

D10.4

Method for time-dependent estimation of travel times



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For Bucharest there have been previous recent studies regarding the time-dependent estimation of travel times (Toma-Danila et al., 2022; 2020). In the MULTICARE Project we intend to improve the framework published in Toma-Danila et al. (2022) and presented in Figure 13. This framework titled “Network-Risk” builds upon previous works of Toma-Danila et al. (2020), Pinto et al. (2012), Hirokawa and Osaragi (2016), or Rohr et al. (2020) and has the following characteristics: 21

Its potential can be seen in Figure 14. Figure 15 presents the results of route analysis for the similar Bucharest Road network dataset, in QGIS with the QNEAT3 plugin. This can serve as an open-source alternative to ArcGIS Pro. The Network-Risk approach showed promising results for scenario-based analysis, but improvements can make them even more relevant for the MULTICARE decision-support framework and multi-hazard and multi-risk contexts. Near real-time integration for example would be an important asset, as well as an improved traffic simulation in post-hazard situations. The development and computation of resilience functions due to transportation networks is also relevant for the project purposes. 21

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GLOSSARY

ACRONYM	FULL NAME
CA	Consortium Agreement
EC	European Commission
EASME	The Executive Agency for Small and Medium-sized Enterprises
GA	Grant Agreement
PC	Project Coordinator
WP	Work Package
TL	Task Leader
DoA	Description of Action
PSC	Project Steering Committee
SQM	Scientific and Quality Manager
DEC	Dissemination and Exploitation Committee
KOM	Kick-off meeting
GER	General Exploitable Result
AB	Advisory Board
PM	Person month
M	Month
INFP	National Institute for Earth Physics, Romania
TUD	Delft University of Technology, Netherlands

1. Introduction

Travel times represent how much time it can take to reach a destination from an origin. They can be calculated:

- for multiple modes of transportation:
 - o terrestrial: using road networks, railways, subway systems etc.
 - o aerial
 - o on waterways: maritime or fluvial
- for different subjects:
 - o people
 - o goods
- under various contexts and situations: considering diurnal or seasonal variations, considering traffic patterns and the impact of multi-hazards. Understanding especially these aspects and how they shape travel time's evolution is the main purpose of this deliverable.

Knowing travel times is important for understanding how long a journey can take. Real-time updates (based on sensors or smartphone apps) prove to be of utmost importance for understanding the status of transportation networks. But all this information can also be highly valuable for proper planning, along with complex modeling of the structural and systemic risks. Time-dependent travel times information helps avoiding delays but also improving safety. Informed decisions about the most efficient routes can be made, potentially reducing fuel consumption or travel-related costs. In the case of emergency management – these can save lives. Embedding such knowledge in a decision-support system as the one intended within the MULTICARE Project is an important layer for reducing especially indirect risk.

The objective of this deliverable is to evaluate the ways time-dependent travel times are being estimated, in order to enable the definition of a viable methodology for the MULTICARE Project, with respect to the multi-hazard and multi-risk components and data availability in the case-study areas (Tecuci and Bucharest cities in Romania).

2. Methods and applications

2.1. Definition of transportation networks

Travel times are generally calculated for transportation networks. The main characteristics of transportation networks and are relevant for the analysis process include:

1. **Mode of Transportation:**
 - o **Definition:** This refers to the various methods or types of transport available in the network, such as road vehicles, public transit, rail, air travel, and maritime transport.
 - o **Importance:** The mode chosen affects factors like speed, cost, capacity, and environmental impact, and influences how the overall transportation network is designed.
2. **Nodes:**
 - o **Definition:** These are the key points or locations in the transportation network where different routes or modes converge. They can include intersections, stations, airports, ports, or terminals.
 - o **Importance:** Nodes serve as starting or ending points for trips and are critical in assessing how well different parts of the system connect.

3. **Links:**

- **Definition:** Links are the paths or routes connecting nodes. They can represent roads, rail tracks, flight paths, or waterways, depending on the transportation mode.
- **Importance:** Links are the main flow channels in the network, and their characteristics (e.g., capacity, speed limits, condition) influence travel times, safety, and efficiency.

4. **Flow/Traffic:**

- **Definition:** This refers to the movement of vehicles, passengers, or freight along the links. It can include car traffic, train movements, freight transport, or air traffic.
- **Importance:** Flow analysis helps identify congestion points, optimize traffic distribution, and improve the overall efficiency of the transportation network.

5. **Capacity:**

- **Definition:** Capacity refers to the maximum volume of traffic or flow that a link can handle within a given period, typically considering the infrastructure (number of lanes, track width, etc.) and technology.
- **Importance:** Capacity analysis is crucial for identifying bottlenecks, managing congestion, and planning infrastructure upgrades or expansions.

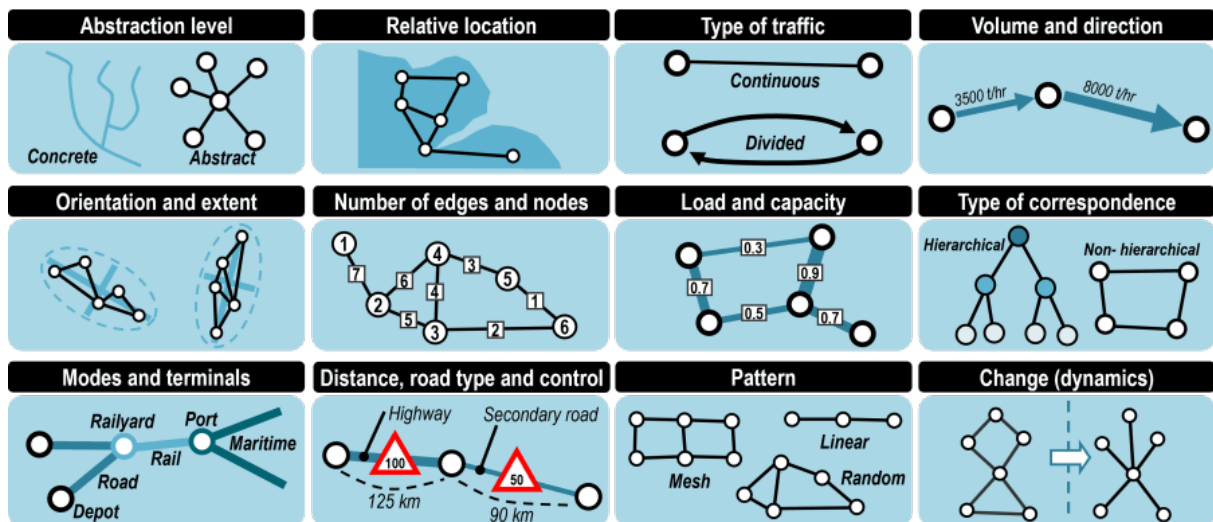


Figure 1 A Typology of Transportation Networks (from Rodrigue and Ducret, 2024)

6. **Travel Time and Distance:**

- **Definition:** Travel time is the duration it takes to travel along a link, and distance is the length of the route.
- **Importance:** Knowing travel times and distances helps in route planning, optimizing travel schedules, and evaluating the efficiency of different routes or modes. Time-dependent estimation refers specifically to the evolution of travel time at different moments.

