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Developing Measures for Node Importance in Critical Transportation Networks - An Illustration to the Analysis of Switches at Finnish Railway Stations

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Estimates on the importance of nodes in transportation networks provide guidance on the allocation of resources to preventive maintenance. As a rule, those nodes whose disruptions would most affect the level of service provided by the network are particularly important and, as a consequence, merit more attention in maintenance planning. Conventionally, measures of node importance have been generated based on structural properties (e.g. degree centrality, betweenness centrality). However, these properties do not account for the extent to which the network is capable of providing its intended level of service, such as enabling the planned traffic volume between terminal pairs that are defined by relevant origins and destinations in the network. In this setting, we extend well-known measures of probabilistic risk importance to prioritize nodes in support of preventive maintenance planning. Specifically, we adapt the risk achievement worth (RAW) measure to assess how much the planned traffic volume between terminal pairs of the network would be compromised due to disruptions at different nodes.
To support the applicability of our methodological advances, we develop a systematic, data-driven, semi-automated approach that makes but modest assumptions about the quality of underlying data. We illustrate this approach with a case study on the prioritization of switches at a representative railway station in Finland, based on an analysis of the reliability of the connections that this station offers to the adjacent railway track segments. We also compare the proposed RAW measure with structural importance measures and elaborate on how these two kinds of measures can be jointly examined to produce complementary sources of information.

Keywords: Importance measure, Probabilistic risk importance measure, Transportation networks, Critical infrastructures, Railways industry, Risk assessment, Risk management, System reliability, Probabilistic risk assessment

1. Introduction

Time-based strategies for maintaining infrastructures, such as transportation networks, are common in the management of real-world assets (Ahmad and Kamaruddin, 2012). However, deriving maintenance decisions solely from a purely time-based maintenance strategy is problematic because all components of the infrastructure would require the same amount of maintenance, regardless of their importance to the level of service provided by the network. For example, key railway switches on the main railway tracks at a capital's main railway station would receive the same amount of maintenance resources as the railway switches located on a side railway track in a peripheral city. As a result, time-based maintenance strategies can lead to comparatively high costs (Kim et al., 2016) when the goal is to maintain the level of service provided by the network. As a remedy to this situation, disruptions in the network should be prevented where the resulting impact on the level of service provided by the network is the greatest.

Estimates of the importance of nodes in transportation networks can be generated to guide maintenance decisions, for example, through recommendations toward allocating most resources to the nodes that matter most or monitoring the condition of such nodes more closely. However, it is not straightforward to assess the importance of nodes. For example, it can be difficult to agree on a single measure that is suitable across many situations and makes modest data demands, allowing it to be computed without resorting to impractically onerous elicitation of expert judgments. In this setting, the development of automated, systematic, and transparent importance measures holds promise.

Several relevant measures of node importance for transportation networks have been proposed in the literature, based on alternative interpretations of ”importance”, which, as an abstract concept, needs to be elaborated on. For example, degree centrality is the number of edges connected to a node; betweenness centrality is the number of shortest paths between all nodes of the network that pass through a given node; closeness centrality represents the average of shortest distances to all other nodes.

In many cases, these measures have been applied to networks in which nodes represent relatively large entities, such as cities or stations. For example, degree, strength (i.e., weighted degree), and betweenness centralities have been associated with China's high-speed railway network (Cao et al., 2019) and the European international railway network (Calzada-Infante et al., 2020). Based on their systematic review on the analysis of maritime traffic as complex networks, Álvarez et al. (2021) note that degree, betweenness, and closeness centralities are quite common. Chopra et al. (2016) analyze the structural vulnerability of the connections between stations in the London metro network with a measure of ”redundancy”. In the same vein, Erath et al. (2009) employ the degree, betweenness, and ”efficiency” centralities to analyze Swiss road and railway networks. Li et al. (2023) utilize a modified PageRank algorithm to analyze an urban transportation network consisting of bus, metro, and taxi networks in Shenzhen, China. Importance measures such as these have often been computed at a relatively high level of aggregation, without paying close attention to the required performance level in different parts of the network. Thus, such measures would need to be tailored to situations in which nodes represent smaller constituent parts of the network, such as road intersections or railway switches.

