Criminal Fugitive Escape Routes

The influence of behavioural route-choice factors on criminal fugitive escape routes

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TU Delft

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by

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Enjoy the reading!

Willemijn Tutuarima
Delft
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Executive Summary

When a crime is committed, the task of the regional control rooms is to use the available situational information to identify the possible movements of a fugitive suspect to use in positioning police units. Currently, the methods to do this rely heavily on the intuition and experience of the control room employees and the speed of technology and communication. To reduce this reliance, there is an increasing demand for methods to objectively determine the tasks to undertake in a fugitive escape situation. Two methods to do this are under development which help in determining the location of a fugitive suspect and the optimal positioning of police units to these locations. However both of these methods still require a demarcation of the possible routes that a criminal fugitive will take to be used effectively. Therefore, this study explored the possibility of making likelihood estimations of possible escape routes.

Because of a lack of reliable data, alternative methods to determine likelihood of escape routes are needed. A method that could be used is simulation. Simulation of human behaviour is however complex and careful consideration of the assumptions in such a model is needed to be able to have a high level of confidence in the resulting outcome. To do this, it is important that the theoretical background on which behavioural factors influence the criminal fugitive route-choice behaviour is complete and it is known how these factors affect the resulting routes. This is the knowledge gap addressed in this study.

To address this knowledge gap, the question of what effect behavioural factors from criminal route-choice behaviour have on escape routes will be answered. This is done by determining which main factors influence criminal fugitive route-choice behaviour and how these factors influence the resulting escape routes. The method used to answer these questions is a combination the development of a theoretical background based on a literature review of existing research and expert opinion and a quantitative sensitivity analysis on a simulation model.

Because of a lack of research on criminal fugitive route-choice behaviour, it was necessary to use literature from the following research fields to find relevant topics: criminal decision-making, rationality in decision making and route-choice decision-making. From the literature in these fields, it was found that many different personal and crime characteristics exist, but it is unknown how these affect route-choice behaviour. Next to this, it was found that rational decision-making cannot be assumed for the criminal situation and that bounded rationality needs to be considered. Lastly, from the route-choice decision-making literature, it was found that many different route-choice factors are relevant. The following list of route-choice behavioural factors was found: obstacle avoidance, risky behaviour, traffic avoidance, route distance and maximum speed, and preference for main or residential roads. For the route choice decision-making modelling methods, the following relevant topics were found: cost-benefit calculations, short or long-term goals, emotional state, choice prioritisation and timing. These two lists of factors should be considered when conceptualising criminal fugitive route-choice behaviour.

In the conceptualisation phase of this study, it was found that while many different suspect and crime characteristics might affect suspect behaviour, no specific behavioural profiles could be used to conceptualise route-choice behaviour. Therefore it was chosen to conceptualise the behaviour by creating dynamic strategy profiles based on behavioural route-choice factors. From the list of behavioural route-choice factors to include in these strategy profiles, it was found that they can be described as either a preference or avoidance of road characteristics. The road characteristics seen to be avoided are cameras, obstacles, one-way roads and high traffic. The preferred road characteristics are a high number of lanes, residential roads, a high maximum speed and short roads. Next, it was found that there is a distinction in decisions based on long or short-term goals, which require either low or full network familiarity. For general route-choice behaviour, the conceptualisation of a route choice as a whole route between an origin and destination location was found to be most appropriate. When considering the rationality of the decisions made for the route choices, it was found that there is too much uncertainty and ambiguity in the considered bounded rationality conceptualisation to use them for a

concrete route-choice conceptualisation. Therefore, alterations to the assumptions of rationality are used to concentualise this. Finally, the emotional state of a fugitive is included in the conceptualisation through the possibility of changing route-choice strategies. This conceptualisation is further used to describe the general criminal fugitive route-choice behaviour in this study.

To measure the influence of the behavioural route-choice factors in the conceptualisation, a route cost model was developed. In this model, the cost of a route is calculated using the characteristics of the edges in a road network. Based on this model, an experimental design is defined including a case study and sensitivity analysis to find the quantitative influence of route-choice behaviour on route metrics describing differences in escape routes through route length and overlap.

When evaluating the results of the case studies and sensitivity analysis, it was found that the influence of behavioural route-choice factors on routes depends on the origin and destination locations and the distribution of edge characteristics over a road network. Next to this, it was found that there were no behavioural profiles leading to routes with specific characteristics and that in practical application, a broad set of strategies should be included when finding important locations is a road network to use for positioning police units. To do this, a method of using heat maps to find these locations was proposed. This method combined with the route cost model described in this study was found to have high applicability but more research needs to be done on the usability of this method.