7. **Cost:**

- **Definition:** Cost includes financial, time, or energy expenditures required to use a link or mode of transportation. It may include tolls, fuel costs, labor costs, or fare costs.
- **Importance:** Cost analysis helps optimize decisions by balancing financial factors with other considerations, such as convenience or time savings.

8. **Demand:**

- **Definition:** Demand refers to the volume of people or goods that need to be transported across the network, often determined by factors like population density, economic activity, or seasonality.
 - **Importance:** Understanding demand helps in planning for transportation capacity, anticipating peak loads, and ensuring the network meets the needs of users.
9. **Network Topology:**
- **Definition:** Topology refers to the structural layout of the transportation network, including how nodes are connected by links.
 - **Importance:** The topology determines the resilience of the network (e.g., how easy it is to reroute traffic during disruptions) and affects efficiency in travel and transportation.

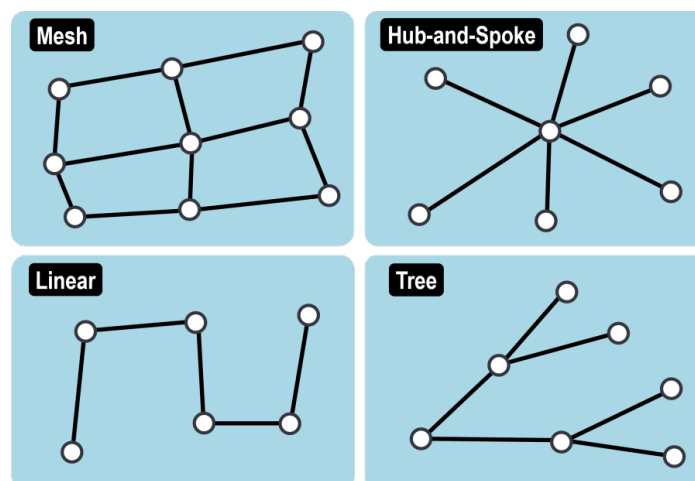


Figure 2 Example of Network Topologies (from Rodrigue and Ducruet, 2024)

10. **Network Performance Metrics:**
- **Definition:** These are indicators that assess the efficiency, reliability, and effectiveness of the transportation network. Common metrics include congestion levels, travel time variability, accident rates, and capacity utilization.
 - **Importance:** Performance metrics provide insights into where improvements are needed and help evaluate the effectiveness of policies or changes made to the network.
11. **Geographical Area or Network Boundary:**
- **Definition:** A transportation network typically serves a defined geographical area, which could range from a local or urban network to a national or global system.
 - **Role:** The size and scope of the area determine the complexity of the network, its connectivity with other networks, and the specific needs it serves (e.g., urban commuting vs. intercity travel).
12. **Accessibility:**
- **Definition:** Accessibility refers to the ease with which people can reach desired destinations within the transportation network, considering factors like proximity, availability of services, and affordability.
 - **Importance:** Accessibility analysis helps in ensuring equity, making sure that different communities or areas have adequate transportation options.
13. **Reliability:**
- **Definition:** Reliability measures how consistent the transportation system is in terms of travel times, arrival times, and overall service quality.

- **Importance:** Reliable systems are crucial for users to plan trips and maintain schedules. Unreliable systems can lead to delays and inefficiencies.

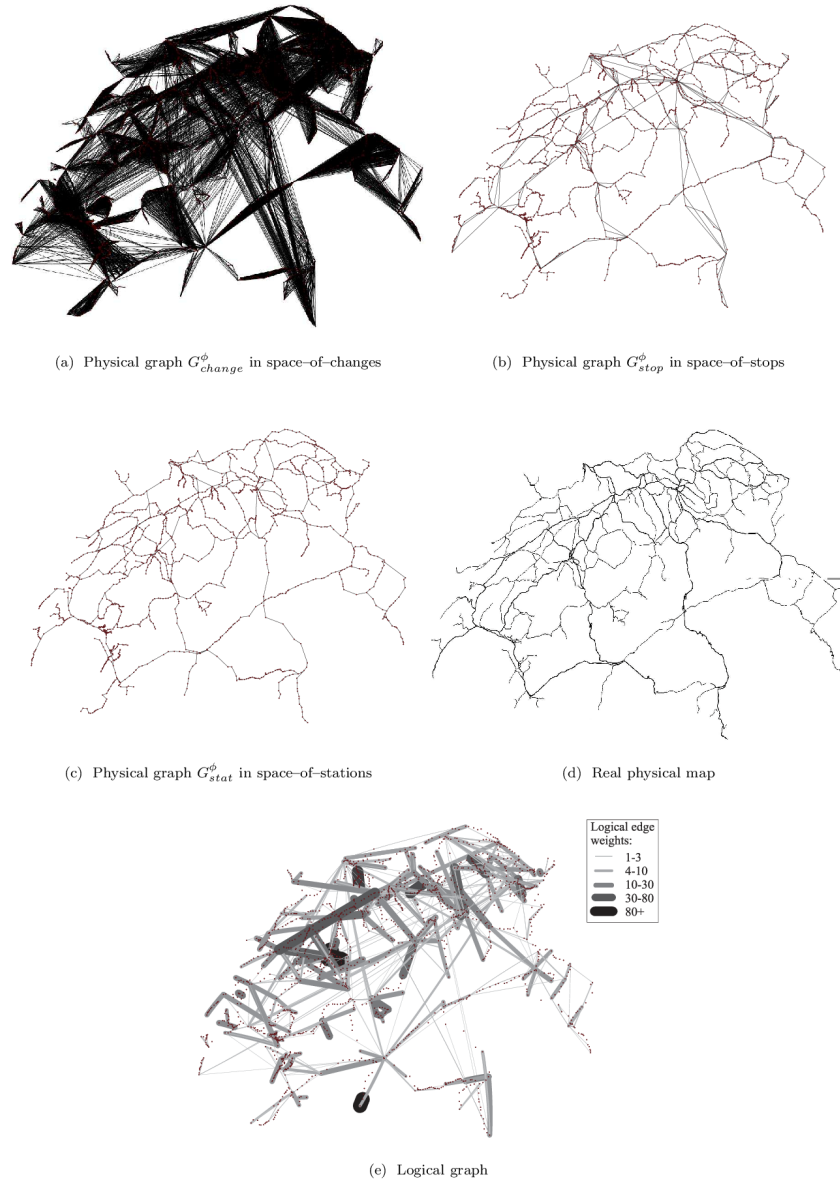


Figure 3 Various representation of the railway network in Switzerland (CH), enabling transportation analysis. (a,b,c) Physical graphs in space-of-changes, stops and stations, respectively. (d) The real map of the rail tracks in Switzerland. (e) The logical graph. Every edge connects the first and the last station of a particular train route; its weight reflects the number of trains following this route in any direction. (from Kurant and Thiran, 2005)

In order to estimate travel times on one or multiple modes of transportation networks, the definition of scenarios and events impacting the transportation network (in a direct or indirect way) is important. These might reflect:

- Structural infrastructure damage
- Change of traffic patterns
- Other restrictions: e.g. accidents, search and rescue operations, repair works, debris

Graph theory provides a mathematical framework to model and analyze transportation systems efficiently, therefore is highly important in transportation analysis. Transportation systems can be modeled as graphs. In a graph, nodes (vertices) represent locations or intersections (such as cities, bus stops, or intersections), and edges (arcs) represent the routes or paths (such as roads, rail tracks, or flight paths) connecting these locations. Graph theory allows for the use of algorithms to find the shortest, fastest, or least-cost path between two points in a transportation network.