A generic limitation of these types of topological importance measures (for example, degree centrality) to the analysis of nodes in transportation networks is that they only account for the *structure* of the network (Cheng et al., 2015), but do not convey what *impact* changes in the operational status of nodes, such as node disruptions, have on the expected level of service that the network provides. This limitation has spurred research on alternative perspectives into characterizing the importance of nodes in transportation networks and, more broadly, in other types of networks as well.

For example, component-specific resilience-based importance measures have been proposed in the context of critical infrastructure networks (see, e.g. Barker et al., 2013; Fang et al., 2016). Resilience-based importance measures for network nodes are typically used to assess *how quickly* and *to what extent* the level of service provided by a network can be restored after a disruption event. In this sense, resilience-based importance measures for components view time as a crucial relevant factor, in contrast to topological importance measures. Yet, many resilience-based component importance measures assume that the disruption event has already occurred, and thus they do not guide preventive maintenance decisions before the disruption event based on *a priori* estimates of relevant uncertainties.

Probabilistic measures of node importance have also been explored. One such example is the terminal pair reliability, which measures the probability that there exists a path between two nodes (Satyanarayana and Hagstrom, 1981) and which can be calculated for a given pair of nodes (e.g. Yoo and Deo, 1988) or, more generally, by considering the probability with which there exists a path from one node to all other nodes (also referred to as source-to-multiple-terminal reliability; see

Satyanarayana and Hagstrom, 1981). However, because transportation networks are rarely constructed for the purpose of providing adequate service between a single terminal pair only, or between a single node and all other nodes, the terminal pair reliability needs to be adapted to meet the specific needs that arise in particular planning contexts.

In the context of safety-critical systems such as nuclear power facilities (e.g. Vesely et al., 1983; Mancuso et al., 2017), risk importance measures based on probabilistic risk assessment (PRA) are widely used and, in many cases, required by regulatory authorities. Furthermore, given that many transportation networks are critical infrastructures, PRA-based importance measures are promising as a basis for assessing the importance of nodes in transportation networks. Examples of PRA-based measures include, among others, risk achievement worth (RAW), risk reduction worth (RRW), Birnbaum importance, and Fussell-Vesely importance (see, for example, Aven et al., 2024). For example, for a given component of a system, the RAW measure indicates by how many times greater the probability of system failure becomes due to the failure of this component. Consequently, components with large RAW values merit particular attention for guiding actions that serve to ensure that the probability of failure for a given component does not increase from its present level.

Because PRA-based measures are built on binary logic, adapting them to the context of transportation networks requires that one can specify whether or not the network is operational for any combination of binary statuses (operational/disrupted) of all relevant network components. Furthermore, the computation of PRA-based measures presumes that one is able to obtain usable information about the disruption probabilities of all its components (Di Mauro et al., 2010). This information does not have to be precise, because even incomplete information on these probabilities may give rise to useful insights into which components matter most for the performance of the network as a system (see, e.g. Toppila and Salo 2017).

In this paper, we analyze transportation networks by proposing PRA-based risk importance measures that reflect the impact of uncertain node disruptions on the level of service of the network, which is measured by the aggregate expected traffic volume for terminal pairs defined by relevant origins and destinations. The resulting importance measures help identify the nodes whose disruptions would cause the largest relative degradation in the level of service. As a result, they provide guidance for planning decisions and, specifically, support the allocation of maintenance resources to those nodes where the impacts of preventive actions are likely to be most effective. The development of these measures has been motivated by the need to provide risk-informed guidance on the maintenance of railway switches, because their maintenance is crucial in responsible asset management. The proposed PRA-based risk importance measures are illustrated by presenting a case study on the analysis of railway switches at a representative railway station in Finland.

This paper is structured as follows. Section 2 presents the methodological development. Section 3 illustrates the methodology with a case study. Section 4 concludes and summarizes the main findings.

2. Modelling Framework

A transportation network can be modeled as a network of (i) nodes that represent subsystems within this transportation network (e.g., railway switches, road intersections) and (ii) undirected edges that represent connections between these subsystems (e.g., railway tracks, road segments). In this paper, we consider a network whose purpose is to enable traffic volumes between a set of pairs of terminal nodes located at the boundaries of the network. For each terminal pair, there is a corresponding traffic volume which is to be enabled by the network.

