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A Methodological Framework for the Resilience Analysis of Road Transport Networks Exposed to Freezing Rain

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Road transport network is one of the major critical infrastructures to be maintained resilient, since its disruption would not only have direct economic consequences, but it could also lead to domino effects on other critical infrastructures. This study proposes a methodological framework for the analysis of the resilience of road transport networks exposed to natural hazards, in particular to freezing rain, that is a precipitation event wherein the supercooled droplets of rain freeze upon contact with any surface, creating a glaze of ice and contributing, in particular, to icy roads conditions. A numerical example is presented that considers a road transportation network exposed to freezing rain, whose probability of occurrence is estimated using historical meteorological conditions; the network disruption and recovery are evaluated for the resilience analysis of the selected road transport infrastructure.

Keywords: Resilience, natural hazard, freezing rain, infrastructure network, road transportation network.

1 Introduction

Transport networks (TNs) are major critical infrastructures, because they play a crucial role for the wellbeing of society as a whole. The disruption of a transport infrastructure network not only has direct economic consequences (e.g., by hindering traffic flow), but also indirect domino consequences on the performance of other critical infrastructures, such as energy, water, waste, ICT, etc. Ensuring the resilience of TNs to natural hazards and extreme weather events (e.g., heavy rainfall, storms, floods, landslides, freezing rain, etc.) has gained increasing attention in recent years, particularly due to the increasing frequency and intensity of natural hazards and extreme weather events (Banholzer, Kossin, and Donner 2014).

Freezing Rain (FR), as a severe weather event, can cause icy roads leading to disruptions in TNs and an increase in accident risk for roads (Malin, Norros, and Innamaa 2019). According to Abaza (2020), in the United States, more than 450 people are killed every year due to the icy road conditions.

Resilience engineering has become one of the major tools for TN management. Resilience can be defined as the ability of a system to resist disruptions and adapt to recover from them quickly (Hosseini, Barker, and Ramirez-Marquez 2016; X. Zhang, Miller-Hooks, and Denny 2015). Resilience concept can be divided into four elements: I) robustness/redundancy, II) rapidity, III) resourcefulness and IV) adaptability (Bruneau et al. 2003; Ganin et al. 2017).

Various studies have focused on risk and resilience modelling and analysis of TNs, for studying, for instance, network service functions, network topology, capacity flexibility, etc. (Jafino, Kwakkel, and Verbraeck 2020; X. Zhang, Miller-Hooks, and Denny 2015).
Other studies focused on structural reliability for the definition of a measure capable of catching the behaviour of some elements of the TNs (e.g. bridges, roads, rails, etc.), for example, by integrating the fragility to natural hazards of such elements with consolidated reliability and risk assessment frameworks (Liu and Song 2020; W. Zhang and Wang 2016; Di Maio, Tonicello, and Zio 2022; Vagnoli, Di Maio and Zio 2018; Sahlin, et al. 2015). Some other studies have, instead, focused on mapping the hazards and infrastructure assets for vulnerability, risk, and resilience assessment of the infrastructure. (Thacker, Pant, and Hall 2017; Kong and Simonovic 2019; Verschuur, Koks, and Hall 2020).

This paper proposes a methodology for assessing the effects of FR on the resilience of road TNs, with focus on the robustness element. Elaborating on the methodology proposed by Zhang and Wang (2016), we use the concept of independent pathways (IPWs) (i.e., all pathways between node u and node o that do not share a common edge) to account for the network topology, length and reliability of edges, traffic flow, and the importance of emergency nodes (e.g., siting of hospitals, fire departments etc.). To provide a methodology that accounts for the geo-spatial distribution of FRs, we integrate it with the topology of transportation networks, leading to a mapped geographical exposure of the TN to the FR hazard.

Edges reliability to FR are estimated and, then, combined with the information regarding the TN topology to provide a resilience performance measure to be compared with a baseline case (i.e., without FR).

The rest of the paper is organised as follows: Section 2 describes the FR phenomenon and underlying meteorological conditions for FR occurrence. Section 3 describes the proposed methodology, and the mapping of FR hazard and road TN. Section 4 illustrates the methodology with a numerical example. Conclusions are provided in Section 5.

2 Freezing rain

FR is a precipitation event wherein the supercooled rain freezes upon contact with any surface resulting in formation of a glaze of ice. The environmental requirement for formation of FR are i) a warm elevated layer, and ii) a subfreezing layer close to the ground (see Figure 1) (Zerr 1997).

