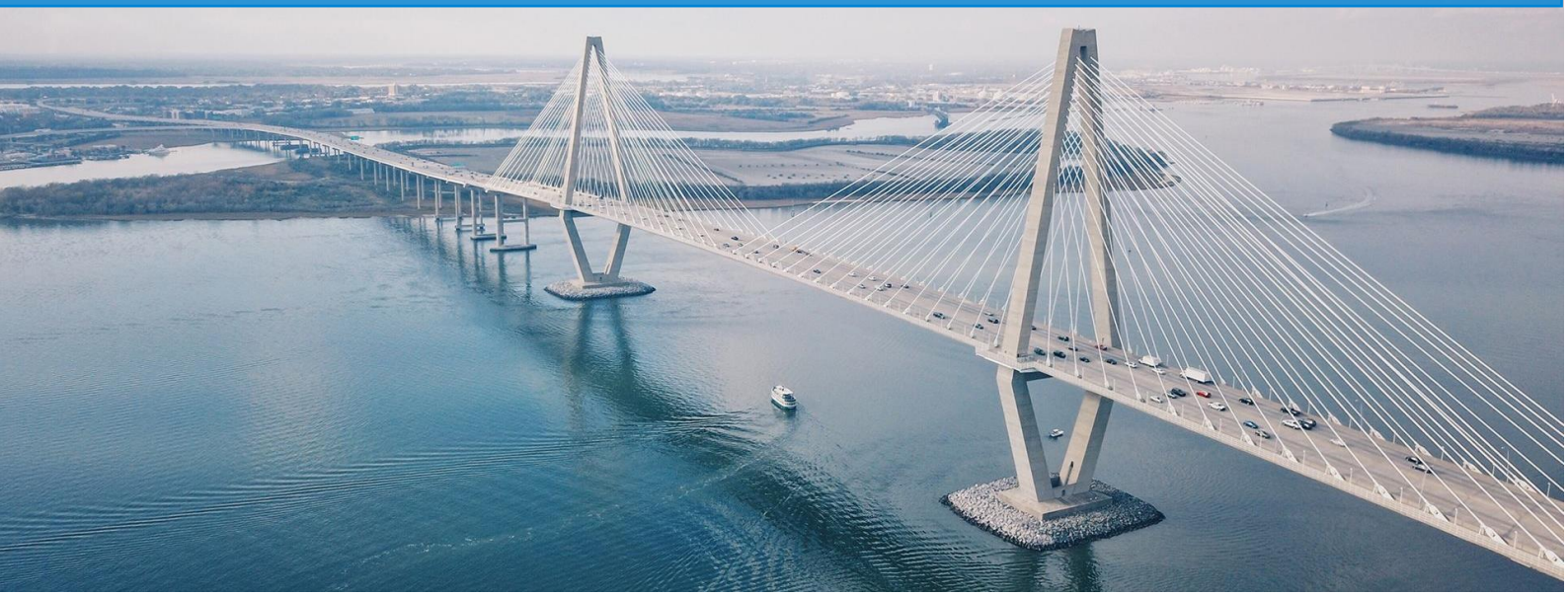
SIRMA

STRENGTHENING INFRASTRUCTURE RISK MANAGEMENT IN THE ATLANTIC AREA



Framework for consequence analysis for transportation infrastructure networks

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SIRMA

STRENGTHENING THE TERRITORY'S RESILIENCE TO RISKS OF NATURAL, CLIMATE AND HUMAN ORIGIN

Application Code: EAPA_826/2018

Framework for consequence analysis for transportation infrastructure networks

WP 4 Climate Change & Natural Hazards in Atlantic Area

Deliverable ID	**D4.3**
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Contributors	

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SIRMA Project Synopsis

SIRMA aims to develop, validate and implement a robust framework for the efficient management and mitigation of natural hazards in terrestrial transportation modes at the Atlantic Area, which consider both road and railway infrastructure networks (multi-modal). SIRMA leads to significantly improved resilience of transportation infrastructures by developing a holistic toolset with transversal application to anticipate and mitigate the effects of extreme natural events and strong corrosion processes, including climate change-related impacts. These tools will be deployed for critical hazards that are affecting the main Atlantic corridors that is largely covered by SIRMA consortium presence and knowledge. SIRMA's objectives will address and strengthen the resilience of transportation infrastructures by:

- Developing a systematic methodology for risk-based prevention and management (procedures for inspection, diagnosis and assessment);
- Implementing a decision-making algorithm for a better risk management;
- Creating a hierarchical database (inventory data, performance predictive models, condition state indicators and decision-making tools), where information can be exchangeable between entities and across regions/countries;
- Developing a real-time process for monitoring the condition state of transportation infrastructure;
- Enhancing the interoperability of information systems in the Atlantic Area, by taking account of data normalisation and specificity of each country.

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Executive Summary

This deliverable proposes a methodology for assessing the consequences of failure of transportation networks within a risk assessment context through the use of transport network analysis. The report provides an overview of the categorisation of failure consequences of transport networks and then introduces the principles of transport network analysis, which is used as the basis for quantification of failure consequences. The details of the case studies that were used to demonstrate the applicability of the methodology are introduced. The concept behind modelling the failures within the transport network models is explained, covering the effect of failure propagation patterns on the magnitude of failure consequences. Focus is given to indirect consequences in terms of traffic delays due to failures observed at various points on the network. The methodology is useful in terms of identifying the critical locations (nodes/sections) of a transport network in terms of their failure consequences. Both single and multi-failure scenarios of nodes/sections are investigated.

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1. Introduction

1.1 Objectives

The main objective of WP4 within the SIRMA project is to assess the vulnerability of transportation infrastructures to interceptable (e.g., deterioration due to chloride ingress) and non-interceptable (e.g., scour) events under various climate change scenarios.

Within WP4, Deliverable 4.3, "Methodology for assessment of infrastructure vulnerability and failure consequences", aims to develop a framework to quantify the failure consequences of transportation networks under different failure scenarios.

1.2 Testbed

The test bed that the Portuguese infrastructure operators have identified for the SIRMA project is the EN6 road, which runs along the coast, and a stretch of the Cascais Railway line, which runs parallel to EN6 at certain sections. Road EN6 has a length of 16 km, and the Cascais Railway has a length of 25.5 km. Figure 1-1 below shows the extent of the test bed. This is a stretch of highway that is extremely busy during the summer months with a high amount of traffic between Lisbon and Cascais. It is also a part of the network that is affected by storms/waves at some of the parts of the road are very close to the sea coast.

Figure 1-1: Test bed in Portugal

2. Background

2.1 Categorisation of failure consequences

Within a risk assessment framework, once the likelihood of occurrence of the hazards that may affect the assets of a transport network is estimated, this should be followed by the assessment of the vulnerability of the network's assets against these hazards and an appropriate assessment of risk. The latter also requires estimation of the consequences of failure, which play an essential role in both qualitative and quantitative risk-based design and assessment of transport networks. Consequences of failure can often be seen as a good indicator of the importance of an asset, given its form, function and location within a transport network. They can range from casualties and injuries to structural damage, reduction in network functionality and may also extend into environmental as well as societal impact. Table 2-1 shows that, in general, consequences resulting from asset failures may be divided into four main categories: human, economic, environmental, and social. Each of these main four categories can be further sub-divided into a number of more specific areas, so that itemisation and appropriate modelling, where possible, may be undertaken.

Figure 2-1: Categorisation of failure consequences for transportation networks

Consequence categories	Examples
Human	Fatalities Injuries Psychological damage
Economic	Replacement / repair costs Loss of functionality/downtime Traffic delay / re-routing costs Traffic management costs Physical damage clean-up costs Rescue costs Regional economic effects Loss of production / business Investigations / compensations Infrastructure inter-dependency costs
Environmental	CO_2 Emissions Energy use Pollutant releases Environmental clean-up/reversibility Noise pollution/impact
Social	Loss of reputation Erosion of public confidence Undue changes in professional practice

Consequences can be classified as either direct or indirect. Direct consequences are considered to result from damage states of individual components. Indirect consequences, triggered by the former, are associated with reduction in, or loss of, system/network. The differentiation between direct and indirect consequences depends on the system boundaries considered in the analysis as well the extent of the time frame that is used; they may, therefore, be subjective to a degree (Faber, 2008).

2.2 Factors affecting failure consequences

A modelling framework for transport network failure consequences should account for their type, the relevant time frame, as well as the system boundaries surrounding the network. The time frame considered (days/weeks/years) plays an important role in consequence modelling; consequences will be different when considering only a short-term post-event time frame or a long-term period extending well after the failure event. The actual duration in considering long-term periods is also expected to affect the magnitude of estimated consequences. For example, an asset failure during the immediate and mid-term aftermath may result in loss of business revenue and high traffic delay costs but over longer periods these might change as new regional equilibria are reached. Lastly, consequence estimation is affected by the definition of the system boundaries; for example, the system may be defined as solely the system of the asset (structural domain) or it may be extended into the transportation network that the asset is within (spatial domain). The extent of the spatial domain is also an important factor, depending on whether a single route (with diversions) or a more widely encompassing spatial network is considered. Here, the level of redundancy of the transportation network in redistributing traffic flows following an asset collapse plays an important role. Further layers can be added to the above systems by addressing wider societal consequences such as business losses, environmental impact, etc.

The consequences of failure vary significantly from asset to asset and may depend on a range of factors which are related to the hazard itself, the asset, and its utilization, as well as the surrounding environment. For example, the source and nature of the hazard leading to the asset failure will considerably affect the consequences. It is expected that the greater the magnitude and duration of a hazard, the greater the consequences will be. The asset type will also influence both its vulnerability and robustness, and, hence, the consequences, which are likely to be sensitive to factors such as the structural form of the asset, the material used, age and condition, as well as quality of construction.