Formally, such a transportation network is represented as a graph $N = (V, E)$, where V is the set of nodes and $E \subseteq \{(v_1, v_2) \mid v_1, v_2 \in V\}$ is the set of edges. The nodes $V = V^S \cup V^T$ are either subsystem nodes V^S or terminal nodes V^T. There are at least two terminal nodes; $|V^T| \geq 2$.

The set of terminal pairs is $T = \{(v_1, v_2) \mid v_1 \in V^T, v_2 \in V^T, v_1 \neq v_2\}$. The edges represent connections between nodes. For the given terminal pair $t \in T$, the planned traffic volume is $f_t \in \mathbb{R}^+$.

In this paper, a *path* in the transportation network is a sequence of nodes that are connected by edges and enable transportation between two distinct terminal nodes. Formally, a path $\pi_i \in P$ of length n_i is a sequence of nodes $\pi_i = (v_{i,1}, v_{i,2}, ..., v_{i,n_i-1}, v_{i,n_i})$ such that $v_{i,1} \in V^T, v_{i,j} \in V, j = 2, ..., n_i - 1, v_{i,n_i} \in V^T$ and $(v_{i,j}, v_{i,j+1}) \in E, j = 1, ..., n_i - 1$. We limit our attention to simple paths on which any node appears only once (i.e., all nodes along a path are distinct). The set of paths for the terminal pair t is denoted by $P_t \subset P$. Thus, if $\pi_i \in P_t$, then the first and last nodes of the path π_i are the same as those of the terminal pair t. The number of such paths is denoted by $n_t = |P_t|$.

Technically, the set of feasible paths P_t that enable the traffic volume between the nodes in the terminal pair $t \in T$ can be a proper subset of the set of all paths that can be constructed from the edges of the network for the nodes in the terminal pair. For example, there may be constraints on the number of nodes along the path or on the total physical length of a path. In this case P_t would not contain sequences that violate such restrictions, given that the set of feasible paths can be limited to those that comply with the specific requirements of the application context (see an example in the case study presented in Section 3).

In this paper, we denote the operational status of a node $v \in V$ by

$$O(v) = \begin{cases} 1, \text{if } v \text{ is operational}, \\ 0, \text{if } v \text{ is disrupted}. \end{cases} \tag{1}$$

The path $\pi_i \in P$ is operational if all its nodes are operational. Thus, we have

$$O(\pi_i) = \begin{cases} 1, O(v_{i,j}) = 1, j = 1, ..., n_i, \\ 0, \text{else}. \end{cases} \tag{2}$$

In the same vein, the terminal pair $t \in T$ is operational if there exists at least one operational feasible path between the terminal pair, in other words,

$$O(t) = \begin{cases} 1, & \sum_{\pi_i \in P_t} O(\pi_i) > 0, \\ 0, & \text{else}. \end{cases} \tag{3}$$

Finally, the transportation network is operational if there exists at least one operational feasible path for all terminal pairs $t \in T$. Thus, the operational status of the transportation network N is

$$O(N) = \begin{cases} 1, & O(t) > 0, \forall t \in T, \\ 0, & \text{else}. \end{cases} \tag{4}$$

Figure 1 shows a fault tree representation of an illustrative transportation network with three terminal pairs, each with a varying number of feasible paths. The top event represents the case where the network is disrupted. As a rule, the probabilities of path disruptions are not independent because there can be nodes that belong to two or more paths, in which case the probabilities of path disruptions are correlated.