From the findings of this study, it can be concluded that criminal fugitive route-choice behaviour is complex and that different possible conceptualisations exist to be used for different purposes of studying general route-choice behaviour or specific behavioural factors. This affects the ability to measure the influence of behavioural factors on the resulting routes. Limitations were found on the measurement techniques used in the quantitative method to measure differences in routes which reduced the ability to interpret the resulting influence of behavioural factors on the routes. This showed that to find the influence of behavioural factors on the routes, the results of this study can show that the route-choice factors defined in the conceptualisation affect the routes but that more qualitative research is needed to find how these factors influence the resulting routes.

To conclude, the findings of this study add to current research by showcasing the complexity of modelling route-choice decision-making and human behaviour in general and the many considerations that need to be taken when doing so. Next, it shows the difficulty of using quantitative and qualitative methods on the data type of routes to determine relations between factors influencing route-choice behaviour and resulting routes. And lastly, it adds to the current literature by developing an overview of the factors influencing criminal fugitive route-choice behaviour that need to be considered in the simulation of fugitive escape routes.

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1 Introduction

1.1. Societal problem

Peace, justice and strong institutions are among the most important goals to create a sustainable and equal world environment (UN DESA, 2022). This goal is operationalised through governmental institutions such as the legal system and law enforcement. These institutions aim to assist people in need, reduce incidents that negatively impact society and ensure that justice is brought to those who violate the laws set out by national and international legal systems. Through these institutions, governments aim to create a safe and sustainable environment for their citizens.

One measure of safety is the extent to which criminal cases are resolved. To keep track of the number of resolved cases, the clearance rate is defined as the proportion of criminal offences where at least one suspect is known by the police, even if this person is a fugitive or denies involvement in the crime (Centraal Bureau voor Statistiek, 2013). In the Netherlands, an average clearance rate of only 27.6% was found in 2021 (Wetenschappelijk Onderzoek en Documentatiecentrum, 2022). It can also be seen that the clearance rate has considerably reduced over the past years among several categories such as road accidents, public violence, and even murder (Politie, 2022). Because there can be many causes of a low clearance rate, different prevention and mitigation policies are needed to increase the number of resolved cases.

Because crime cannot always be prevented, it's important that those who break the law are held accountable for their actions. This ensures that they face appropriate consequences, such as fines or incarceration, and that the harm they caused to their surroundings is appropriately compensated. This is also important so that risk is associated with committing a crime, thus discouraging people from committing a criminal offence. There are two methods to differentiate how people are brought to justice: directly after an incident, thus red-handed, or after a longer time period, through a criminal investigation. Combining the two methods is also an option in specific criminal cases. In some cases, however, there might be insufficient physical evidence to prosecute a suspect through subsequent investigation. Because of this possible lack of evidence and the limited resources of police departments for criminal investigation, catching a suspect red-handed is beneficial.

The task of identifying a suspect directly after an incident can be seen as the responsibility of two units: the regional control room and the police units on the streets. These units receive the information regarding an incident and can best determine the relevant information, such as who, where, when and how a crime was committed. A suspect, however, will often not stay at the crime scene and attempt to escape being detained. It is thus an important task of the police and control room to use the provided information to determine the possible movements and actions that a suspect makes to ensure optimal chances of catching them.

Different methods that can help to determine the actions and movements of a suspect after an incident can range from following a suspect using cameras, using intelligence to determine who the suspect is or surveying the crime scene's surroundings to attempt to find the suspect. These methods rely on either the speed of technology, such as the speed of attaining and prioritising camera feed, or the level of experience of police and control room employees. Depending solely on experience and intuition is not necessarily incorrect, as it can often be reliable and efficient for making decisions quickly. But in this method, the amount and type of experiences of the law enforcement employees can greatly influence the outcomes and reduce objectivity when making decisions.

To aid in this process, there is an increasing demand for a supporting method to increase the level of objectivity and reduce reliance on experience and intuition when making decisions on which tasks to undertake in the situation of a fugitive suspect. The police have previously identified two methods to do this. The first method is to use police positioning software that determines the optimal police unit distribution over specified positioning locations. In this software, the positioning locations still need to be specified, which is currently done by randomised routes from a crime location. The second method is to create catch-chance circles in a map surrounding the crime scene location. This can be used to find possible positions of a fugitive based on the initial crime scene location and the speed at which a suspect travels. Keeping the entire circle can create a range that the limited number of available police units cannot fully cover. Therefore, indicating which routes among these circles are most probable could help reduce the number of locations considered during the positioning of police units. Both of these methods still require some scientific basis for the likelihood of certain escape routes in a network to be used effectively. The topic of determining if making these likelihood estimations of escape routes is possible and how this could be done is the focus of this study.