2.2. Methods to compute travel times

Methods for time-dependent estimation of travel times

Time-dependent estimation of travel times refers to calculating the travel duration, accounting for variations in conditions: due to traffic, roadwork, weather, and other dynamic factors that change over time. Accurate time-dependent estimation is essential for route planning, traffic management, and system optimization (Flügel et al., 2020). Here are several methods commonly used to estimate travel times that vary based on time. The first three can be considered as data-driven.

1. Historical Data-Based Methods

- **Description:** These methods use past travel time data to predict future conditions based on patterns or trends observed at specific times of day or days of the week or different types of incidents.
- **Techniques:**
 - **Statistical Analysis:** Analyze historical travel time data to identify time-of-day patterns (e.g., rush hour, off-peak hours) and seasonal variations. Models like **regression analysis** or **time-series forecasting** can be used to predict future travel times.
 - **Data Aggregation:** Aggregate data from past trips to calculate average travel times for specific time intervals (e.g., hourly averages) or specific segments of the day.
- **Advantages:** Relatively simple, easy to implement with available data, and useful for capturing broad patterns.
- **Limitations:** Historical data might not apply to newer context (such as new types of vehicles and socio-economic context).

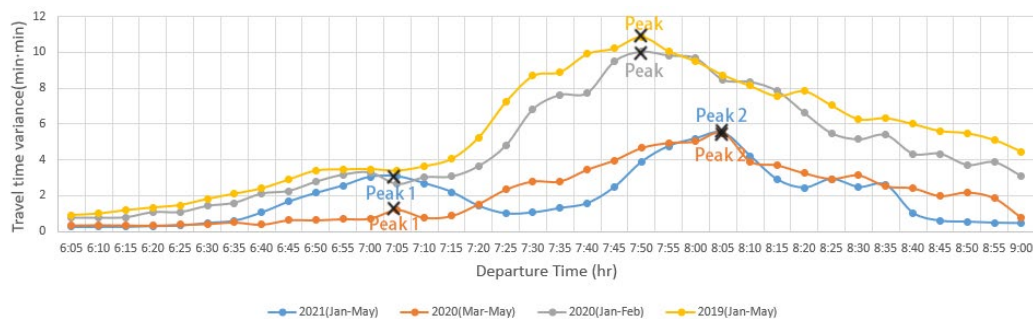


Figure 4 Travel time variance ($\sigma_2(t)$) during morning peak period in 2019, 2020 and 2021. This graph shows the evolution of travel-times during the COVID-19 pandemic (from Yang and Levinson, 2021)

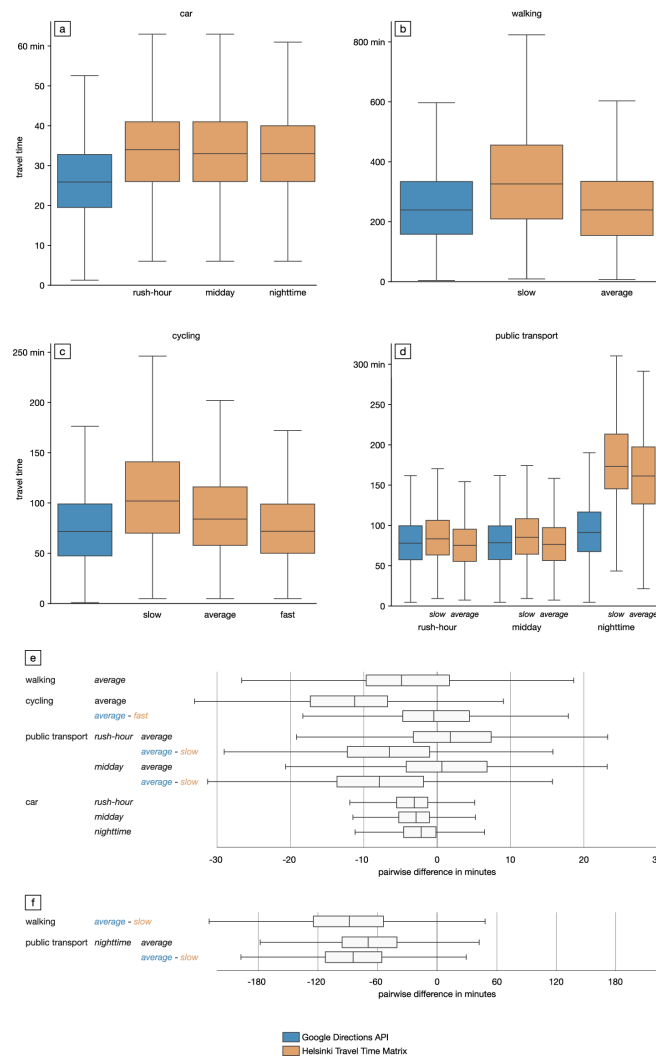


Figure 5 Comparison between the travel times computed by our approach and the travel times retrieved from the Google Directions API for different modes of transport with different parameters. Panels a-d show a comparison of the distribution of absolute values of travel times, panels e-f the distribution of pairwise differences (from same origin to same destination) (from Fink et al., 2024)

2. Real-Time Data-Based Methods

- **Description:** These methods use real-time data to estimate current and future travel times.
- **Techniques:**
 - **Traffic Flow Models:** Use real-time data on traffic speed and congestion to update travel time predictions. This often involves monitoring sensors, GPS data along specific road segments and crowdsourced data (e.g., from navigation apps like Google Maps or Waze).
- **Advantages:** responsive to real-time changes, and takes into account unexpected events.
- **Limitations:** Requires access to real-time data, which can be costly or complex to implement on a large scale.