We model uncertainties regarding the occurrence of node disruptions with probabilities. Specifically, the probability that subsystem node $v \in V^S$ is disrupted is

$$\mathbb{P}[O(v) = 0], \forall v \in V^S, \tag{5}$$

which is a parameter that can be estimated based on the use of statistical data analysis or the elicitation of expert judgements, for example. Thus, the probability that the path $\pi_i \in P$ is disrupted due to the disruption of a node is

$$\mathbb{P}[O(\pi_i) = 0] = 1 - \prod_{v_{i,j} \in \pi_i} \mathbb{P}[O(v_{i,j}) = 1]. \tag{6}$$

The terminal pair $t \in T$ is disrupted if and only if all paths $\pi_i \in P_t$ are disrupted. This event occurs with probability

$$\mathbb{P}[O(t) = 0] = \mathbb{P}[\bigwedge_{\pi_i \in P_t} O(\pi_i) = 0], \tag{7}$$

which is commonly referred to as the terminal pair reliability and can efficiently be computed, for example, with the modified Dotson algorithm (Yoo and Deo, 1988) [a]. Another approach to calculate

[a] The modified Dotson algorithm considers edge disruptions rather than node disruptions. However, this difference does not matter for the present development, as the disruption of every node is equivalent to the disruption of all its adjacent edges.

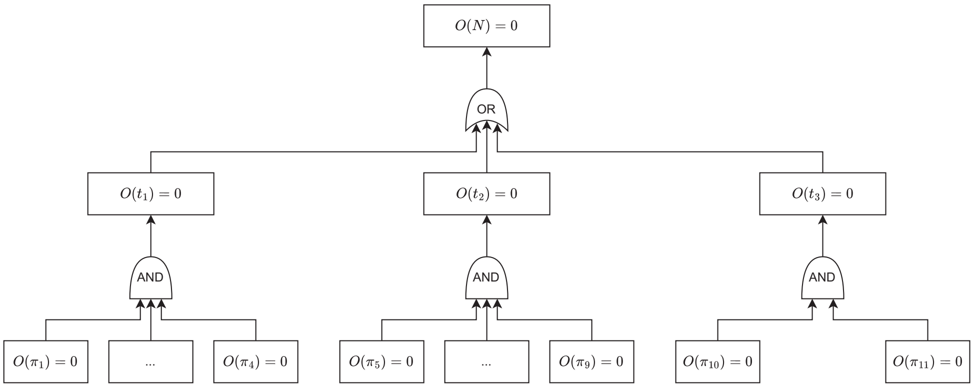

Fig. 1. Fault-tree visualization of a transportation network with three terminal pairs.

the probability for the disruption of a terminal pair is to use exhaustive enumeration of the operational statuses of all nodes, even if this is computationally tractable only when the number of nodes is relatively small.

In the absence of evidence to the contrary, one may assume that node disruptions occur independently of each other. This would be the case, for example, if the disruptions can be attributed primarily to local technical failures that are not catalyzed by disruptions at other nodes of the network. Still, this assumption would not account for the fact that the remaining operational nodes might have to carry a greater traffic volume because of rerouting decisions which, in turn, could lead to a higher probability of disruption at these nodes.

Based on the probabilities of disruption for terminal pairs, PRA-based risk importance measures can now be associated with the subsystem nodes. Although several risk importance measures can be adapted, we focus on the well-known risk achievement worth (RAW). Specifically, given the need to ensure the traffic volume for the terminal pair $t \in T$, this RAW measure can be defined as

$$\mathrm{RAW}_t(v) = \frac{\mathbb{P}[O(t) = 0 \mid O(v) = 0]}{\mathbb{P}[O(t) = 0]}. \tag{8}$$

For a given terminal pair $t \in T$, the ratio (8) also represent the relative increase in the expected traffic volume that is obstructed for t due to the disruption of node v. This ratio is independent of the planned volume of traffic for t.

To characterize the importance of the node $v \in V$ in the transportation network N, the measure (8) can now be extended further to account for (i) the planned traffic volume associated with one, several, or all terminal pairs, and (ii) underlying uncertainties that are represented by the probabilities of node disruptions. The advantages of this joint approach are twofold. First, it makes it possible to derive an importance measure that reflects the performance of the network in terms of changes in the expected aggregate traffic volume. Second, it also allows such information to be pooled into a single scalar importance measure that has a concrete meaning and is therefore easy to interpret.