1.2. Scientific problem and knowledge gap

To estimate the likelihood of possible escape routes, data on previous escape routes could be used. For the fugitive route-choice behaviour, however, little data is publicly available, and when it is available, it can suffer from certain bias problems. An example of this is a version of survivor bias where most of the data found for a particular phenomenon is only known for situations, such as a fugitive capture operation, that were successful. Unsuccessful cases are thus not represented in the data. This has a considerable bias, and the data set does not describe the actual situation. Currently, data can thus not be used as an information source to predict criminal fugitive escape routes.

Alternatively, the likelihood of escape routes can be estimated using modelling. Models are useful because they can give insights into behaviour and help determine essential relations and factors within a system. When using modelling, assumptions on behaviour are used to demarcate the possible reactions of an agent in a certain system. Challenges can be found during this process of modelling human decision-making because human behaviour is complex and can have many degrees of freedom, causing high uncertainty in their conceptualisation and possible underrepresentation of complex behavioural processes (de Koning, 2019). Examples of this complexity are personal differences in behaviour and the lack of rationality when making decisions. Because of such limitations, careful consideration must be made when modelling human behaviour (Kennedy, 2012). Because of this complexity, the assumptions made in a model of human behaviour need to be examined carefully, and it is essential that the theoretical background is complete and incorporates the essential aspects of the behaviour being studied.

A previous study that attempts to model the criminal fugitive route choice behaviour was done by Kempenaar (2022), who created a criminal fugitive escape route model based on assumptions from Dual Process Theory (Simon, 1990). This theory attempts to conceptualise bounded rationality through the theory that humans have two different types of thinking. Bounded rationality is described as making non-optimal choices and is found when decisions must be made fast and without much information (Bellini-Leite, 2022). It has been theorised to influence criminal human choice behaviour through different processes such as mood and emotions (Van Gelder, 2013). Kempenaar's study distinguishes between “cold” and “hot” situations where the stress levels of the fugitive depended on whether the police were chasing them. In his conceptualisation, assumptions on the actual route choices are based on expert opinion by creating behavioural profiles dependent on the level of organisation and the mental mode of the fugitive. These assumptions are based on specific types of fugitives and contextual factors and do not describe general criminal fugitive route choice behaviour. Although this is useful for comparing specific behavioural patterns, it does not encompass the complexity and multitude of different behaviour in criminal fugitives. More broad modelling of route choice behaviour is thus needed to estimate the likelihood of escape routes.

To conclude, to estimate the likelihood of escape routes in the general fugitive escape situations using modelling, a more general theoretical background needs to be considered that includes different sources of information. To be able to do this, more understanding is necessary about the behavioural route choice factors relevant for criminal fugitives and how these affect the resulting routes from the choices made. This knowledge gap that this study addresses.

1.3. Research question

With the described knowledge gap, the following research question was formulated for this study:

What effect do behavioural factors from criminal route-choice behaviour have on escape routes?

To answer this question, the relevant behavioural factors need to be identified, and their influence on escape routes needs to be evaluated. For these two steps, the following sub-questions need to be answered:

Sub-question 1: What are the main factors influencing criminal fugitive route-choice decision-making?

The answer to this sub-question will consist of an explanation of the theoretical background of criminal fugitive route-choice behaviour. This is formed using information sources of literature and expert opinion. This theoretical background is then used to conceptualise the different factors influencing the behaviour and how these need to be specified to create a concrete description of the behaviour of interest. The assumptions in this conceptualisation are validated using expert interviews. The answer to this question can then be used to formalise the behaviour in a model to answer the following sub-question:

Sub-question 2: What effect do behavioural route-choice factors have on the routes resulting from criminal fugitive route-choice decision-making?

To answer this question, the resulting conceptualisation from sub-question 1 is used to formalise a model. This model is implemented on the Rotterdam road network to determine the influence of the behavioural factors previously defined based on the literature. To quantify the influence of a behavioural factor, route metrics are defined, which will be used to compare escape routes. The influence on these metrics by the behavioural factors is determined using an experimental design based on an open exploration of the model. For this purpose, a case study and a sensitivity analysis are used. These illustrate differences in routes and quantitatively measure the influence of the behavioural factors on the resulting routes. The answer to this question, combined with the conceptualisation created for sub-question 1, can then answer the overall research question of what effect behavioural factors from criminal route-choice behaviour have on escape routes.