Asset location is one of the major factors expected to influence the magnitude of failure consequences. The type of road or rail route served by the asset influences the traffic intensity and, hence, the number of people exposed to any given hazard, as well as the traffic delay costs. Moreover, the availability of emergency services and accessibility to treatment for injuries is likely to be more accessible in urban areas, hence, the number of fatalities may be lower in such locations. Finally, the cost of repair or reconstruction of the asset may be higher in rural areas due to increased labour, materials and transportation costs. On the other hand, access might be easier and inter-dependency issues might be less critical than in urban areas. The time of the day that an asset failure may take place will also have an effect on human consequences. For example, bridges will experience high levels of traffic during peak times and the potential for mass casualties is thus higher.

2.3 Quantification of failure consequences

Quantification of failure consequences is, in all but the simplest of cases, challenging and multi-faceted. The level and sophistication of the various analysis types increases considerably as the range and extent of considered consequences widens. It is often practical to express consequences in terms of monetary units, though this is rarely easy to do so. Difficulties are encountered in expressing loss of life or injuries in monetary units and in quantifying economically social and environmental impacts.

Sources for the quantification of consequences from bridge failures can be found in natural hazard loss estimation manuals, reports analysing past failures, industry and regulatory authorities' guidelines and the general literature. Some examples of models for assessing failure consequences are presented below.

2.3.1 Human consequences

Human consequences, considered as the most serious type, are highly variable between different events and subject to considerable uncertainty both in terms of predicting as well as valuing. An alternative in assigning monetary values to human consequences is to consider them separately, thus leading to multi-objective optimisation criteria in risk assessment.

A contentious issue in casualty modelling is the determination of an economic value for a human life, for which a range of methods can be found, including (i) willingness-to-pay and willingness-to-accept approach (ii) insured value statistics (iii) cost per (statistical) life saved approach (iv) dependents' lost earnings estimates and (vi) societal lifesaving cost estimates. As might be expected, there is considerable variation in the values that have been determined, reflecting different circumstances, varying social and economic contexts, as well as differences in the adopted methodology and the decision under consideration. Notwithstanding such differences in scope and context, it is worth noting that many estimates of the value of human life are within the €1.5 to €3 million range across Europe (Van Essen et al., 2004).

As an example, for the specific case of a bridge failure in a transportation network, an important parameter in quantifying human consequences is to estimate the number of casualties and/or injuries resulting as a consequence of a bridge collapse. The HAZUS methodology (FEMA, 2010), employed within a regional loss estimation framework in the US, provides an empirical expression for the number of fatalities in a bridge collapse, K_s, related to the commuter population, N_C, and a 'usage' factor, F, which depends on the assumed time of the accident, namely

$$K_s = 0.07 \times F \times N_c \tag{2-1}$$

with suggested values for F being 0.02 during peak times and 0.01 otherwise. Suggestions for estimating the commuting population, based on census data, are also given in FEMA (2010).

In addition to fatalities, a bridge failure can result in human injuries. Quantifying the consequences of injuries is an even more challenging task due to the wide range of different injuries that may result. As a result, different injury severity scales have been developed in the past such as the five-scale abbreviated injury scale (AIS) (Wong et al. 2005) and a two-scale distinction (minor/slight and major/serious) suggested by the UK transport regulatory

authorities (Department for Transport, 2007; RSSB, 2008). Another example is the four-scale injury severity categorisation and estimated injuries falling in the different categories expected to result from a bridge collapse given in FEMA (2010). Information on injury costs can be found in the Judicial Studies Board (2022).

2.3.2 Economic consequences

Economic consequence models are, on the whole, available for assets, especially with respect to repair/reconstruction costs, typically linked to a damage severity index. An important distinction between structural and non-structural costs is often made, though data for the latter are more difficult to collect and categorise. Reconstruction time is an important parameter since the duration of the unavailability of the asset will govern the traffic delay costs in the highway/railway network but estimates for this duration are subject to uncertainties. Typical reconstruction times and associated uncertainties for different types of assets are given in FEMA (2010). Values of time for different modes of transport and for different passenger types are available which may be used in estimating traffic delay costs for both highway and railway networks; such values are expected to be different from country to country, whereas further data on traffic management costs can be found in Wong et al. (2005) and Highways Agency (2009). All the above costs can be used, together with site specific information regarding traffic and/or rail service levels, to produce estimates of economic losses as a result of asset restrictions or unavailability. Wider and long-term losses require the availability of econometric models, which analyse how detours and delays might affect supply and demand for goods and services in a region, although such estimates are expected to be characterised by a high degree of variability.

2.3.3 Environmental consequences

Environmental consequences range from CO_2 emissions associated with clean up, reconstruction and traffic delays to the release of toxic or other pollutants that might affect water or air quality and human health. In terms of the former, life cycle assessment analyses can be used to estimate typical CO_2 content per tonne of construction material used in repair/reconstruction. Similarly, emissions from traffic detours and delays can be estimated as a by-product of the economic analysis of such costs. Typical values of emissions from different types of vehicles per distance travelled can be found in DEFRA (2022). Further hazardous substances which can be considered are PM_{10} and NO_x, especially as the detours around the bridge will increase pollution to surrounding regions and households. The environmental damage caused by the latter two pollutants is usually expressed in terms of €/household/1 µg/m³ for PM_{10} and €/tonne for NOx.

A further environmental cost that may be considered is the increase in noise pollution to households along the detour routes. By using an estimate of the households disrupted, a cost factor can be applied based on the number of decibels imposed on the area.

If deemed appropriate, the above quantities can be expressed through monetary units, although, at present, there is a very wide range of values quoted for the economic cost of CO_2 emissions. Environmental consequences may also be considered within a multi-criteria

decision analysis, in conjunction with human, economic and social consequences, without the need for monetization.

2.3.4 Social consequences

There have been asset failures in the past that have resulted in significant impact in terms of wider implications to the engineering profession and associated costs. For example, a failure of a bridge due to an inherent lack of understanding in design may mean the strengthening or replacement of a whole class of structures, each designed according to the same criteria as the one which collapsed. Changes in codes of practice may also need to be introduced following a bridge collapse. An example is the I-35W bridge collapse, which prompted the US Department of Transportation to order the immediate inspection of all similar bridges in the country, followed by changes in maintenance practices, resulting in considerable additional costs incurred by the bridge stock as a whole.

Finally, it is worth noting that past events in the UK (failure of bridges due to flooding in Cumbria in 2009) and elsewhere, have focused attention on crucial inter-dependencies that exist between critical infrastructures. For example, loss of a bridge may result not only in transport being disrupted but also in other utilities (electricity, water) being adversely affected. Such losses are perhaps more difficult to quantify but should be borne in mind in evaluating the robustness of structures whose function provides a critical link within a multi-layered utility network (Bloomfield et al., 2009; Pederson et al., 2006).

2.4 Some examples of previous studies on transport network failure consequences

The analysis of consequences of failure of transport networks has been performed in a number of studies for different hazards including earthquakes, extreme rainfall and others (Carey et al., 2017; Chang et al., 2010; Clark et al., 2016; Enke et al., 2008; Hackl et al., 2018; Postance et al., 2017; Pregnolato et al., 2017). Transport network impacts are commonly analysed using two methodologies including those measuring network topology (i.e. graph theory) and system operation (i.e. travel time and cost) (Postance et al., 2017). The topological method provides a more simplistic representation of the network with no consideration of route choice and periodic demand (peak and non-peak) on travel time and cost. However, the second method uses traffic models to simulate network flows that are more realistic, although the computational and data demands become more complex. These transport models are used in conjunction with hazard models to quantify the impacts of extreme weather events. A comprehensive review of these analytical assessment model-ling techniques for disaster events can be found in Faturechi & Miller-Hooks (2015).

A previous study by Postance et al. (2017) assessed the impact of landslide disruptions by coupling hazard data with a transport network model. The methodology followed in the study was to: i) establish the road network, ii) evaluate the vulnerability of the road network, iii) create an event set of landslide disruptions, iv) develop a micro-meso network model to simulate the traffic flow, and v) measure the impact of each event. The study however did not capture wider long-term impacts such as reductions in business investments. A further study simulated the impacts of closing different sections of the road network in Switzerland (Erath et al. 2008). Failure consequences were calculated using subnetworks and compared against

the option of using a full network. The study however was limited in that it assumed each of the failure scenarios to be mutually exclusive, which is an oversimplification for natural hazards such as floods. Pregnolato et al. (2017) developed a simple transport network and used a depth-disruption function to represent the vehicle speed through floodwater. The traffic simulations were then coupled with a flood model. This study only focused on one mode of transport (roads). Hackl et al. (2018) proposed a new approach to support network operators in quantifying the risk related to their networks. The authors quantified risk from a source event to its societal event over space and time. The consequences were then monetised into direct and indirect costs, considering restoration interventions, prolongation of travel time, and missed trips. The paper also defined four damage states: 0: operational, 1: monitored, 2: capacity-reduced, 3: closed. In another study, a conventional analytical framework to simulate traffic flows was used under different flood scenarios in the Boston Metropolitan Area (Suarez et al., 2005). Direct costs from the damages were not considered as part of the study. There was also no consideration of network restoration, which is crucial to know when estimating indirect consequences.