According to Adhikari and Liu (2019), there are two accepted mechanisms for FR formation: 1) through the "melting process" (see Figure 1-A), in which, FR starts as snow/ice, completely melts after falling through a warm air layer, becomes supercooled after passing through the sub-zero layer close to the earth's surface, and finally freezes on contact with the ground surface, and 2) through "warm rain process", which is similar to the melting process except for precipitation that starts as rain due to warm cloud temperatures and, then, continues to become supercooled at a sub-zero layer close to the ground (see Figure 1-B).

FR can have severe consequences on most critical infrastructures. However, the main area of effect of this hazard is air transport infrastructures and road transport infrastructures due to the formation of ice on roads (Forbes et al. 2014). For instance, a severe FR event partly affected south-eastern Romania between 24-26 January 2019, and resulted in closure of multiple roads and damage to 759 cars (Andrei et al. 2019).

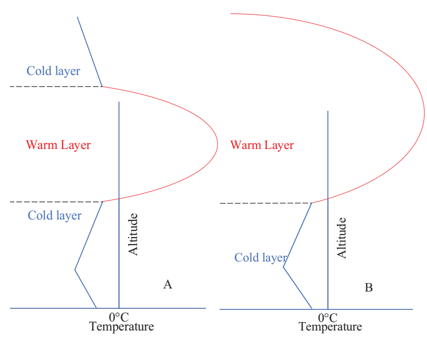

Fig. 1. Temperature profiles for formation of freezing rain adapted from (Forbes et al. 2014). A: "Melting process", B: "Warm rain process".

3 Methodological framework

An overview of the proposed methodology is presented in Figure 2. The first phase includes hazard mapping that is comprised of estimating the hazard occurrence probability, its magnitude and the geographical extent. The result of this step leads to the geo-spatial mapping of the hazard, which is illustrated as "Hazard Plane" in Figure 3-A.

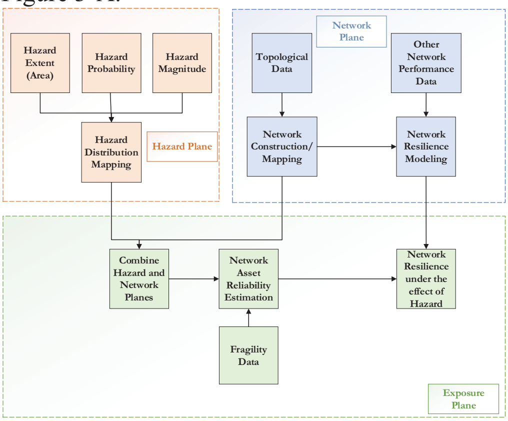

Fig. 2. Illustration of the methodology

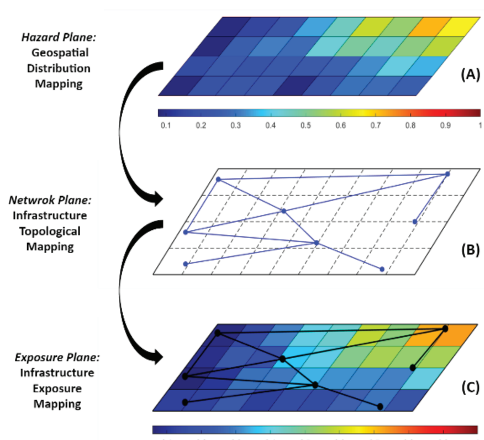

Fig. 3. An illustration of the mapping on an infrastructure network exposed to natural hazard

The following step consists in using the available data to map the infrastructure network topology, illustrated as "Network Plane" in Figure 3-B. The "Hazard Plane" and the "Network Plane" are integrated in the "Exposure plane" in Figure 3-C, where the infrastructure exposure to the hazard is mapped. Fragility data of the network edges are used to estimate their reliabilities.

The methodology for analysing the road network resilience developed by Zhang and Wang (2016) is, then, adopted to calculate the IPWs and, by accounting for the length and reliability of each edge, the traffic flow, the importance of emergency response nodes (e.g., hospitals, fire departments etc.), estimates the network resilience.

3.1 Hazard plane model

The hazard plane consists in modelling the FR geospatial, magnitude and probability of occurrence distributions.

