, some of the used functions must be calibrated with real data, while in this case, the values of the parameters were obtained using the generated data and experts' opinions. Calibration of parameters is an important issue that may depend on specific conditions (i.e., territory, urban areas with different socio-economic characteristics, etc.). This is also essential for applying the A-link approach to real-world cases.

Table 3. Average values resulting from assignments with and without q_l.

	Average Number of Paths *per od*	Average Number of Critical A-Links *per* Path	Average Travel Cost *per* Path
only c_l	2.9	3.2	20 min
both c_l and q_l	1.8	1.3	35 min

However, despite these preliminary comments, it is worthwhile to note that the simulation is realistic, and the data are generated based on an available database concerning real systems. In this perspective, the results can be considered representative of the proposed approach, and the discussion that follows is in line with potential real-world cases.

As a first comment, the average number of paths per *od* considering the standard link features, i.e., without including land use/territorial features, is practically the same as the maximum number of potentially generated paths, which was set to 3. On the contrary, when A-links are considered, the average number of paths per *od* pair is significantly lower. This difference depends on the diverse features of the links in the two cases. In fact, the overall cost for using the link is less when only c_l is considered compared to when both c_l and q_l are considered, which results in a greater number of paths falling in the considered range, i.e., each next path must not exceed the minimum cost path by more than 10%. In other words, when only endogenous factors are considered, the number of generated paths is greater than the number of paths generated by considering both endogenous and exogenous factors. In this latter case, it is possible to identify paths that are less subject to criticality in emergency conditions because the number of critical links included in the generated paths is lower. In fact, Table 3 shows that the number of critical links per path is significantly lower when both endogenous and exogenous link features are included (1.8 vs. 3.2).

This is an important result for setting an emergency plan based on exogenous link features because in disrupted conditions, particularly caused by external events, maintaining viable paths between key locations remains crucial. In general, to ensure the connection among pairs of relevant points in a given area by a transport system, it is required that, for each selected pair, there is at least one path identified on the transportation network. The transportation network model T makes it possible to calculate paths between pairs of points based on criteria such as efficiency (e.g., lowest cost) or effectiveness (e.g., the route that serves the most areas) according to the considered goal, where a path is defined as a suitable sequence of links in the network. In the tested environment, there are several paths, composed of A-links, that do not include critical links, thus ensuring reliable connections between *od* pairs in case of emergency conditions. This ability is an important aspect of network resilience.

Finally, the average travel cost per path is less when considering only endogenous link features, which is in line with the results concerning the difference in the number of paths per *od* in the two conditions. In fact, when considering both endogenous and exogenous features, A-link costs, which include both c_l and q_l, increase. This, in turn, leads to the generation of paths with increasing costs with respect to the minimum one, thus increasing path costs on average.

To summarize, in order to measure the resilience of the urban transportation network following external events that make transport infrastructure (such as roads, bridges, and tunnels) partially or entirely unusable, it is necessary to model the transport system in the area under consideration, which includes the identification of the nodes at the origin and/or destination of journeys, and to analyze the routes available under standard conditions (or the base scenario) and under critical conditions (or the analysis scenario). To include the effects of external events and analyze the network resilience when extreme events happen, the A-link approach proposed in this study had the following advantages:

1. The paths composed of A-links (or augmented paths, in analogy with A-links) include, on average, a limited number of critical links. In fact, when identifying the paths based on the minimum cost criterion, the most attractive paths are the ones with reduced or null exogenous features, because these lead to increasing costs;
2. Although the augmented paths are on average costlier than paths composed of simple links (i.e., without exogenous features), they have, on average, a reduced or null number of critical links, which makes them more resilient in the case of emergency conditions;
3. The identification of augmented paths and critical links allows us to select links where careful monitoring must be ensured for maintaining suitable network resilience, i.e., connections between *od* pairs, particularly in emergency conditions;
4. The A-link approach allows us to verify the existence of paths during potential disruptions without the need to simulate scenarios. This is because the inclusion of exogenous features directly in the link characteristics allows us to compute paths that are more resilient. In other words, the paths identified through augmented links account for the actual usability of the links considering their current state during disruptions.

Although these are encouraging results, several further developments are expected. First, the parameters and functions concerning link-exogenous features must be calibrated based on real data for several contexts in order to make the approach suitable for real-world applications. Second, a before–after testing procedure should be conducted on a real case in order to verify how resilient paths identified by the model are coherent with the effective connections available during real emergency conditions. Third, other criticality functional forms could be explored to better assess the effective link usability.

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