A study by Adjetey-Bahun et al. (2014) used a simulation-based model to measure resilience indicators in railway transport systems using different scenarios. The paper showed that efficient crisis management plans could reduce the impact of undesirable scenarios on a system. However, the study was limited in that it did not look into scenarios with consequences such as casualties and injured passengers. In Chang et al. (2010), a macroscopic traffic simulation of a road flooded in Portland was performed. The consequence assessment was limited to only one scenario, with the complete closure of links. Others considered the impact of closing different bridges in Stockholm with two scenarios of bad weather leading to a 15% reduction in free-flow speed (Berdica & Mattsson, 2007). The transport model however was not calibrated as part of the study, providing a lower confidence in the results.

3. Methodological approach

3.1 General framework

In the literature, there are several risk assessment approaches existing that can be utilised, depending on the type of infrastructure, the available information and the aim of the assessment (Adey *et al.*, 2014; Faturechi and Miller-Hooks, 2015; Hosseini, Barker and Ramirez-Marquez, 2016; Papathanasiou *et al.*, 2018). However, the more typical steps required to carry out a risk assessment for a road network, is demonstrated in Figure 3-1.

Figure 3-1: General risk assessment framework

It is worth noting that this deliverable focuses only on the last two steps of the framework (highlighted in blue) in Figure 3-1. In this study, for the demand analysis, a transport network analysis approach has been taken that looks at the performance of the network as a whole. Other methods such as asset level analysis is beyond the scope of this investigation.

The steps that are discussed here to carry out a consequence assessment using a transport analysis method are general and can be carried for any transport network irrespective of its size.

The main steps that were involved in creating this consequence framework using a transport analysis approach are:

1- Deciding on the model type and the capability of the software being used as this gives an indication down the line of the necessary performance indicator required for the consequence framework.
2- Development of the transport model, acquiring data and deciding on what assumptions need to be made.
3- Running an initial simulation of the base network and fixing errors or warnings.
4- Validate against a simple graph theory model or granular AADT data.
5- Deciding on the failure scenarios runoff interest and the different absorption profiles.
6- Identification of critical links via scenario testing of all links and nodes in the network.
7- Post processing the results to investigate and classify correlations, patterns, and trends for different failure scenarios, performance indicators and failure propagation profiles.
8- Quantifying consequences as a function of performance indicators considered.

The data requirements for each network should be carefully studied, as choosing different consequence methods in the long term can require a different performance indicator (described in 3.2.8.1) to be utilised. Section 3.2. provides a more detailed account of transport modelling steps in the context of the testbed case study. This is followed by the

implementation of the framework to a smaller benchmark network and the testbed to demonstrate the application.

3.2 Development of the Transport model

3.2.1 Model type

The model has been developed in Aimsun Next version 22. Aimsun is a fully integrated application that includes macroscopic, mesoscopic simulation and microsimulation. This means all functions are contained in one application, operating on a single project document. A single software for the entire project allows consistency, quality, and cost efficiency rather than a separate software package for specific tasks.

3.2.2 Study Area

The model study area is shown in Figure 3-2 below. A set of links and nodes is used to represent the transport network.

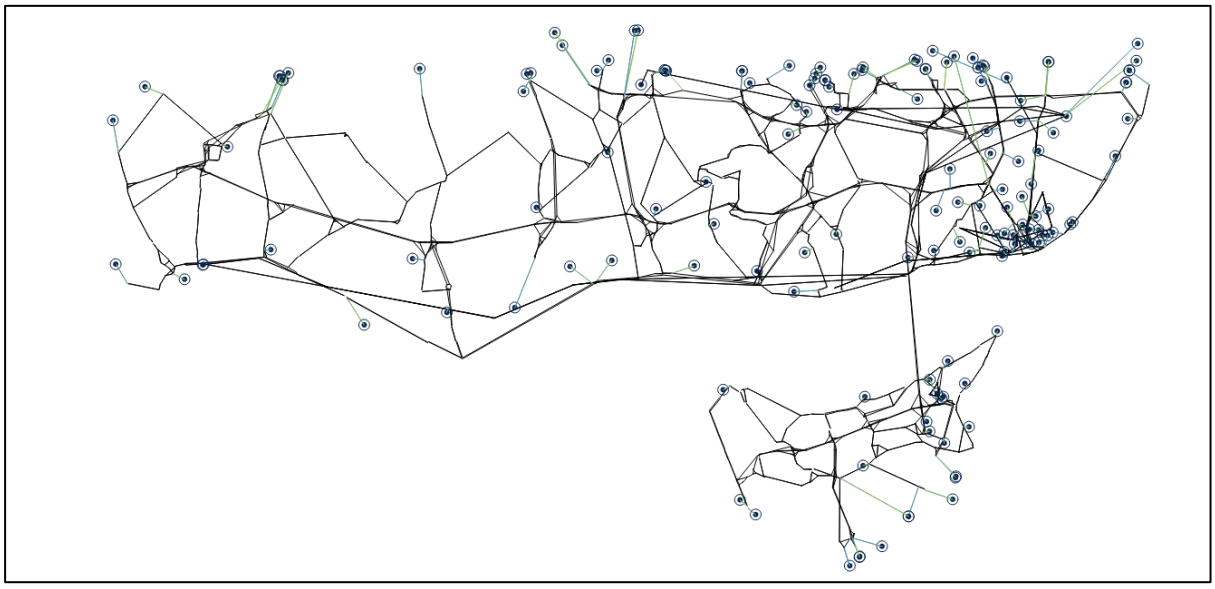

Figure 3-2: The network model of the Portuguese test bed in Aimsun

3.2.2.1 Nodes

Nodes are the point where sections in the transport network are linked, such as junctions or bridges. It is the location where vehicles can move to the next section. In this model, there are 1,888 nodes in the network.

In microsimulation models, conflict points (where two vehicles can potentially clash) are also used to model the detailed interaction between two vehicles as individual vehicles make discrete lane choices. Usually, in junction modelling, junctions or nodes are modelled to have the lowest possible number of conflict points. An example of conflict points is highlighted in circles in Figure 3-3

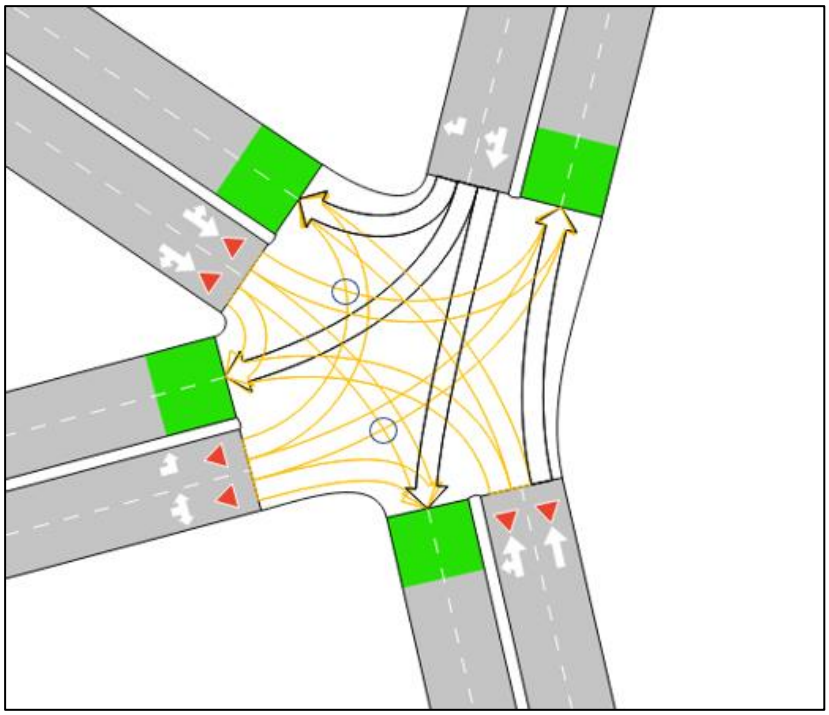

Figure 3-3: Conflict points in a node

3.2.2.2 Links

Sections or links are a group of adjacent lanes where vehicles move in the same direction (Aimsun, 2022). The sections also allow for classifying different road types for the simulation, allowing for different parameters such as speed to be set. This model has a total of 3,431 sections, including bidirectional sections.

3.2.2.3 Centroids

Centroids define the origin and destination of trips in the network when using OD matrices (Aimsun, 2022). The case study model has a total of 151 centroids that introduces flow into the network (highlighted in blue) and extracts flow from the network (highlighted in green). They can be connected to either a node or link directly. An example of a centroid and its connections is shown in Figure 3-4.