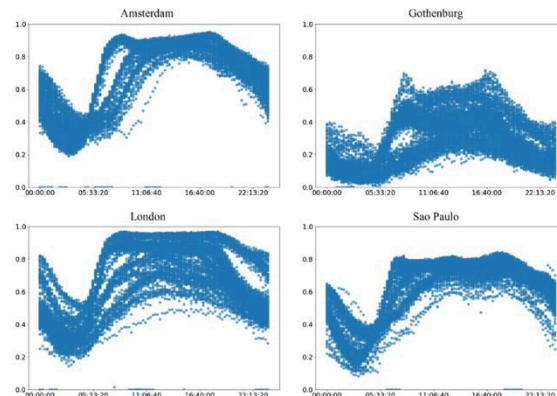


Figure 6 Share of real-time traffic data, distributed across time of day. Traffic data with real-time information (vertical axis) as share of roads, vs. time of day (horizontal axis). Examples from four cities during 6 months, where time has been adjusted to the local time zone. In general, day times are associated with a higher share of real-time measurements, suggesting that larger traffic volume is significantly (from Verendel and Yeh, 2019)

3. Machine Learning and Artificial Intelligence (AI)

- **Description:** Machine learning (ML) and AI techniques can be used to predict travel times by learning from large volumes of data, identifying patterns, and making predictions based on both historical and real-time data.
- **Techniques:**
 - **Supervised Learning:** ML algorithms (such as **regression trees, recurrent neural networks, long short-term memory networks, or random forests**) are trained on historical travel time data and real-time data (Mussah & Adu-Gyamfi, 2022) to make predictions about future travel times (Boukerche et al., 2020; Zheng et al., 2023).
 - **Reinforcement Learning:** This method involves training models that adapt to traffic conditions over time, learning the best strategies for predicting travel times based on dynamic inputs.
- **Advantages:** Can handle large and complex datasets, account for a variety of factors influencing travel time, and adapt to changing conditions.
- **Limitations:** Requires large amounts of labeled data for training, and models can be complex to develop and interpret.

4. Simulation Models

- **Description:** Microsimulation models simulate the behavior of individual vehicles and their interactions at a detailed level, accounting for factors like vehicle type, driver behavior, traffic signals, and intersections.
- **Techniques:**
 - **Agent-Based Simulation:** Involves modeling individual vehicles (or agents) and their movements based on dynamic factors like traffic flow, congestion, or road conditions.
 - **Time-dependent Traffic Assignment Models:** These models allocate traffic flow over a network based on time-varying demand and supply conditions, simulating how traffic congestion evolves over time (Min and Wynter, 2011).
 - **Queuing Models:** These are used to estimate waiting times as a consequence of specific barriers (e.g., a tollbooth, intersection). The queue is modeled as a service system where vehicles wait in line (queue) to pass through a particular section of the road.
- **Advantages:** Provides detailed, dynamic estimates that reflect real-world conditions, including congestion, traffic incidents, and variations in driving behavior.

- **Limitations:** Computationally intensive, requiring large datasets and sophisticated software for accurate modeling.
- 5. Dynamic Traffic Assignment (DTA)**
- **Description:** DTA models estimate travel times by considering both the current and predicted traffic conditions over time. DTA accounts for changes in traffic flow as vehicles move through the network, adjusting travel times accordingly (Wang et al., 2018).
 - **Techniques:**
 - **Time-dependent User Equilibrium:** This method assumes that travelers make route choices based on minimizing their travel time and adjusts the traffic assignment based on current congestion levels.
 - **Stochastic Models:** These models introduce randomness to simulate the impact of uncertain factors (e.g., accidents, weather) on travel time, providing probabilistic travel time estimates.
 - **Advantages:** Accounts for time-dependent and stochastic variations in traffic, enabling better predictions of travel time (Bliemer et al., 2017).
 - **Limitations:** Requires significant computational resources and detailed traffic data for accurate predictions.

With regards to **cost-benefit analysis**, travel time is less costly if it can be spent productively, but also consideration of comfort and safe need to be accounted for.

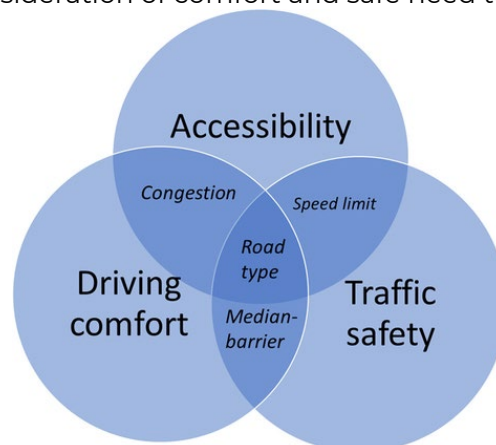


Figure 7 Illustration of relationship between driving comfort, accessibility and traffic safety with road type as a shared characteristic (from Flügel et al., 2022)

Algorithms for travel-time computation

Classical algorithms like Dijkstra's, A*, Bellman-Ford, Floyd–Warshall or Johnson help in routing vehicles or travelers through the most efficient paths, which is vital for reducing travel time, fuel consumption, or congestion.

The Dijkstra's algorithm is widely used in applications such as routing algorithms, GPS navigation systems, and network analysis. **A*** can be seen as an extension of Dijkstra's algorithm; it uses heuristics to guide its search. As a comparison (GeeksforgEEKS, 2024), A* algorithm is commonly used in pathfinding and graph traversal problems, such as video games, robotics, and planning algorithms. Once a node is marked as visited, the Dijkstra does not reconsider it even if there is another shortest path. Due to this reason, the Dijkstra algorithm does not work when there is a negative edge weight in the graph.