Specifically, to account for the aggregate performance of the network, the measure (8) can be extended by summing over *all* terminal pairs to obtain the total importance measure

$$\mathrm{RAW}^f_{\mathrm{tot}}(v) = \frac{\sum_{t \in T} f_t \times \mathbb{P}[O(t) = 0 \mid O(v) = 0]}{\sum_{t \in T} f_t \times \mathbb{P}[O(t) = 0]}, \tag{9}$$

which gives the relative increase in the aggregate expected traffic volume that is obstructed due to the disruption of node v.

3. Case Study

In this case study, we illustrate the above measures $\mathrm{RAW}_t(v)$ and $\mathrm{RAW}^f_{\mathrm{tot}}(v)$ in evaluating the importance of switches at a representative railway station located in eastern Finland. Figure 2 shows the network structure at this railway station, consisting of switches (small squares for subsystem nodes), terminal nodes (large squares) and lines for railway tracks (edges). Switches are physical devices that allow the train to proceed along the railway track and, depending on the position of the switch, also to move from one railway track to another.

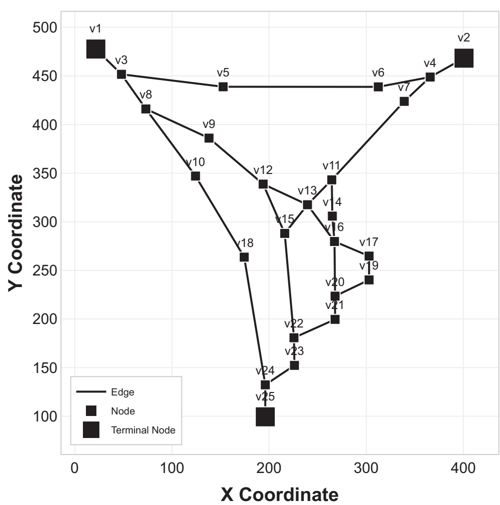

Fig. 2. An illustrative railway station network.

At this station, there are three terminal pairs that enable traffic volumes between the three directions represented by the terminal nodes: south-west (SW), south-east (SE) and east-west (EW). The feasible paths of the south-west direction are shown in Figure 3 (figures for the feasible paths of the other directions are omitted due to space limitations). For technical reasons relating to train operation, only paths in which the maximum turning angle does not exceed 90 degrees are feasible; but there are no other constraints on the feasibility of paths.

For the sake of illustration, we assume that the probability of disruption of switches is 1% and that of terminal nodes is 0%. Thus, $\mathbb{P}[O(v) = 0] = 1\%, \forall v \in V^S, \mathbb{P}[O(v) = 0] = 0\%, \forall v \in V^T$. This assumption can be readily revised to account for other assumptions about the disruption

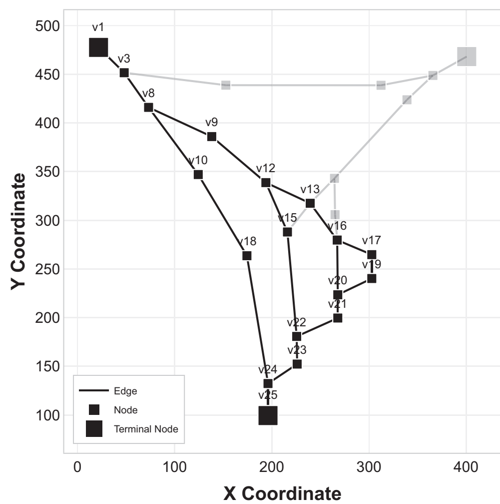

Fig. 3. Feasible paths for the south-west (SW) terminal pair.

Table 1. Illustrative traffic volumes for the terminal pairs.

Terminal pair	Planned number of trains
South-west (SW)	7547
South-east (SE)	1373
East-west (EW)	3035

probabilities.

Table 1 lists the planned traffic volumes for each terminal pair, measured in terms of the number of trains. For example, there are more trains for the terminal pair south-west than for the two other terminal pairs combined. Table 2 reports the RAW measures RAW_t for each node and terminal pair, as well as the overall traffic volume-weighted measure $\text{RAW}^f_{\text{tot}}$, calculated from (8) and (9). In the second, third and fourth column, the $\text{RAW}_t, t \in \{\text{SW}, \text{SE}, \text{EW}\}$ value of 1.00 indicates that the disruption of a node does not impact the operational status of the corresponding terminal pair. For example, node v5 does not belong to any path in the south-west direction, and hence its disruption does not affect this terminal pair.