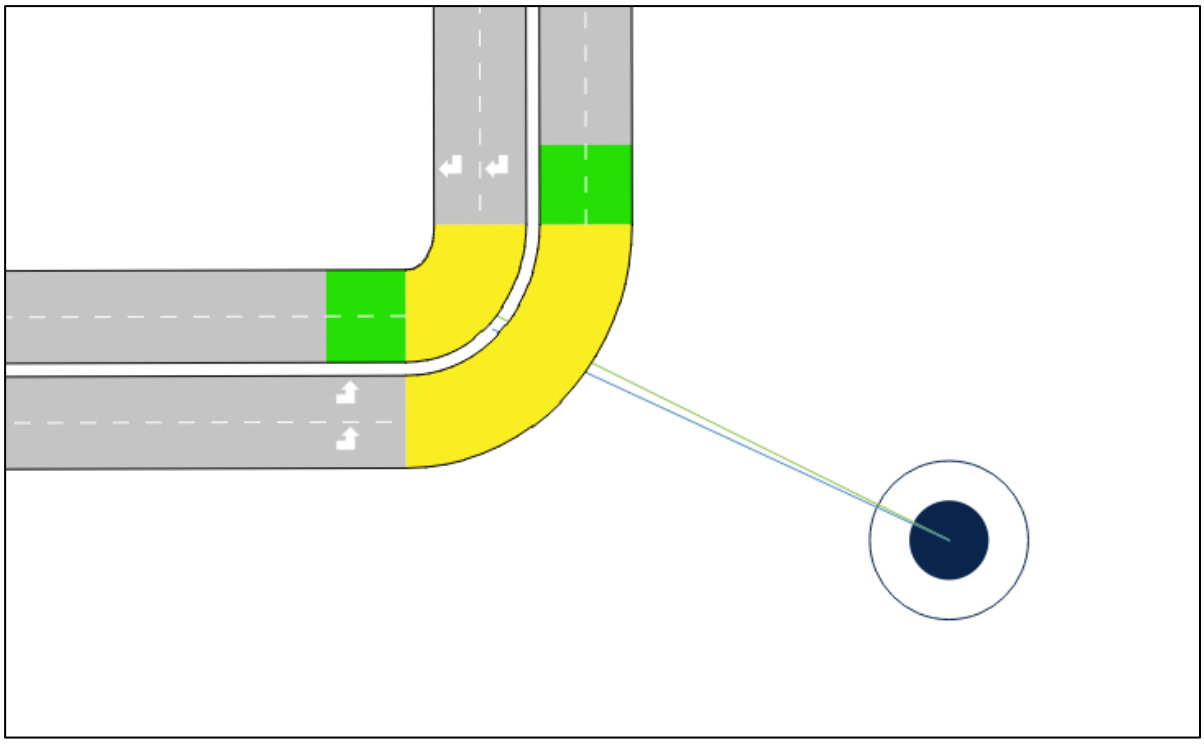

Figure 3-4: An example of a centroid in the Aimsun model

3.2.3 Network Data, Checking and Coding

The network has been generated using the raw data and corresponding EMME network model provided by Infraestruturas de Portugal (IP). The network was then checked and improved using a combination of aerial photography and Google Street view photography. The details incorporated in the model include the following:

- Detailed representation of junctions (e.g., stop, give-way, traffic signals) and banned movements.
- Detailed representation of geometry, including the number of lanes, lane widths, and stop lines.
- Detailed representation of traffic signals at all signal-controlled junctions. The traffic signals have been defined using the control plan configuration in Aimsun. The macroscopic model uses fixed-time approximations.

One of the best methods to check for errors and inconsistencies that require attention in Aimsun is using the built-in "check and fix" tool (Transport for London, 2021). Figure 3-5 and Figure 3-6 show the check and fix window before and after cleaning the model, respectively. There were approximately 332 warnings associated with the model that was primarily related to inconsistencies in centroid connections to the links during the importation of the model into Aimsun from EMME. The warnings were all addressed before proceeding further with the simulations, as shown in Figure 3-6.

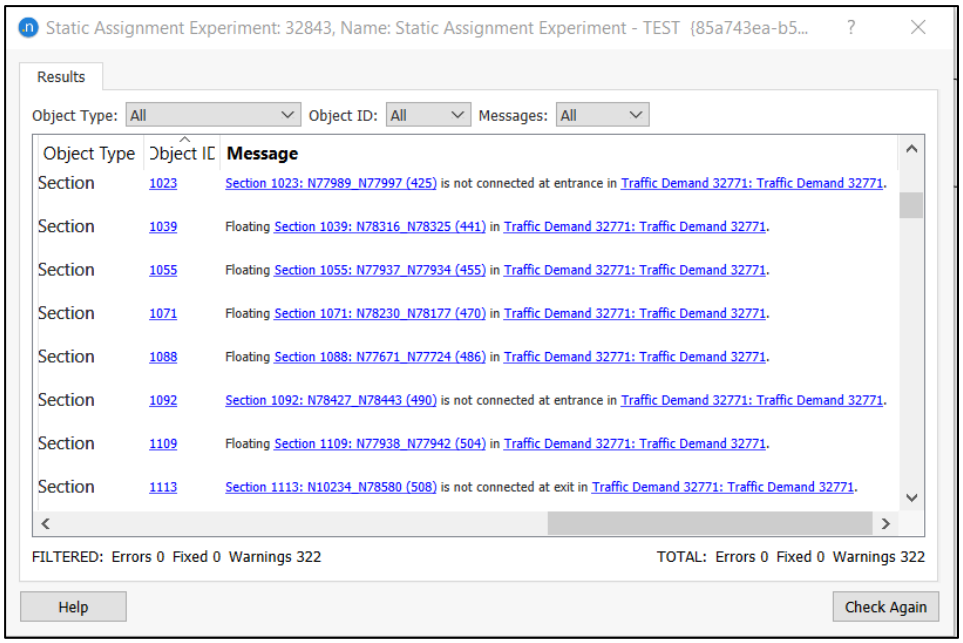

Figure 3-5: Before model clean up

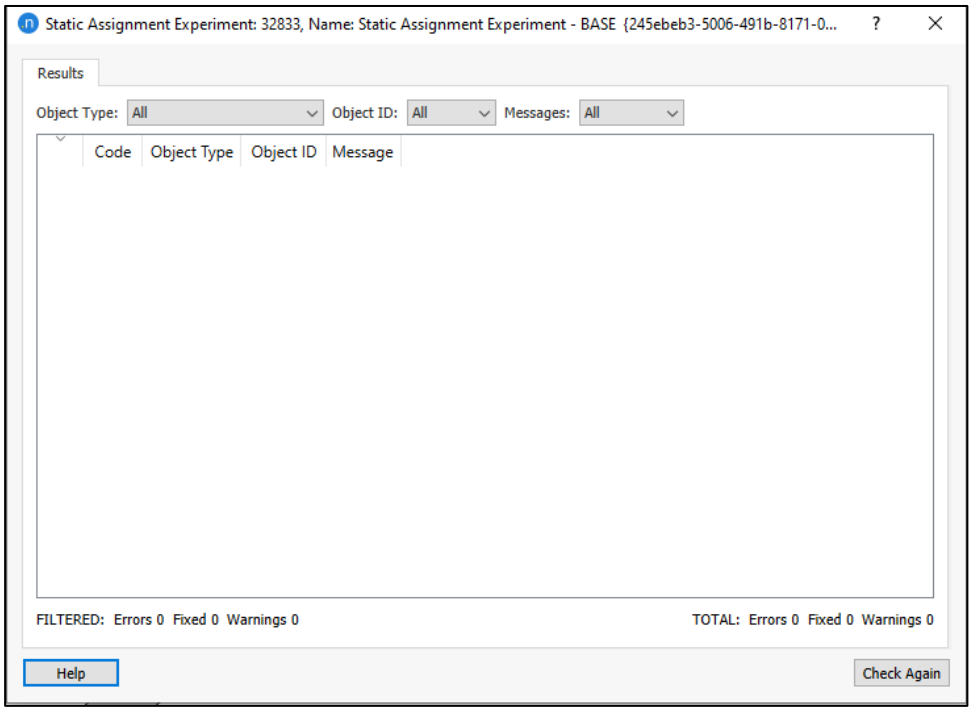

Figure 3-6: After model clean up

3.2.4 Vehicle Types

Vehicle Types in Aimsun are used to represent vehicles with different physical characteristics and behaviour. The following vehicle types are considered in the model:

- Car
- Heavy Goods Vehicle (HGV)

Vehicle driver dimensions for all the vehicle types have been kept as the default values in Aimsun and are summarised below in Table 3-1:

Table 3-1: Vehicle Dimensions

Vehicle type	Length (m)	Width (m)
Cars	4.0	1.8
HGVs	8.0	2.25

Table 3-2: Passenger Car Unit (PCU) values for different vehicle types

Vehicle type	PCU Value
Cars	1.0
HGVs	2.3

3.2.5 Travel Demand Data

The traffic demand in Aimsun Next is defined using a traffic demand object which can be coded in two ways: OD matrices or Traffic States. The travel demand data for this study was also provided by IP for the testbed case study. An OD matrix provides the number of trips that depart from each origin to each destination for each vehicle type and time interval (Transport for London, 2021). However, to use OD matrices, Centroids are created and connected to the road network as they are used to define the structure (rows and columns) of the OD matrices.

On the other hand, a traffic state gives input flows at all road sections and the turning percentages at nodes for each vehicle type and time interval (Aimsun, 2022). However, if DUE experiments or static assignments are used, it is not recommended to use this type of method as it is computationally expensive to achieve convergence (Transport for London, 2021). Therefore, we have used an OD matrix in this study, which is the data type received from IP. The data was in raw format, sorted, and cleaned up before being inserted into Aimsun.

The demand input for the model has been split into two OD matrices based on the vehicle type: one for cars (95% of demand) and one for HGVs (5% of demand). The demand input is shown in Figure 3-7.

The model is run for a one hour period with six minutes of warm up so that the model is populated with vehicles when the measurement starts as described in (Transport for London, 2021).