1.4. Scoping of study

Because of the time scope of this study, it is chosen only to include route choices in car-based escape situations. This was chosen because it was seen that for many different methods of travel, different external factors were seen to influence behaviour. Examples of this are using disguises or hiding in buildings for situations where fugitives are on foot. In the case of travel by car, these external behavioural factors are less present than other transport methods, and route choice behaviour is more isolated from the remaining contextual environment. Therefore, car-based suspects are the reference perspective in both the theoretical framework and modelling space.

Next to this, when considering the contextual environment, the specific road network influences the relevance of assumptions. This is seen through both the type of behaviour found in fugitives and the possible effect of environmental factors on the behaviour. Two considerations were taken into account when choosing a specific network. Firstly, a complex network can showcase more complex behaviour and should include different environmental factors such as road types and complex infrastructures. Secondly, to evaluate the validity of possible escape routes, a road network should be used for which experts can validate the route choice behaviour. Familiarity with the network of these experts is thus preferable. Because of these limitations, it was chosen to use the road network of Rotterdam for the scope of this study.

1.5. Research design and thesis outline

To answer the research question and sub-questions described in Section 1.3, different research methods are used. These questions are of a relational type of inquiry and thus require a research approach that answers how the behavioural factors in route choice affect the resulting routes. The method to reach this can be seen as combining two quantitative approaches: a literature synthesis and a simulation model. For the first phase of this study, a conceptualisation of fugitive route-choice behaviour is created. Chapter 2 provides an overview of the decision-making process used by Dutch emergency control rooms during a criminal chase. This helps to better understand the context of fugitive behaviour and how it is handled by emergency responders. After this, in Chapter 3, a theoretical background is built for the criminal fugitive route-choice research field. Because of a lack of literature on this topic, studies from related fields are combined to create an overview of the relevant theory needed to describe criminal fugitive route-choice behaviour. This theoretical background is used in Chapter 4 to conceptualise fugitive route-choice behaviour. This chapter highlights the difficulty and limitations of conceptualising this behaviour. It describes the choices made in this study to define fugitive route choice decision-making to be used to model this behaviour.

In the second phase of the study, the conceptualisation of fugitive route choice behaviour in Chapter 4 is used in Chapter 5 to define a formal model of this behaviour. This includes the basis of a model defined on this behaviour and specifics on the implementation. To determine the influence of behavioural factors on routes resulting from the model, route metrics need to be defined to measure differences in fugitive routes. These metrics can be found in Chapter 6. To find the relations between the inputs of the formalised model and the defined route metrics, an experimental design is proposed in Chapter 7. This chapter describes the methods of analysis, the sampling methods and the scenario and output definition used in these methods. These are then used to define a case study experiment to illustrate the influence of factors on routes and several experiments with aggregation over location sets to be used in a sensitivity analysis to find the quantitative influence. In Chapter 8 and Chapter 9, the results of the analysis of these experiments are described. Finally, the discussion of the results and limitations described during the conceptualisation and modelling phase can be found in Chapter 10 and conclusions from these results are drawn in Chapter 11.

This research design can be seen as a mixed design method of exploratory sequential nature, as proposed by Creswell and Creswell (2018) because the information from the theoretical framework is used as input for the simulation model. An overview of the different steps in this study can be found in Figure 1.1.