For the sake of completeness, the table also reports importance measures for the terminal nodes. This is instructive in that it reflects the how sig-

Table 2. The RAW-based importance measures for terminal pairs and the aggregate traffic volume.

Id	RAW_{SW}	RAW_{SE}	RAW_{EW}	RAW^f_{tot}
v1	32.82	1.00	47.53	28.43
v2	1.00	16.90	47.53	12.37
v3	32.82	1.00	47.53	28.43
v4	1.00	16.90	47.53	12.37
v5	1.00	1.00	3.67	1.45
v6	1.00	1.00	3.67	1.45
v7	1.00	16.90	1.87	4.59
v8	32.82	1.00	1.87	20.66
v9	1.61	1.00	1.87	1.52
v10	2.24	1.00	1.00	1.76
v11	1.00	16.90	1.87	4.59
v12	1.61	1.00	1.87	1.52
v13	1.01	1.62	1.87	1.29
v14	1.00	1.15	1.00	1.03
v15	1.02	1.46	1.00	1.11
v16	1.01	1.31	1.00	1.07
v17	1.00	1.00	1.00	1.00
v18	2.24	1.00	1.00	1.76
v19	1.00	1.00	1.00	1.00
v20	1.01	1.31	1.00	1.07
v21	1.01	1.31	1.00	1.07
v22	1.61	16.90	1.00	4.82
v23	1.61	16.90	1.00	4.82
v24	32.82	16.90	1.00	23.95
v25	32.82	16.90	1.00	23.95

nificant an impact the loss of a given direction might would be for the planned traffic volume. For example, the largest RAW^f_{tot} values are associated with nodes v1 and v3, which are crucial for the large traffic volume associated with the connection to the west.

Figure 4 shows a plot of the degree centralities and overall importances RAW^f_{tot} in (9) for all nodes. In particular, we note that the correlation (-19.33%) between the volume weighted overall importance RAW^f_{tot} in (9) and the centrality of the degree is negative. This suggests that, in this context, degree centrality is not a particularly meaningful measure of risk because many switches have roughly same number of edges connected to them, and that this measures does not consequently reflect the more significant consequences that the position and operational status of a switch has for the possibility to enable the traffic volume for a given terminal pair.

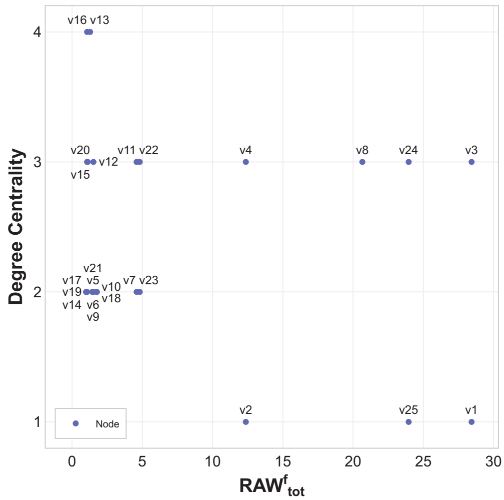

Fig. 4. Scatter plot of the overall traffic volume-weighted importance RAW^f_{tot} and the degree centrality of the nodes (correlation -19.33%).

4. Conclusions

In this paper, we have proposed importance measures for transportation networks by adapting a commonly used probabilistic risk importance measure, risk achievement worth, and augmenting it by using information about the planned traffic volume. The numerical results of our illustrative case study on the analysis of switches at a representative Finnish railway station suggest that the proposed measures are instructive and help identify switches that merit particular attention in preventive maintenance. We have also compared these importance measures to degree centrality and presented evidence which suggests that the proposed PRA-based risk importance measures may be more suitable for risk-informed decision making in this planning context, where nodes represent switches and edges represent railway tracks.