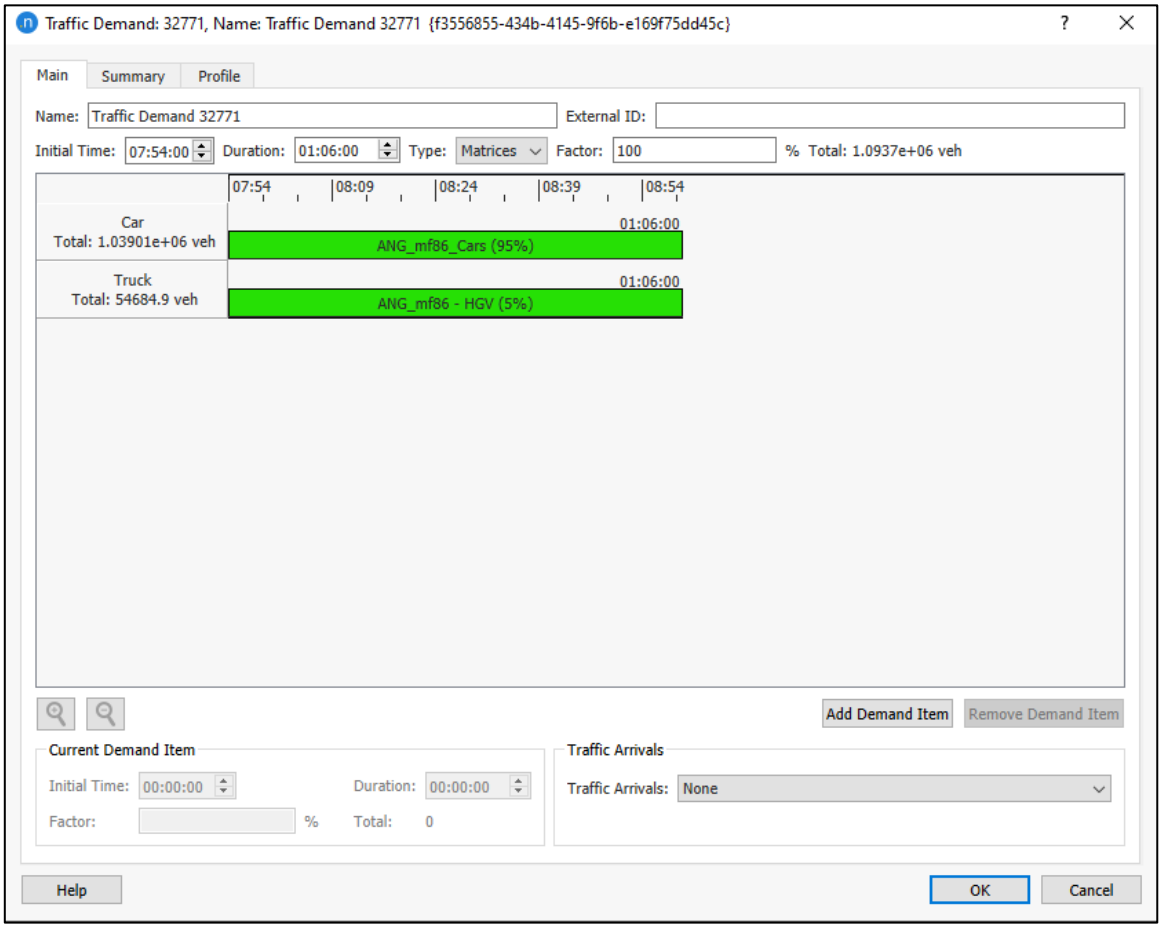

Figure 3-7: Traffic demand window in Aimsun

3.2.6 Signal Timings

There are different methods of controlling signals in Aimsun. The options for different forms of signal control are Uncontrolled, Fixed, Actuated, and External. In Uncontrolled, the node is managed by stops and give-ways. No traffic signal control is present at the node. In fixed, the node is managed by traffic signals with fixed timings. In actuated, the traffic signal stages may be called when vehicles pass over detector loops. In external, external control policy is implemented using the Aimsun Next API Extension.

In this study, a combination of uncontrolled and fixed are used. The fixed and uncontrolled control plans are based on the data provided by IP and street view photography, as described in section 3.2.3. The location of the fixed traffic signals in the test bed is highlighted in Figure 3-8.

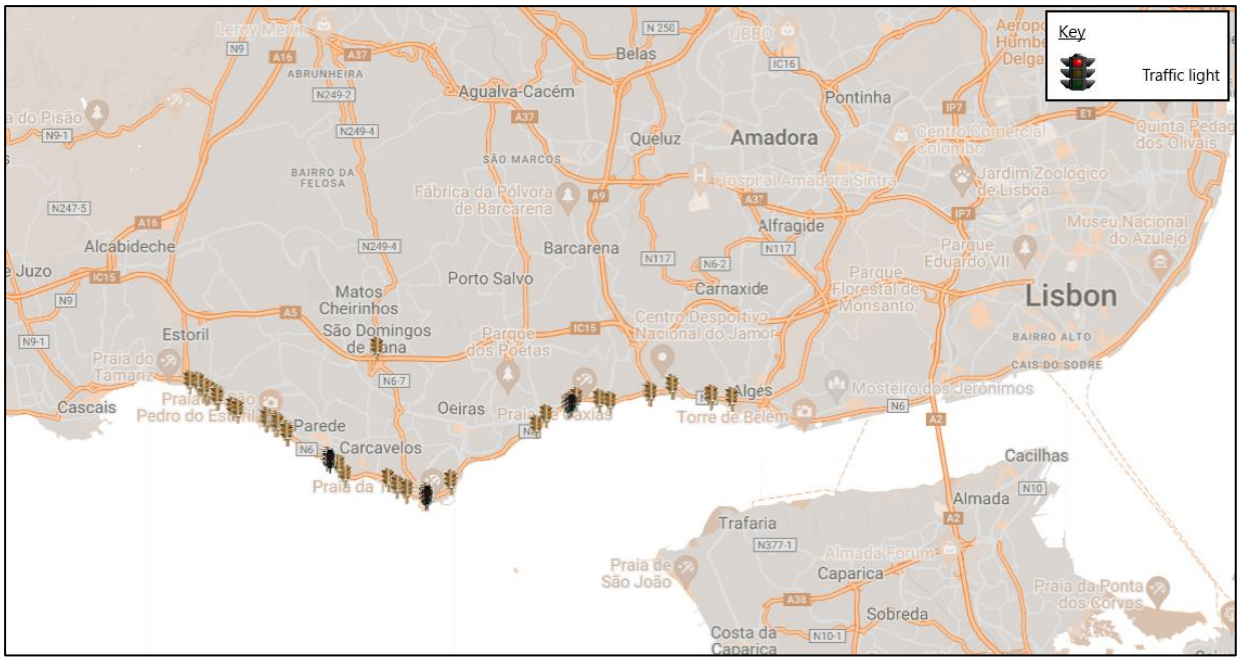

Figure 3-8: Traffic signal locations in the Portuguese test bed

A sample of the fixed control plans inserted into the Aimsun model with signal timings is shown in Figure 3-9.

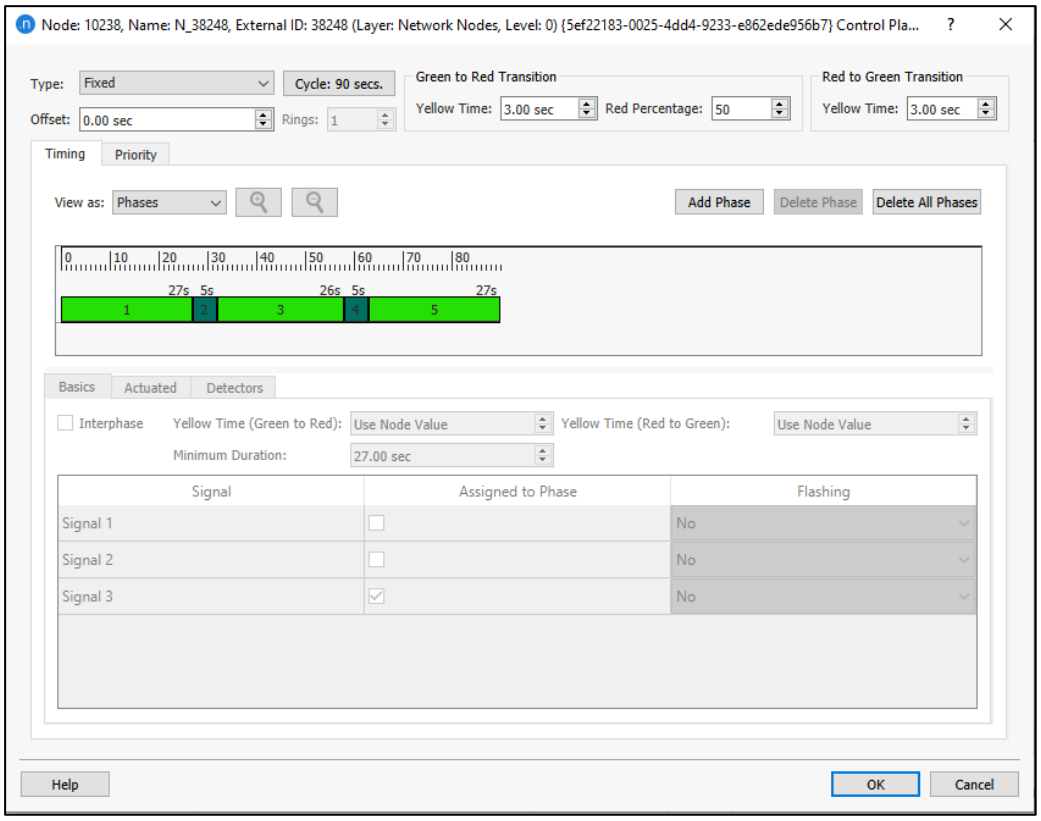

Figure 3-9: A sample of the fixed control plan for node (N_38248)

3.2.7 Traffic Assignment Methodology

3.2.7.1 Macro assignment

Traffic in the Aimsun model has been assigned using a static assignment method entitled FrankWolfe for the macro assignment. The reason for using this assignment method is due to its ease of use and modest computer memory requirements (Calderón et al., 2011). In this assignment, the traffic equilibrium is assumed to have additive path costs, users with perfect information, fixed demand, no link interaction in the network, and the cost functions are also monotonic, differentiable, and continuous. The User Equilibrium (UE) objective function is given by equation (3-1):

$$\min z(x) = \sum_a \int_0^{x_a} t_a(w)dw \tag{3-1}$$

Subject to (3-2):

$$\sum_k f_k^{rs} = q_{rs} \qquad f_k \geq 0 \tag{3-2}$$

Where x_a is the flow on link a, t_a represents travel time on link a, f_k^{rs}represents the flow on path k connecting origin r and destination s, and q_{rs} is the trip rate between origin r and destination s during the analysis period.