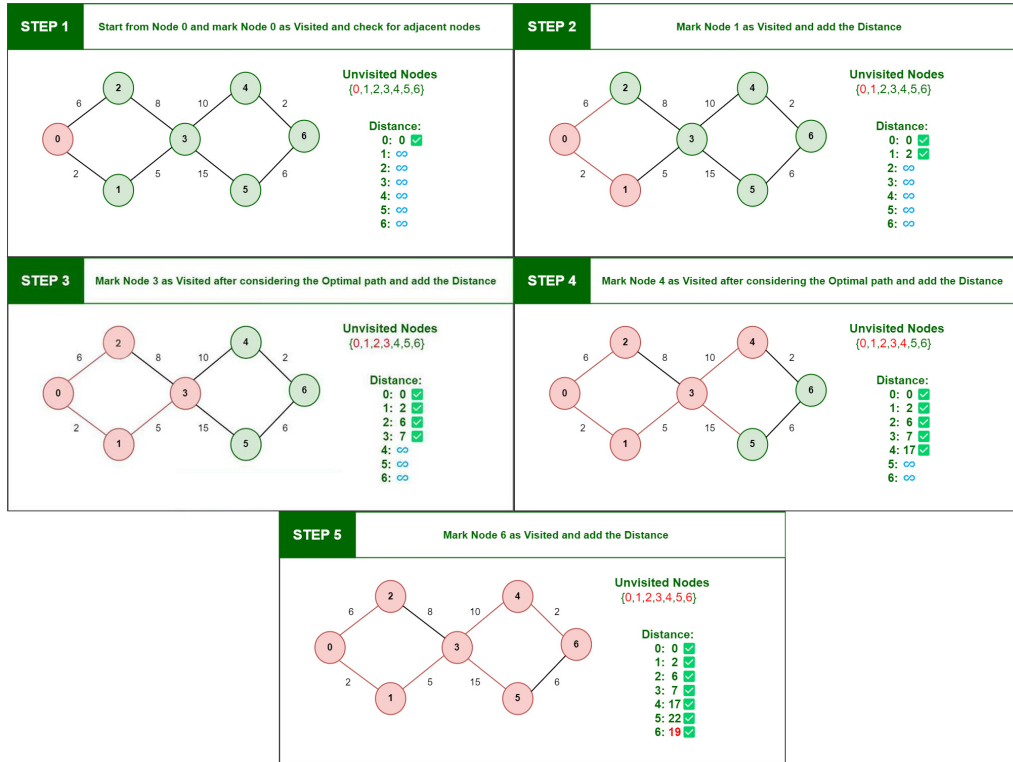


Figure 8 Visual representation of the Dijkstra's Algorithm for shortest distance calculation (modified from Geeksforgeeks, 2024)

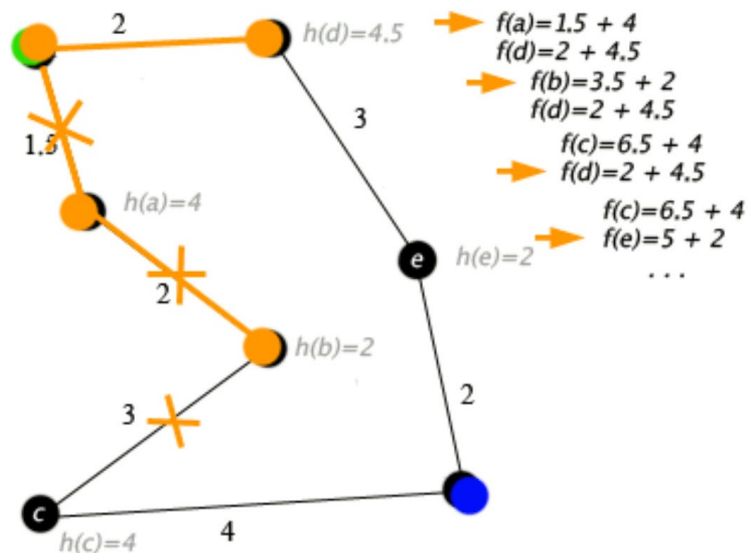


Figure 9 An example of A* algorithm in action (nodes are cities connected with roads, $h(x)$ is the straight-line distance to the target point) Green: Start, Blue: Target, Orange: Visited (from CountingPine, CC0, via Wikimedia Commons)

Dynamic programming (DP) can be used to solve many network optimization problems, such as the shortest path problem, the maximum flow problem, and the network reliability problem (Rong and Tayalarajan, 2024). It can be applied to both deterministic

and stochastic problems. The following elements are needed to be identified in order to apply DP to network optimization:

- the state of the network: its configuration or condition at a given time;
- the decision variables: choices or actions that affect the state of the network;
- the objective function: a measure of performance or quality of the network;
- the constraints: limitations or requirements that must be satisfied.

Among the algorithms that are considered in the DP category are:

- The **Bellman Ford algorithm**. This can be used when the edge weight is negative. It systematically updates the shortest path estimates, ensuring that the final path lengths reflect the minimal distances from the source. This is achieved through a series of edge relaxations, iteratively improving the estimates until the optimal paths are determined (Nair, 2024).
- **The Floyd-Warshall method**. This uses a technique of DP can determine the shortest route across all pairings of vertices in a graph with weights. The method compares each pair of vertices' potential routes through the graph. It gradually optimizes an estimate of the shortest route between two vertices to determine the shortest distance between two vertices in a chart. With simple modifications to it, one can reconstruct the paths (Chiradeep, 2024).

Reinforcement Learning (RL) is a type of machine learning where an agent learns to make decisions by interacting with an environment. The agent takes actions in the environment, and based on those actions, it receives feedback in the form of rewards or penalties. The goal is for the agent to learn a strategy (called a policy) that maximizes the cumulative reward over time. The dynamic evolution process of complex network can be modeled using for example a Markovian decision process (Song et al., 2022). RL can be:

- Model-Free: The agent learns through trial and error, without explicitly modeling the environment. Examples include Q-learning and Policy Gradient methods.
- Model-Based: The agent builds and uses a model of the environment to predict outcomes of its actions and plan ahead.

Meta-heuristics are a class of optimization algorithms designed to find approximate solutions to complex optimization problems (Iliopoulou et al., 2019), especially those that are too large or difficult to solve using exact methods. These algorithms are used when traditional optimization methods (like linear programming, dynamic programming, or branch and bound) fail or are too computationally expensive. Meta-heuristics typically do not guarantee an optimal solution but aim to find a good-enough solution in a reasonable amount of time. Common Meta-Heuristic Algorithms are the **Genetic Algorithm, Simulated Annealing, Ant Colony Optimization or Tabu Search**.

Testing all of the above approaches (however choosing one that is viable in near-real time implementation) will help in determining reliable time-dependent estimation of travel times, for which we will also seek real validation using data from the case-study areas: Tecuci and Bucharest (Romania).

2.3. Analysis of elements that can impact travel times

In travel times estimation, an important role is played by determining which are the potential incidents that might affect the transportation network. This means that an identification of vulnerable elements which might affect specific network segments and then propagating the implications at systemic level needs to be performed. That is why in this sub-chapter we will look at ways to quantify damage at component level, with impact in the outcome of methods applied for travel-time computation, described in sub-chapter 2.2.

Damage to transportation network structures

Fragility functions are essential tools in infrastructure risk analysis as well as for buildings, helping to quantify the vulnerability of infrastructure systems to natural hazards and inform decisions on how to improve resilience, reduce risk, and optimize investments in infrastructure safety. They offer valuable insights into the potential impacts of extreme events, guiding strategies for mitigation, response, and recovery.

Fragility functions are mathematical models or curves that describe the likelihood of a certain level of damage or failure occurring in a system or component of infrastructure when exposed to a particular level of hazard. A fragility function represents the probability that an infrastructure element (like a bridge, building, or power grid) will reach or exceed a certain damage state when subjected to a specific intensity or severity of a hazard. On the other side, consequence, vulnerability or resilience functions provide an additional dimension, reflecting aspects such as expected repair time, direct or indirect losses. Structural damage estimation can contribute to systemic analysis.

Numerous studies in literature focus on the main issues in vulnerability of bridges structures, such as classification of bridges, methods for deriving fragility functions, selecting proper intensity measures, damage states and damage measures in order to estimate the seismic loss accurately. There are various methods to develop fragility curves for bridge structures such as:

- empirical;
- expert opinion;
- numerical (nonlinear static and dynamic analyses);
- parameterized methods.