Let us consider a geographical area divided into regions, denoted by $j = 1, \dots, m$. The probability of occurrence of FR on a specific day, $D = 1, \dots 365$, in such region, can be estimated assuming that if, without loss of generality, we limit our interest to the FRs induced by the "Melting process" of Figure 1-A, in order for FR to happen, there are three specific conditions that need to be met: 1) rain should occur, 2) air temperature close to the surface, usually measured at 2m height, needs to be below the freezing point (i.e., occurrence of cold layer, see Figure 1), and 3) air temperature at altitude, approximately at 1000m, should be warm enough (i.e., above freezing point (Zerr 1997)). Thus, the occurrence of FR can be expressed as:

$$FR_{i,j}^{D} = \begin{cases} 1 & if\ Z_{i,j}^{D} = 1, T_{air}{}_{i,j}^{D} \geq 0, T_{0}{}_{i,j}^{D} < 0 \\ 0 & Otherwise \end{cases} \quad (1)$$

where $FR_{i,j}^{D}$ indicates the FR realization on day $D = 1, \dots 365$, of year $i = 1, \dots, n$, with n being the total number of years for which historical data is available for region $j = 1, \dots, m$. $Z_{i,j}^{D}$ denotes the realization of rain on day D, region j, and year i, where

$$Z_{i,j}^{D} = \begin{cases} 1 & Rain \\ 0 & Not\ Rain \end{cases} \quad (2)$$

and $T_{air}{}_{i,j}^{D}$ and $T_{0}{}_{i,j}^{D}$ are air temperatures at 1000m and 2m, respectively, on day D, region j and year i.

Meteorological data for each region can be available from weather stations, or from reanalysis data (Naseri and Samuelsen 2019). Such meteorological data can be used to estimate FR_j^D, the FR probability of occurrence on day D in region j, by Eq. (3):

$$\Pr\left(FR_j^D = 1\right) = \frac{\sum_{i=1}^{n} FR_{i,j}^D}{n} \quad (3)$$

An illustration of the FR distribution and probabilities of occurrence is presented in Figure 2-A. Without loss of generality, in this study, we assume identical FR magnitude for each FR occurrence, despite it might be assumed also that the hazard magnitude, which is the thickness of ice formed due to FR is a function of a number of meteorological and weather data including, precipitation, cold and warm layer temperature, etc. (Forbes et al. 2014).

3.2 Network plane model

By using the terminology of graph theory, the transport network can be defined by $G = (V, E)$ in which $V = \{1,2,\ldots,u\}$ is a set of nodes, denoting cities. A sub-set of V, which is denoted by B, is considered a set of critical nodes where emergency response facilities are located. $E = \{1,2,\ldots e\}$ is a set of edges that correspond to roads connecting network nodes. This paper uses the concept of adjacency matrix for network definition. Adjacency matrix (A) indicates the connectivity of the nodes in the network, with respect to each other,

$$A = \begin{bmatrix} 0 & \cdots & a_{ou} \\ \vdots & \ddots & \vdots \\ a_{uo} & \cdots & 0 \end{bmatrix}$$

where $a_{uo} = 1$, if nodes u and o are connected, and $a_{uo} = 0$, otherwise, while $u \neq o$. An illustration of the road network is presented in Figure 3-B.

3.3 Exposure plane model

Exposure plane modelling consists of modelling network resilience performance and hazard effects on the network edges, which affects the reliability of the roads. Exposure plane illustrates the exposed areas of the network to the hazard in question. Exposure plane is illustrated in Figure 3-C "Exposure plane, infrastructure exposure mapping". In this model, the reliability data for edges (roads) are estimated using the probability of occurrence of FR in each region, for each day described in Section 3.1. To this aim, the concept of fragility of the infrastructure assets given the occurrence of hazards can be used to estimate the asset failure probability as a function of hazard magnitude. In this study, we assume that, regardless of magnitude, the road becomes inaccessible once FR occurs. Depending on the geographical resolution of the study, a network edge may overlay several regions of the hazard plane (see Figure 4). Thus, the reliability of an edge can be defined as

$$R_{edge} = \prod_{q \in Q}\left[1 - Pr\left(FR_q^D\right)\right] \quad (4)$$

where Q is the set of the indices of the regions on which the edge overlays. For instance, as illustrated in Figure 4, the reliability of edge θ is obtained by:

$$R_\theta = \prod_{q \in \{1,2,3\}}\left[1 - Pr\left(FR_q^D\right)\right] \quad (5)$$