Further work can be pursued by adapting other risk importance measures (e.g., risk reduction worth, Birnbaum, Fussell-Vesely) to networks such as the one considered in our case study, for example in view of planning situations where the aim is to fortify the network through significant reductions in the disruption probabilities. Although the relative ranking of nodes is not very sensitive to the assumption about the magnitudes of these probabilities, the characterization of these probabilities also merits attention: here, techniques of statistical data analysis can be combined with procedures for structured expert judgment elicitation. Multiple concurrent disruptions may also have to be addressed, especially if the disruption events at nodes are correlated, for instance, due to common causes such as challenging weather conditions. In summary, we contend that the parallel consideration of multiple importance measures may offer important insights for risk-informed planning.

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References

Ahmad, R. and S. Kamaruddin (2012). An overview of time-based and condition-based maintenance in industrial application. *Computers & Industrial Engineering 63*(1), 135–149.

Álvarez, N. G., B. Adenso-Díaz, and L. Calzada-Infante (2021). Maritime traffic as a complex network: A systematic review. *Networks and Spatial Economics 21*(2), 387–417.

Aven, T., D. R. Insua, R. Soyer, X. Zhu, and E. Zio (2024). Fifty years of reliability in operations research. *European Journal of Operational Research*.

Barker, K., J. E. Ramirez-Marquez, and C. M. Rocco (2013). Resilience-based network component importance measures. *Reliability Engineering & System Safety 117*, 89–97.

Calzada-Infante, L., B. Adenso-Díaz, and S. Carbajal (2020). Analysis of the European international railway network and passenger transfers. *Chaos, Solitons & Fractals 141*, 110357.

Cao, W., X. Feng, and H. Zhang (2019). The structural and spatial properties of the high-speed railway network in China: A complex network perspective. *Journal of Rail Transport Planning & Management 9*, 46–56.

Cheng, Y.-Y., R. K.-W. Lee, E.-P. Lim, and F. Zhu (2015). Measuring centralities for transportation networks beyond structures. *Applications of Social Media and Social Network Analysis*, 23–39.

Chopra, S., T. Dillon, M. Bilec, and V. Khanna (2016). A network-based framework for assessing infrastructure resilience: a case study of the London metro system. *Journal of The Royal Society Interface 13*(118), 20160113.

Di Mauro, C., S. Bouchon, C. Logtmeijer, R. D. Pride, T. Hartung, and J.-P. Nordvik (2010). A structured approach to identifying European critical infrastructures. *International Journal of Critical Infrastructures 6*(3), 277–292.

Erath, A., M. Löchl, and K. Axhausen (2009). Graph-theoretical analysis of the Swiss road and railway networks over time. *Networks and Spatial Economics 9*, 379–400.

Fang, Y.-P., N. Pedroni, and E. Zio (2016). Resilience-based component importance measures for critical infrastructure network systems. *IEEE Transactions on Reliability 65*(2), 502–512.

Kim, J., Y. Ahn, and H. Yeo (2016). A comparative study of time-based maintenance and condition-based maintenance for optimal choice of maintenance policy. *Structure and Infrastructure Engineering 12*(12), 1525–1536.

Li, Z., J. Tang, C. Zhao, and F. Gao (2023). Improved centrality measure based on the adapted PageRank algorithm for urban transportation multiplex networks. *Chaos, Solitons & Fractals 167*, 112998.

Mancuso, A., M. Compare, A. Salo, and E. Zio (2017). Portfolio optimization of safety measures for reducing risks in nuclear systems. *Reliability Engineering & System Safety 167*, 20–29.

Satyanarayana, A. and J. N. Hagstrom (1981). A new algorithm for the reliability analysis of multi-terminal networks. *IEEE Transactions on Reliability 30*(4), 325–334.

Toppila, A. and A. Salo (2017). Selection of risk reduction portfolios under interval-valued probabilities. *Reliability Engineering & System Safety 163*, 69–78.

Vesely, W., T. Davic, R. Denning, and N. Saltos (1983). NUREG/CR-3385 Measures of risk importance and their applications. `https://www.nrc.gov/docs/ML0716/ML071690031.pdf`.

Yoo, Y. and N. Deo (1988). A comparison of algorithms for terminal-pair reliability. *IEEE Transactions on Reliability 37*(2), 210–215.