3.2.7.2 Micro assignment

For the micro model, the Stochastic Route Choice (SRC) assignment method has been used to assign trips in the model, which is embedded in Aimsun. The Micro assignment method allows the dynamic effect of time to be captured.

The SRC calculates, after each cycle of the running simulation, the least cost path trees to each destination (paths from all network links to one centroid) and updates the cost of path trees found previously; once these trees are updated, the algorithm distributes the vehicles between the available alternative paths with a discrete choice function (C-Logit)(Aimsun, 2022).

3.2.8 Modelling of Failure in Aimsun

The functionality of a transport network does not always drop to 0% when a hazard affects the network (Gajanayake *et al.*, 2020). This reduction of functionality (termed “failure” here), can take place in different forms and rates depending on the nature of the hazard and how quickly it unfolds. For example, flooding in a part of a highway network can expand gradually and may initially affect only part of a road (i.e. just one lane) progressively leading into total closure (0% functionality). On the other hand, if an extreme wind gust event leads to the failure of an asset, that segment (link) of the network which contains the asset will lose its functionality immediately. Therefore, in this study, the failure of links is defined for four different failure absorption profiles: Sudden failure (drop to 0%), linear failure, exponential failure and compound failure, in order to quantify their effects on the transport network performance. These failure absorption profiles are shown in Figure 3-10.

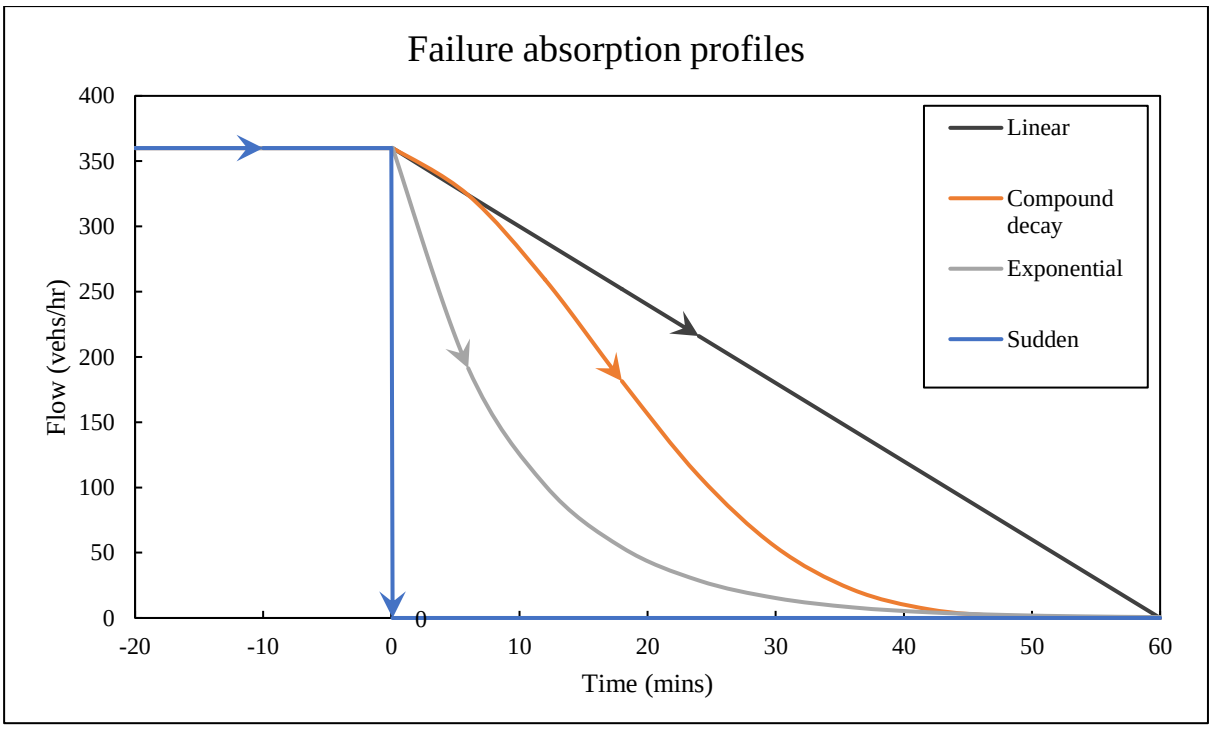

Figure 3-10: Failure absorption profiles used in the study

To carry out the transport simulation for different failure profiles, these failure profiles need to be modelled into Aimsun's ramp metering object in control plans to obtain a close enough representation of the flow. The external control plan is used with ramp metering to control flows, which allows the representation of failure profiles into sections. An example of a ramp meter is highlighted in green in Figure 3-4.

The flow in the ramp meter was controlled using an external script to run the scenarios and a separate Advanced Programming Interface (API) file for each failure profile so that the flow in the model, which replicates the failure, is controlled during the simulation. The API is only used in the microsimulation analysis, which is required to run the linear and exponential failure scenarios.

For the sudden failure scenario, the macrosimulation traffic assignment is used as there is no need to control the model flows during the simulation as it drops to 0% in each scenario from the start of the simulation. By running the model in macro, extensive computing time is saved as well. For example, running a single scenario of the model in macro can take up to 30 minutes, while in micro this would take a minimum of 2.5 hours.

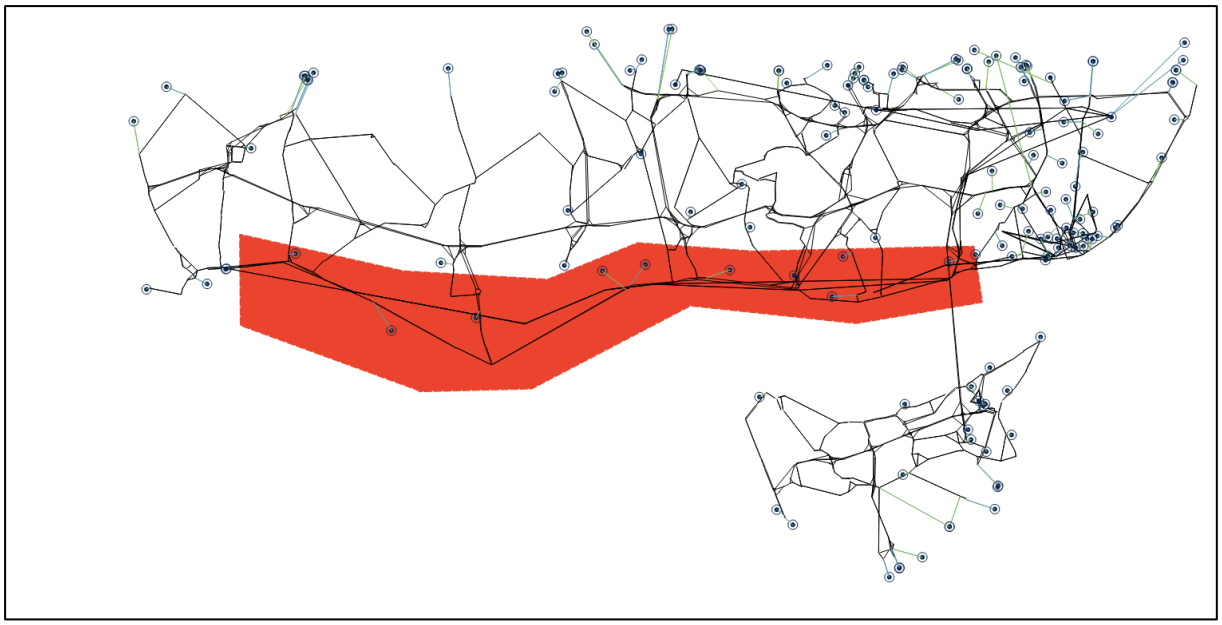

Figure 3-11: The area of the subnetwork, which includes the EN6 route

3.2.8.1 Performance indicator

Typical performance indicators include traffic delay time, extra distance and the level of traffic capacity (Hosseini, Barker and Ramirez-Marquez, 2016; Sun, Bocchini and Davison, 2020). Travel time is one of the most important and common metrics used as a performance indicator for transport modelling. Studies that have used travel time as a metric to understand the importance of a transport network after disruptions are (Suarez *et al.*, 2005; Jenelius, 2007; Enke, Tirasirichai and Luna, 2008; Basöz and Kiremidjian, 2010; Stergiou and Kiremidjian, 2010; Jenelius and Mattsson, 2012; Knoop *et al.*, 2012; Adey *et al.*, 2014). In this study, both travel time and distance are used as performance indicators.

According to equation (3-3), to calculate the total travel time ($TotalTravTime_{sys}$) in a simulation-based approach to a transport network, it is crucial to know the time a vehicle has entered and the time a vehicle has left the system (Ortuzar and Willumsen, 2011).

$$TotalTravTime_{sys} = \sum_{i=1}^{N_{sys}} (TEX_i - TEN_i) \qquad (3\text{-}3)$$

where TEN_i = Entrance time of the i-th vehicle in the network (seconds), TEX_i = Exit time of the i-th vehicle in the network (seconds).

3.2.8.2 Failure analysis flowchart using the Aimsun transport model

The methodology used in this study to find the vulnerability of each link defined in the subnetwork (Figure 3-11) is shown in the flowchart below (Figure 3-12).