For analysing the network performance, we adopt a methodology proposed by Zhang and Wang (2016) that used the concept of independenth pathways, network redundancies, traffic flow, edge reliabilities, and the role of the emergency nodes in the network performance, in order to develop a resilience-based performance metric, known as Weighted Independent Pathways (WIPW), given by Eq. (6) (Zhang and Wang 2016):

$$WIPW(G) = \sum_{v=1}^{u} w_v r_v \quad (6)$$

in which, $WIPW(G)$ is the weighted independent pathways in the network and is the network resilience performance metric, w_v is the weight of node $v \in V$, inversely proportional to the shortest distance from node v to the nearest emergency response facility, and r_v is the average number of independent pathways between any node v and any other $u - 1$ nodes in the network, as given by Eq. (7) (Zhang and Wang 2016):

$$r_v = \frac{1}{u-1} \sum_{o=1, o \neq v}^{u} \sum_{k=1}^{k_{(u,o)}} w_k(u,o) \cdot R_k(u,o) \quad (7)$$

where, $k_{(u,o)}$ is the total number of IPWs between nodes u and o, $R_k(u,o)$ is the reliability of the kth IPW between node u and node o, which is a function of each edge reliability, and $w_k(u,o)$ is the weighting factor applied to the kth IPW between node u and node o, and is a function of average daily traffic and length of each IPW. More details on this resilience-based performance metric can be found in (Zhang and Wang 2016).

The required inputs for the edge weights, w_k, in Eq. (7) are average daily traffic (ADT), which can be collected from historical traffic data, and length of each edge/road, that can be obtained from open-source maps. The inputs for the weight of nodes are only dependent on the minimum distance of each node from the nearest critical/emergency node (sub-set of B). Having such data, and assuming edge reliabilities equal to one (i.e., perfect roads with no failure), a baseline resilience-metric is estimated for the network. The resilience-performance reduction on the network G on day D, can, then, be calculated by:

$$PRF(G)^D = 1 - \frac{WIPW(G)^D}{WIPW_{Baseline}(G)} \quad (8)$$

where $WIPW_{Baseline}(G)$ is the baseline network resilience performance when the edge reliabilities are assumed equal to one.

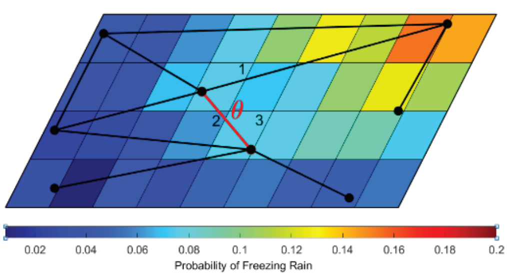

Fig. 4. Exposure plane – edge reliability as a function of FR occurrence probabilities in each region

Daily variations of the FR parameters (e.g., hourly data or the upper and lower bounds of air temperatures T_{air}, $T_{air}{}_{i,j}^{D,l(u)}$ and $T_0{}_{i,j}^{D,l(u)}$ as the lower (upper) bounds of air temperatures at 1000m and 2m, respectively) can be used to express the occurrence of FR as in Eq. (9):

$$FR_{i,j}^D\big|_{l(u)} = \begin{cases} 1 \ \ if \ Z_{i,j}^D = 1, T_{air}{}_{i,j}^{D,l(u)} \geq 0, T_0{}_{i,j}^{D,l(u)} < 0 \\ 0 \ \ Otherwise \end{cases} \quad (9)$$

and thus,

$$\Pr\left(FR_j^D\big|_{l(u)}\right) = \frac{\sum_{i=1}^{n} FR_{i,j}^D\big|_{l(u)}}{n} \quad (10)$$

in which $\Pr\left(FR_j^D\big|_{l(u)}\right)$ is the probability of occurrence of FR corresponding to the lower (upper) bound of air temperatures at 1000m and 2m, on day D, year i and region j. Such probabilities can be used in Eq. (4) in order to obtain the edge reliabilities corresponding to the lower (upper) bound of air temperatures, and consequently the network resilience performance using Eq. (6).

4 Numerical Example

We illustrate the proposed methodology with a numerical example. Let us consider a geographical area 400×300 km^2, divided into 12 regions, $j = 1, \ldots, 12$, for which the temperature at 2m, T_0, and the precipitation data can be obtained from some weather stations (see Figure 5). The data for the air temperature at 1000m are usually estimated using climate models and can be obtained from meteorological institutes.

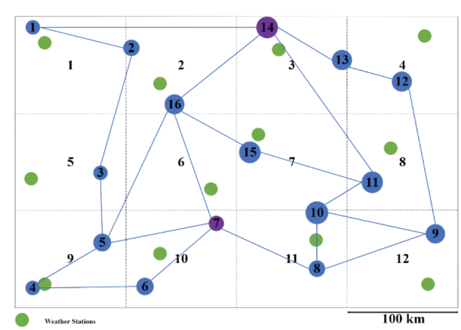

Fig. 5. An overview of the geographical area of the study divided into 12 regions

The network used in this numerical example consists of 16 nodes and 22 edges; nodes 14 and 7 are critical nodes in the network (i.e., $B = \{7,14\}$), as illustrated in Figure 5. By assuming no FR can occur, $P\left(FR_j^D\right) = 0$ (i.e., assuming edge reliabilities $R_{edge} = 1$), the baseline network resilience performance can be obtained using Eq. (4), $WIPW(G)^1_{baseline} = 2.5211$, representing the average number of independent pathways between all node-pairs in the network.