Empirical and opinion-based curves are the first introduced and limited ones in the literature, while most previous studies use numerical analysis. The advantage of implementing the numerical (analytical) method is that it can take into account all uncertainties successfully. However, the analysis is time-consuming, very sensitive to modeling and computationally inefficient. For tunnels, fewer fragility functions have been developed.

A representative review on existing fragility functions but also vulnerability and resilience functions for infrastructure elements can be seen in:

- The TURNKEY Project deliverables: Tiganescu et al. (2022), D'Ayala et al. (2021)
- ReLUIS-DPC RINTC Database of fragility functions: Chioccarelli and Iervolino (2024)
- An online platform for bridge-specific fragility analysis of as-built and retrofitted bridges: Stefanidou et al. (2022)
- SYNER-G: Typology Definition and Fragility Functions for Physical Elements at Seismic Risk: Pitilakis et al. (2004)
- HAZUS functions: FEMA (2003)

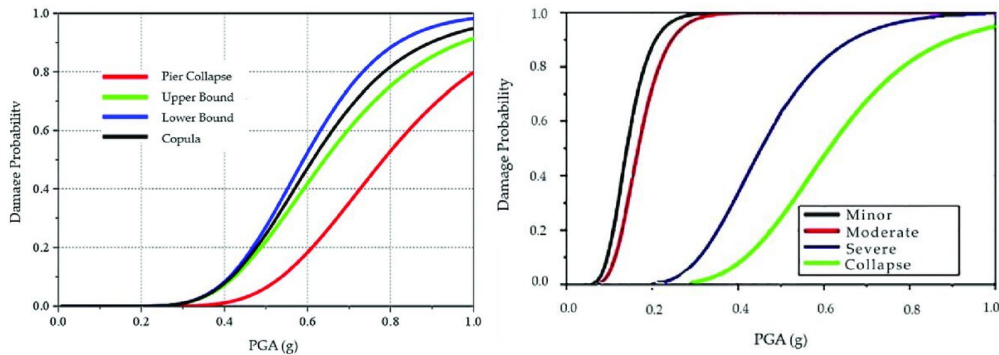


Figure 10 Examples of fragility functions for a bridge (from Liu and Yang, 2021)

Debris potential

Estimating debris potential refers to assessing the likelihood of debris accumulation that can cause direct and indirect (delay) losses for transportation networks. Debris can include items such as rocks, fallen trees, branches, mudslides, snow, buildings and building materials or even materials from accidents. Estimating this potential helps in proactive road maintenance, traffic management, and safety planning. The analysis can be conducted using:

- **Historical Data Analysis:** It can analyze past incidents of debris accumulation along different sections of the road network to identify patterns and regions more prone to debris. Can include data Accident and Incident Reports, Weather and Road Condition Data or Maintenance Records. This method is reactive and doesn't account for future changes in environmental conditions or infrastructure.
- **Debris Risk Modeling:** by using predictive models that incorporate various factors such as weather conditions, terrain, traffic data, and historical debris incidents to estimate the likelihood of debris accumulation in different road segments. Both statistical and simulation models can be implied. Among the studies that provide relations between the collapse of buildings and road debris blockage we mention Argyroudis et al. (2015), Osaragi and Oki (2017), Zanini et al. (2017).
- **Monitoring and Sensor Systems:** Using modern sensor technologies and automated systems to monitor road conditions in real time, identifying debris as it occurs and helping to predict potential debris accumulation. Remote sensing imagery, evaluated by deep-learning algorithms, can reflect the areas which face problems. Crowdsourcing provides real-time information on debris accumulation and areas where the risk is higher.

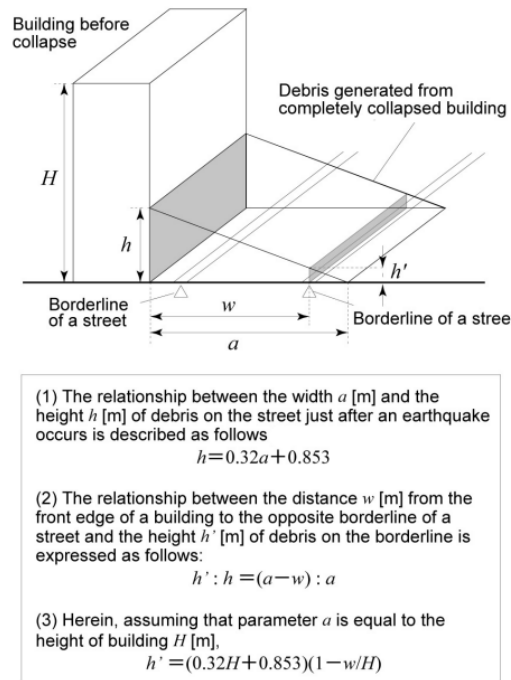


Figure 11 Modeling of height of debris generated from completely collapsed building (from Osaragi and Oki, 2017)

2.4. Software for travel times analysis

Among the software that provide capabilities for travel time analysis, using customized transportation network definitions, are:

- **AIMSUN**: a traffic simulation and modeling software that offers travel time analysis along with real-time traffic management.
- **ArcGIS Pro**, with the Transportation Analyst module (ESRI, 2024)
- **QGIS** with the QNEAT Plugin
- **MATSim (Multi-Agent Transport Simulation)**: an open-source, agent-based simulation software for modeling transportation networks, including travel time and congestion analysis.
- **SYNCHRO** and **SimTraffic**: SYNCHRO (by Trafficware) and its associated simulation tool, SimTraffic, are used for traffic flow analysis, including travel time estimation and congestion management.
- **TransCAD**: a GIS-based transportation planning software that includes tools for travel time analysis, route optimization, and transportation network modeling.
- **VISSIM**: a traffic simulation software that allows for the modeling of road traffic and public transit systems, including the analysis of travel times.

Other software solutions that provide travel times information, using also crowd-sourced information, but do not allow for transportation network customization, are:

- **Google Maps**: it can also provide through an API information regarding Real-time traffic data and routing, Distance and travel time estimation.
- **Waze**
- **Moovit**

There is also software that does not provide travel time analysis, but focuses on risk assessment and implication of various hazards on infrastructure, which can serve as an important input for travel time analysis. Among this software we mention HAZUS, INCORE, WNTR, and OOFIMS, which are summarized in Poudel et al. (2023). This reference

also highlights the potential of OpenQuake (which is proposed to be part of the MULTICARE rapid seismic loss estimation system) for infrastructure risk analysis, with capabilities to estimate seismic ground motion but also liquefaction potential, possibility to evaluate damage probabilities for buildings, bridges or other structures using fragility functions and possibility to model consequences, resilience capacity (GEM, 2024) and connectivity analysis (Figure 12), with the help of additional Python packages such as **NetworkX** (Hagberg et al. 2008).