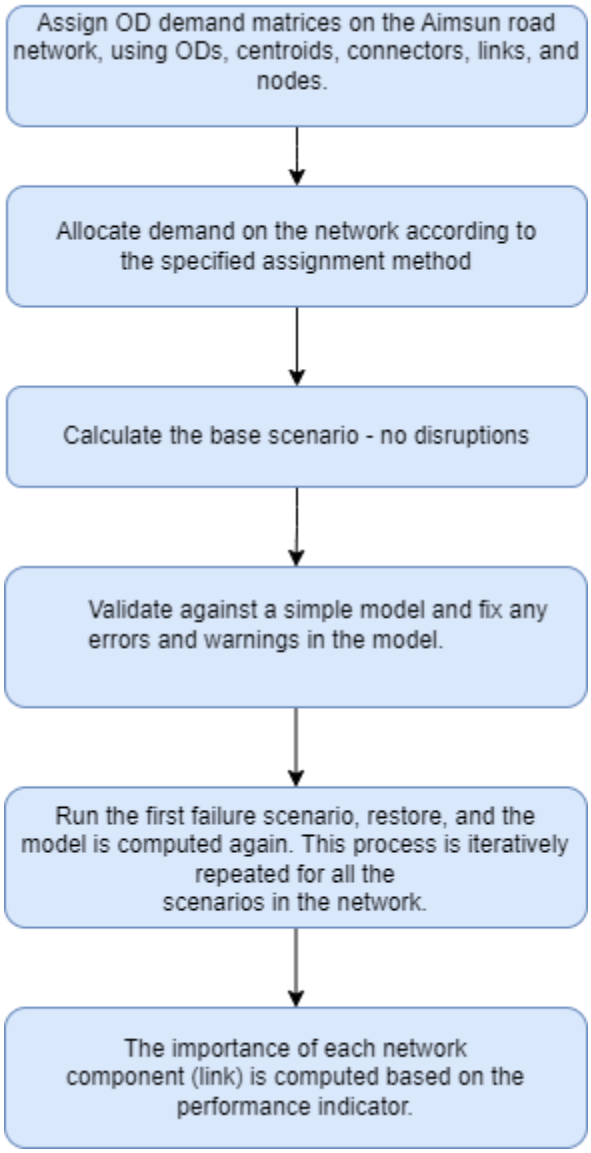

Figure 3-12: Failure analysis methodology

4. Implementation of the framework

4.1 Benchmark model

4.1.1 Network layout

The benchmark model was developed in Aimsun Next version 22. The model has 11 nodes and 32 links with four centroids. The traffic demand in the network was 6,000 vehicles with an equal distribution between all four centroids. Cars were the only vehicle type used. The layout of the model is shown in Figure 4-1 below.

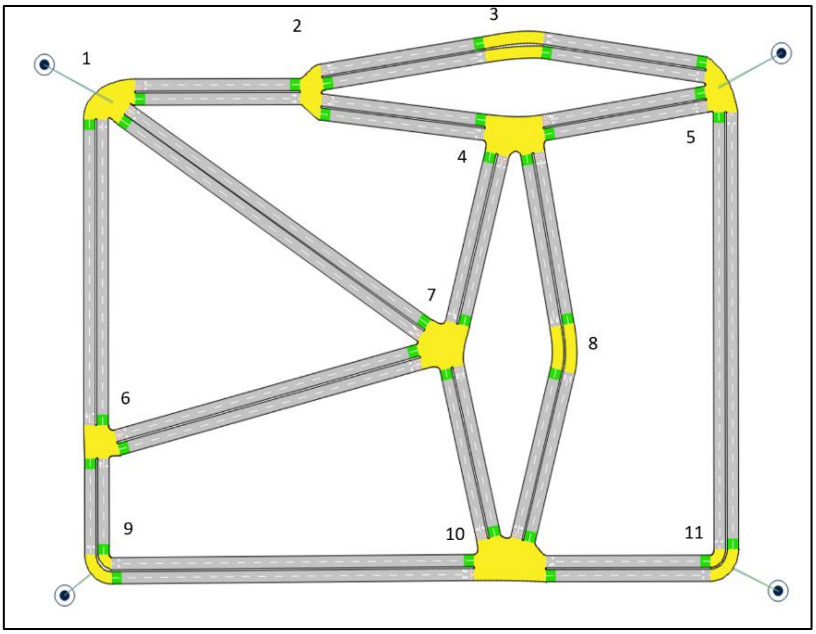

Figure 4-1: Benchmark model layout

4.1.2 Travel time for each section (link) in the network subject to failure

The results in Figure 4-2 show the travel time of the network for each section. The range for each section includes four results for each failure absorption profile (Sudden, Linear, Exponential and Compound decay). The results show that all sections have a more significant travel time when there is a failure compared to the base scenario (normal conditions), which shows that any disruption, no matter how small on such a network, will negatively impact users. The result of the base scenario when there are no disruptions is 2226.5 secs. The lowest travel time, 3044.86 secs, when there is a disruption at section 6-9 with an exponential failure profile and the highest travel time, 6189.28 secs when there is a disruption, is at section 10-11 with a linear failure profile. To explore the results more, the sections with the highest impact have been highlighted in orange. These failure scenarios correlate to the top six travel times, which are all above 5,500 secs and above the 75 percentile threshold. The six sections are 10-11, 10-7, 2-1, 4-5, 3-5, and 6-9.

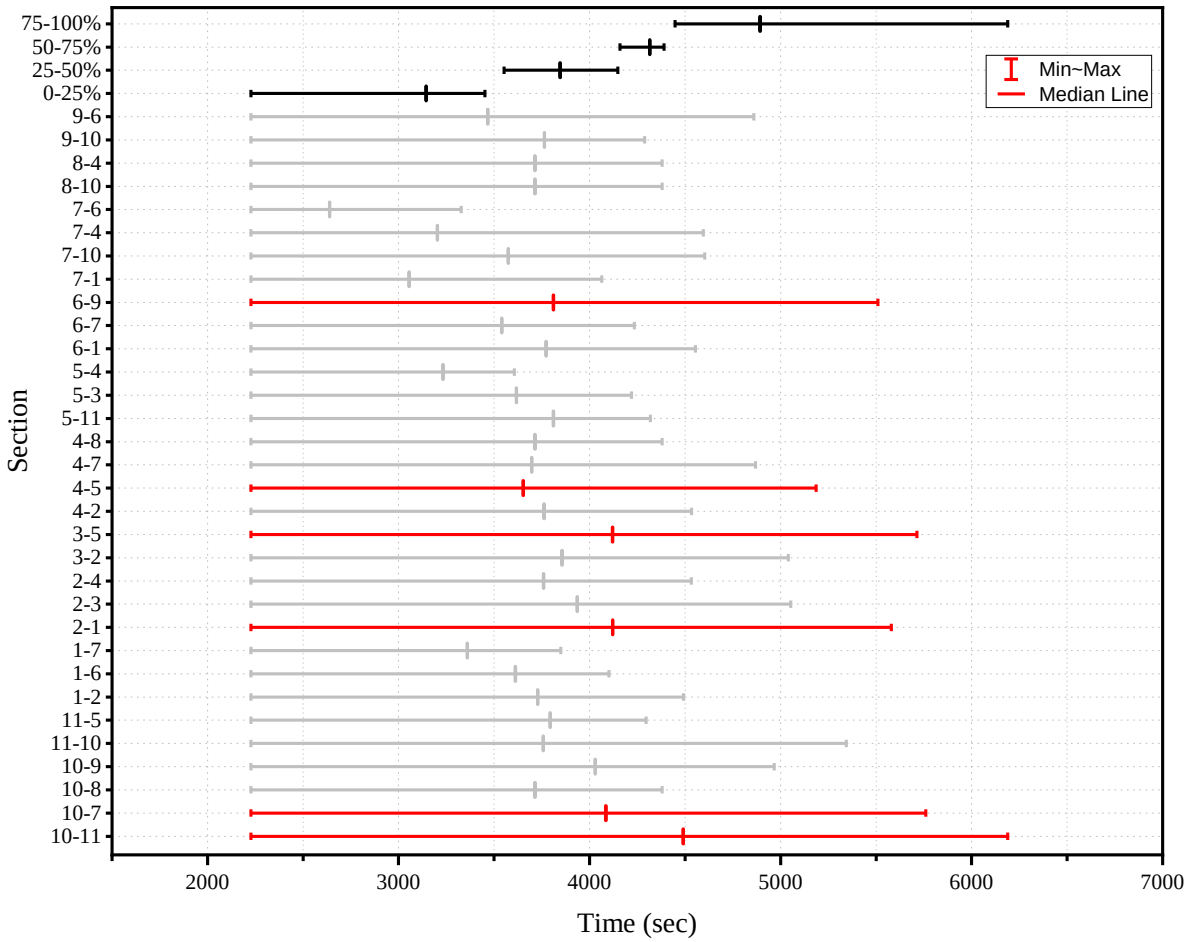

Figure 4-2: travel time per section where grey is all the scenarios, red is the high-impact scenarios, and black represents the data across different ranges.

4.1.3 Travel time difference between different failure absorption profiles

Figure 4-3 demonstrates the distribution of failure scenarios with respect to the considered failure patterns. This can be used in investigating the impact of different possible failure propagation profiles in performance indicators and corresponding consequences.

The failure absorption profile of each pattern in Figure 4-3 was obtained using different assignment methods. The sudden pattern used a macro assignment method, while the rest used a micro assignment method, as described in section 3. The figure, however, does not allow us to conclude that using only one assignment method is enough, as the micro assignment leads to the highest impact scenarios for the linear pattern and the lowest compared to the base scenario. The sudden failure lies relatively in the lower middle of the table for a 1.5 IQR with some outliers in the top 75% distribution in Figure 4-2.