In the next step, the hazard plane is built. An overview of some temperature and precipitation data for region $j = 1$, and day $D = 1$ is presented in Table 1 and then used in Eq. (1) for estimating the occurrence of FR.

Table 1. An example of historical data for region $j = 1$, on day $D = 1$: Air temperature at 1000m, T_{air} $(°C)$ [Lower, Upper], air temperature at 2m, T_0 $(°C)$ [Lower, Upper], and precipitation P (mm)

i	Year	$T_{air\,i,1}^{\,1}$	$T_{0\,i,1}^{\,1}$	$P_{i,1}^1$	$Z_{i,1}^1$	$FR_{i,1}^1$
1	1996	[-2,2]	[-7,-5]	5	1	0, 1
2	1997	[-1,1]	[-6,-3]	0	0	0, 0
3	1998	[3,7]	[-6,-3]	3	1	1, 1
…	…	…	…	…	…	…
24	2020	[-4,-1]	[-6,-4]	0	0	0, 0
25	2021	[-7,-5]	[-9,-8]	0	0	0, 0

The probability of occurrence of FR on $D = 1$ (1st of January) and region $j = 1$ of the map can be obtained using Eq. (3). Table 2 lists the FR probability for each region ($j = 1, \ldots, 12$) when the lower and upper bounds of air temperatures at 1000m, and 2m are considered. Figure 6 illustrates the network exposure plane for $D = 1$, that is constructed by integrating the hazard and network planes.

Table 2. FR probabilities in each region corresponding to the lower and upper bounds of air temperature at 1000m, and 2m on $D = 1$

Region	$P\left(FR_j^1\big\|_l\right)$	$P\left(FR_j^1\big\|_u\right)$
1	0.12	0.20
2	0.04	0.08
…	…	…
11	0	0
12	0	0.04

By assuming that the roads are inaccessible upon the occurrence of FR, edge reliabilities can be obtained from Eq. (4) and the information available from the network exposure plane (Figure 6). Table 3 presents the edge reliabilities for $D = 1$.

Edges reliability for the road network which is exposed to FR is used to obtain the network resilience performance for each day with respect to the specific hazard of FR. As an example, the network resilience performance on $D = 1$ results to be equal to $WIPW(G)^1 \in [1.5059, 1.8539]$ for the lower and upper bounds of air temperatures at 1000m, and 2m. In other words, we can claim that the average of independent pathways between all node-pairs in the network under the impact of FR is between 1.5059 and 1.85390. By comparing the network resilience performance against the baseline performance, the reduction of the network resilience metric under the impact of FR on $D = 1$ is $PRF(G)^1 \in [0.265, 0.403]$.

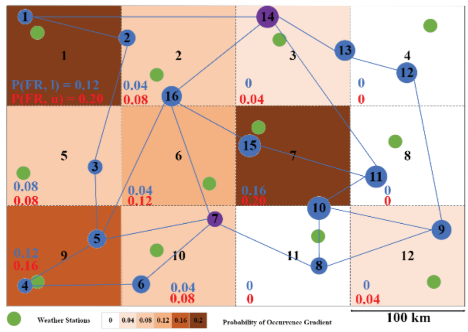

Figure 6. Network exposure map at $D = 1$.

Table 2. Edges reliability corresponding to the lower and upper bounds of air temperature at 1000m, and 2m on $D = 1$

Edge	$R_{edge}^1\big\|_l$	$R_{edge}^1\big\|_u$
(1,2)	0.8000	0.8800
(1,14)	0.7066	0.8448
…	…	…
(14,16)	0.8832	0.9600
(15,16)	0.6477	0.7741

5 Conclusion

This paper combines network analysis and hazard mapping techniques to model the effects of freezing rain on the overall resilience performance of a road TN. A baseline network resilience performance is obtained for the network based on the network topology, redundancy level, traffic flow, where edge reliabilities are assumed to be one (i.e., a perfect network). Edges reliability is estimated based on spatial distribution of freezing rain frequency and the mapped network, and used to estimate the network resilience performance conditioned on the occurrence of freezing rain. The calculated performance reduction shows the adverse effects of FR on the network, which gives a measure for comparing the network performance before and after being subjected to FR.

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