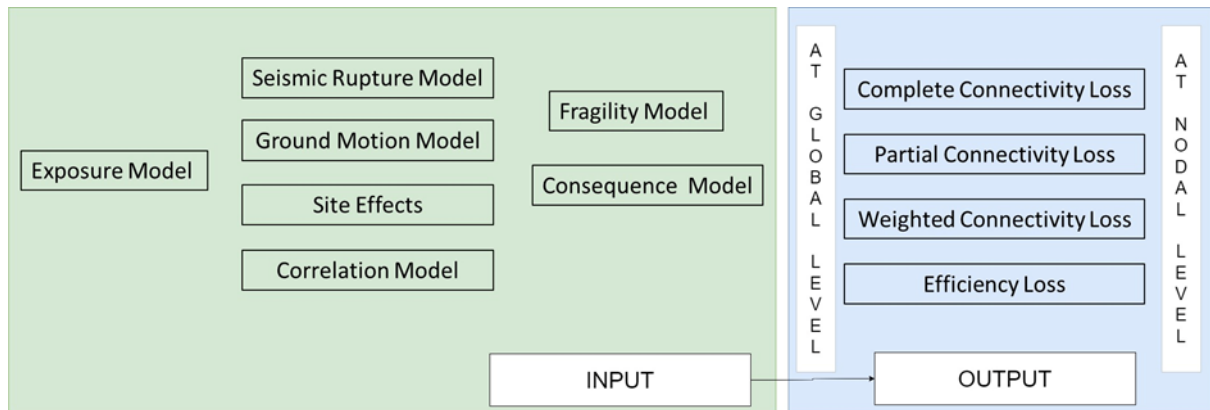


Figure 12 Input models required, and output obtained in OpenQuake for infrastructure risk assessment at connectivity level (from GEM, 2024)

3. Preliminary testing

For Bucharest there have been previous recent studies regarding the time-dependent estimation of travel times (Toma-Danila et al., 2022; 2020). In the MULTICARE Project we intend to improve the framework published in Toma-Danila et al. (2022) and presented in Figure 13. This framework titled “Network-Risk” builds upon previous works of Toma-Danila et al. (2020), Pinto et al. (2012), Hirokawa and Osaragi (2016), or Rohr et al. (2020) and has the following characteristics:

- can handle historical and real traffic (ESRI, 2024), providing time-dependent analysis;
- can incorporate road blockage analysis (due to structure damage or debris);
- takes advantage of ArcGIS Pro and its Network Analyst extension, allowing easy integration of OpenStreetMap road or railway data; there are also options to accommodate multi-modal transportation;
- results can consist of shortest or safest routes, service areas, origin-destination matrixes or custom performance indicators can be added;
- the shortest-path routing algorithms is Dijkstra;
- can be used for simulations based also on the MonteCarlo approach.

Its potential can be seen in Figure 14. Figure 15 presents the results of route analysis for the similar Bucharest Road network dataset, in QGIS with the QNEAT3 plugin. This can serve as an open-source alternative to ArcGIS Pro. The Network-Risk approach showed promising results for scenario-based analysis, but improvements can make them even more relevant for the MULTICARE decision-support framework and multi-hazard and multi-risk contexts. Near real-time integration for example would be an important asset, as well as an improved traffic simulation in post-hazard situations. The development and computation of resilience functions due to transportation networks is also relevant for the project purposes.

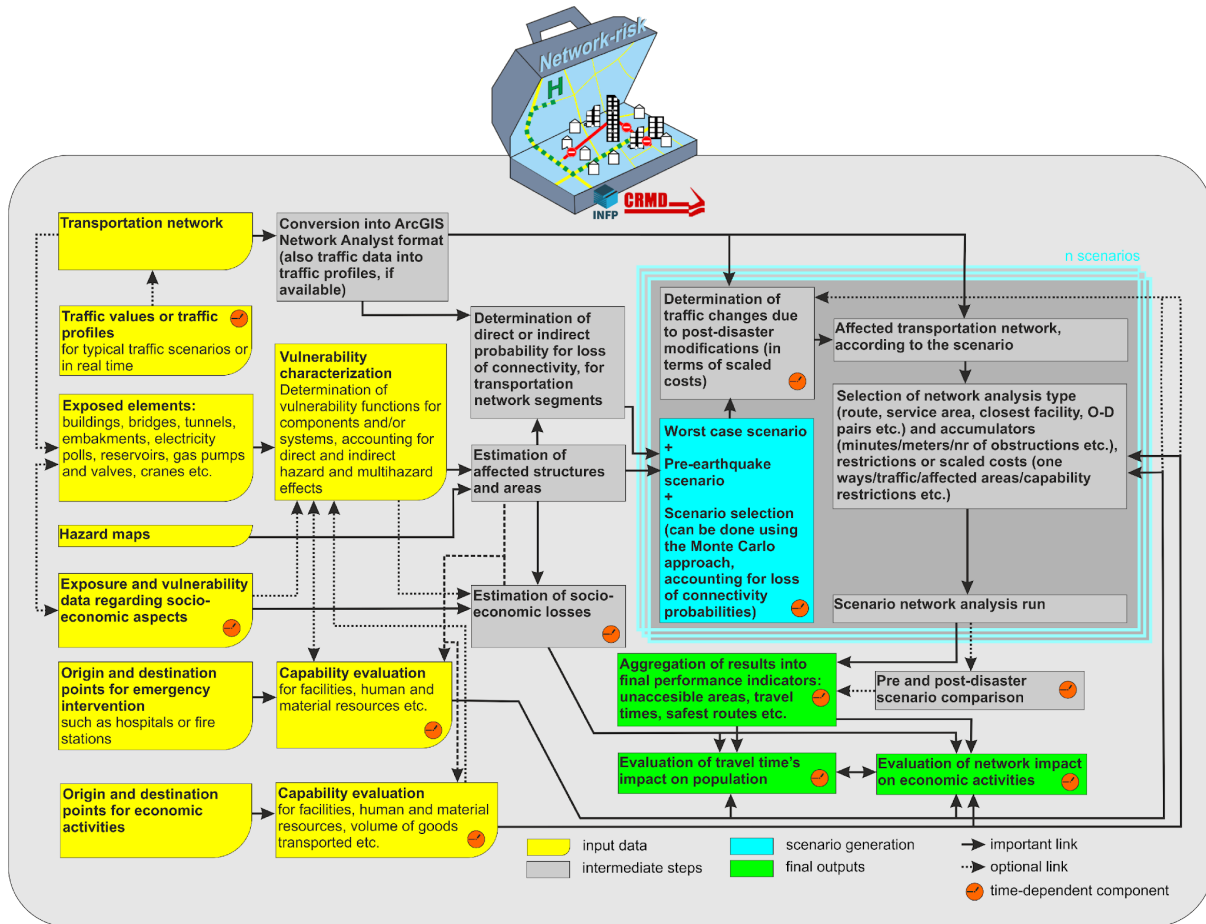


Figure 16 Network-risk methodology (from Toma-Danila et al., 2022)