From the first observations of Figure 4-3, it can be seen that in all failure cases, there is a negative impact on travel time compared to the no-disruption scenario under normal conditions. The Linear pattern has the most extensive range of results. This profile also includes the failure scenarios with the highest travel time. Since the linear propagation profile covers a wide range of scenarios but also the most critical scenarios, it can be concluded that

at minimum, linear failure propagation profile should be considered in the failure scenario testing attempts.

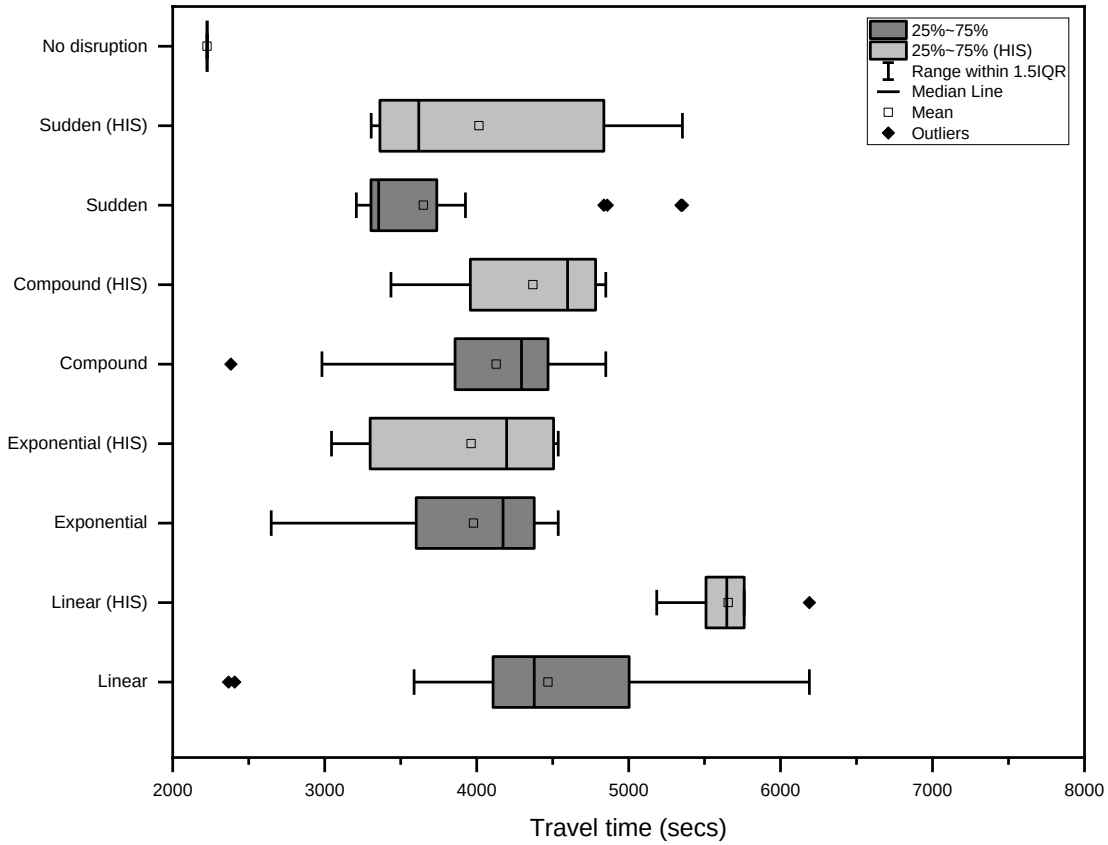

Figure 4-3: Travel time impact by pattern and the highest impact scenarios (HIS) for each pattern

4.2 Case study model

The location of each of the top five critical links is shown in Figure 4-4. The results for the top critical links show that when there is a sudden drop of performance to 0%, the links on the EN6 route can be critical with a higher increase in travel time. However, none of the bottom five results is linked to the EN6 route but instead to roads that feed into the network.

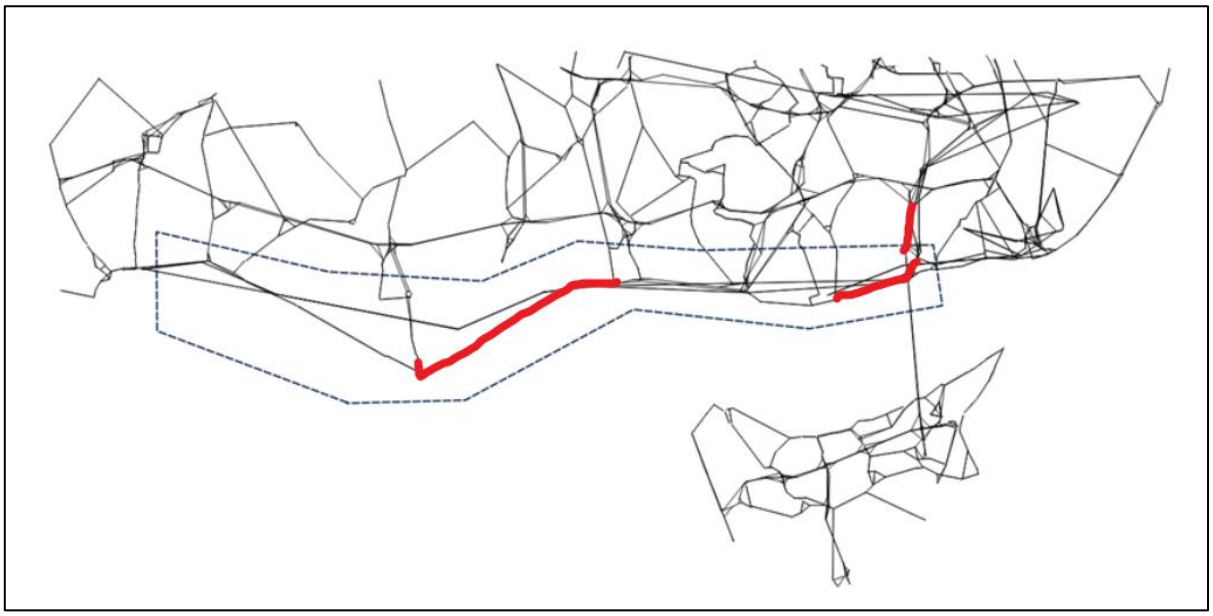

Figure 4-4: Top five sudden failure scenario results

Table 4-1 presents the location and link ID of critical links and the corresponding relative change in time and distance of the scenarios compared to the base scenario. The table shows that the 1842 link has the most significant impact on the network, with a 55.2% change in travel time following its failure.

As can be seen, both time and distance are linearly correlated hence it can be concluded that using time as the performance indicator alone can provide a quantitative measure of network performance following a failure.

Table 4-1:Travel time and distance results for the top five (in red) sudden failure scenarios

Scenario external ID in Aimsun	Link ID	Travel time - ΔT	Distance - ΔD
Base scenario	N37980_N37998	0.0%	0.0%
1250	N37980_N37998	10.9%	0.8%
2220	N37998_N38099	10.9%	0.8%
704	N38024_N38040	15.4%	2.2%

1532	N38040_N38245	16.2%	2.7%
3365	N38245_N38240	16.7%	2.4%
1842	N37776_N37444	55.2%	3.5%

4.3 Consequence Analysis of the case study

As shown in Section 2 earlier, there are various methods to analyse the failure consequences of a transport network. Within the context of this case study, only economic consequences are considered for illustrative purposes. One of the most common methods for quantifying economic consequences is the value of time method. Time value is likely to be different for different contexts and locations as the value of time is not constant over time. For example, the value of time for personal and work trips is not the same (Department of Transport, 2014). In transport economics, time is perceived as a limited good, and with increased productivity and income in countries, the value of time increases too. However, due to much uncertainty around this, it is common to apply a simple approach using estimates measured as described in (Wardman, M., Chintakayala, P., de Jong, G. and Ferrer, 2012).

Pregnolato *et al.* (2017) use the following equation (4.1) to calculate the cost of delay per vehicle C_{veh}:

$$C_{veh} = \Delta T . VoT \tag{4-1}$$

where, ΔT = variation in journey time (h), VoT = value of time (Euros/hr). The number of vehicles in the study is 45,571.

The monetary values are expressed in euros per hour in 2010 prices based on (Wardman, M., Chintakayala, P., de Jong, G. and Ferrer, 2012). For Portugal, a VoT of 55.2 Euros per hour is used. However, this is just an indication value; as described above, defining time's actual value require further description of the context in which is investigated.

Table 4-2 provides a summary of the quantified economic consequence values for the top five critical links on the EN6 testbed. As expected, the results corroborate the observations driven from the analysis conducted on the performance indicator used in this study; therefore, we see that link 1842 has the highest consequence of 1,388,567 Euros per hour. This approach provides a quantitative measure of the range of variation in economic consequences considering different potential scenarios and appraising critical zones within a network.

Table 4-2: Economic consequence of failures (per hour) of the top six critical links on the EN6 testbed

Scenario external ID in Aimsun	Link ID	Travel time - ΔT	Economic Consequence (Euros)

Base scenario	N37980_N37998	0.0%	N/A
1250	N37980_N37998	10.9%	274,191
2220	N37998_N38099	10.9%	274,191
704	N38024_N38040	15.4%	387,390
1532	N38040_N38245	16.2%	407,514
3365	N38245_N38240	16.7%	420,091
1842	N37776_N37444	55.2%	1,388,567

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