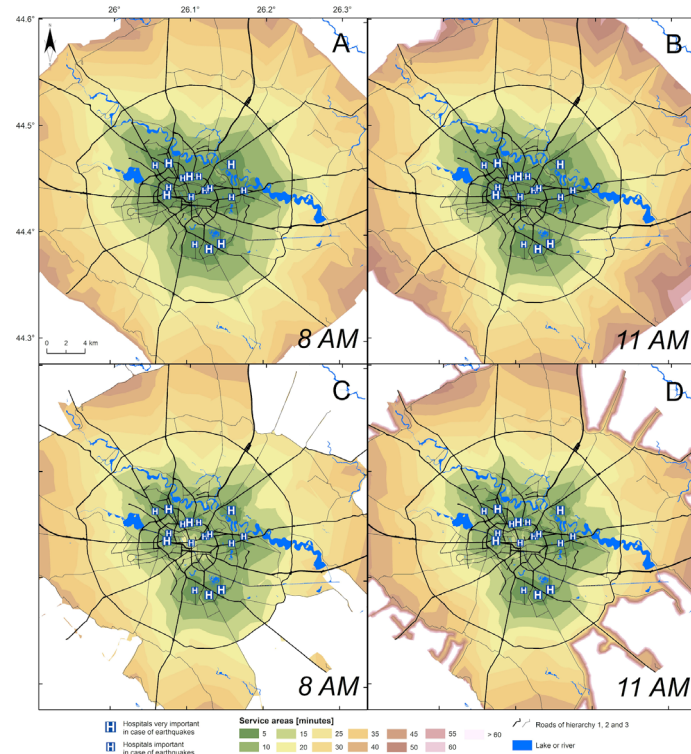


Figure 17 Maps showing Service Area times for hospitals with very high and high importance in case of earthquakes, in pre-earthquake (A, B) and post-earthquake (C, D) conditions, for an earthquake occurring at 8 LT on a typical weekday (from Toma-Danila et al., 2022)

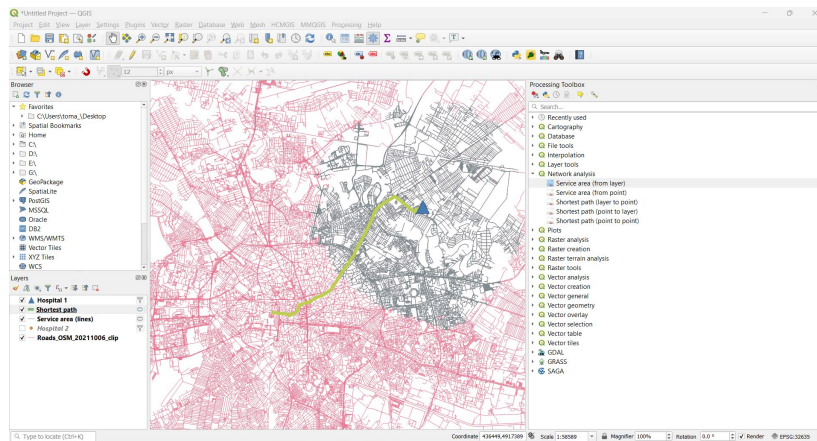


Figure 18 Results of route analysis for Bucharest road network, using OpenStreetMap data and QGIS Network Analysis

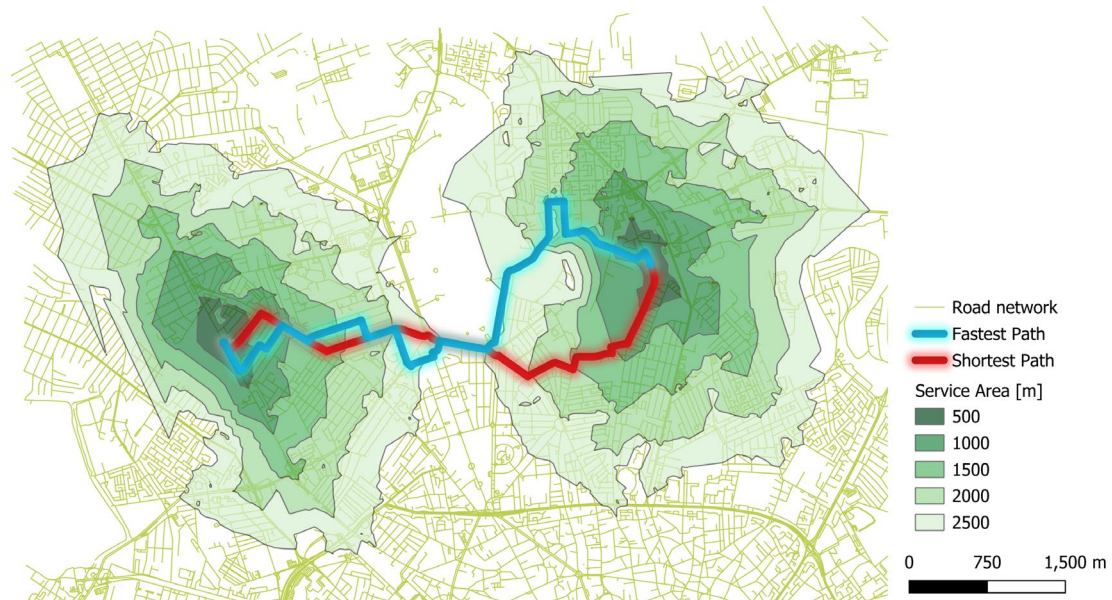


Figure 19 Results of route and service area (iso-lines) analysis for Bucharest Road network, using OpenStreetMap data and the QNEAT3 Plugin in QGIS, using typical 8 AM Monday traffic values

4. Conclusion

Time-dependent estimation of travel times is influenced by the specific needs of the system, by available data, and by the level of accuracy required. Historical data-based methods and time-of-day adjustments are useful for general estimates, while real-time data and machine learning provide more precise and dynamic predictions. Microsimulation and dynamic traffic assignment models can offer in-depth analysis - that is why it is desirable to include these in the MULTICARE analysis. Combining several methods can often provide the most accurate and reliable travel time predictions. Beside modeling capacities, validation is also necessary; that is why real data acquisition (based on sensors but also crowdsourcing) will need to be performed in the case-study areas. In MULTICARE we will first of all evaluate road transportation networks from the perspective of first responders, city managers but also casual drivers (which are most relevant for the Tecuci case-study area) and we will also consider the impact of earthquake and floods (non-simultaneous). By using GIS integration, we will be able to provide decision support actors a tool that is useful for spatial analysis and risk mitigation. Among the major challenges in network analysis is the proper definition of transportation networks; through a good collaboration with Tecuci City Hall (which is directly a partner in the MULTICARE Project) we will manage to have access to relevant data, including aspects regarding infrastructure quality, road works and vulnerabilities.

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