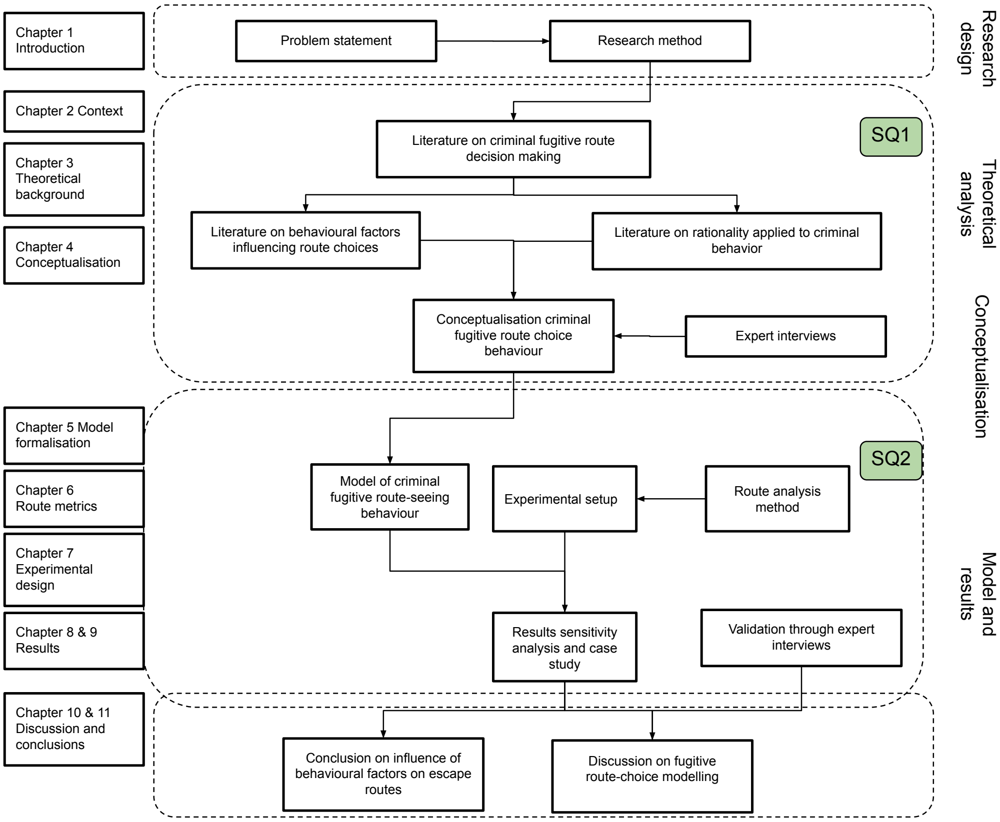


Figure 1.1: Diagram of research design

1.6. Limitations of research methods

When interpreting the results from this study, it is important to consider the limitations of the used research methods. For the literature phase of this study, several limitations were found. Firstly, the lack of research on criminal fugitive route-choice behaviour and, therefore, a lack of data directly related to the studied situation. Because of this, a more general approach is used to find relevant literature by using an initial literature review on route-choice behaviour in high-stress situations. This literature review is then used to determine which research fields need to be reviewed in more detail. A limitation in this method is the assumption of generalisation of these situations and, therefore, the assumption that behaviour found in a specific high-stress situation applies to all high-stress situations. To cope with this limitation, the findings of the general literature review will be assessed on relevance in the criminal fugitive route choice situation. This is done through validation using expert interviews, indicating the need for a specific theory based on practical evidence.

For the simulation phase of this study, it is important to discuss the limitations of modelling as a research method. As previously mentioned, human behaviour is complex and modelling it can strongly simplify the modelled behaviour. This simplification process is visualised in Figure 1.2. This figure shows how a model is a formal system representation of the real world through encoding. This encoding process cannot fully represent the complexity of the natural system, and the model is thus not equal to the real world. Because of this, assumptions in the model are made to cover the most vital factors so that the model behaviour acts similarly to the real-world behaviour. The results from the model are then decoded to make recommendations for use in the natural system. In the research method of modelling, this process of encoding and decoding needs to be carefully considered, and its implications on the conclusions and recommendations. In this study, this consideration is made by using both sources of theory and expert opinion when making assumptions and by validating the made assumptions with these experts. This will increase the level of confidence put in the results and the conclusions from the model.

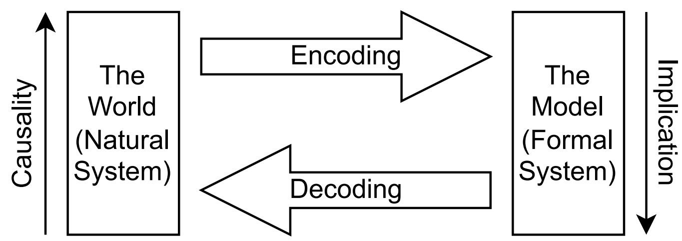


Figure 1.2: Relation between a model and the natural world, as adapted from Rosen (2012, p. 71-75)

2 Context

In this chapter, the contextual information surrounding a police chase is explained. This will give an overview of the information flow and availability through the organisational structure of the police and the internal decision-making process during a chase. This also indicates the societal relevance of the topic of this study and how it could add to the handling of fugitive situations.

2.1. Dutch national police

The national police force of the Netherlands is divided into 10 Regional Units, the Central Unit and the Police Services Centre (Government of the Netherlands, n.d.). A Chief Constable manages each regional unit, comprising of districts divided into Frontline Teams. These districts encompass (part of) a municipality or multiple smaller municipalities. These units ensure district safety and create a pleasant living environment. Their tasks include answering calls for emergency assistance, patrolling neighbourhoods and advising and resolving critical situations. The Central Unit supports the Regional Units during, for example, cross-regional operations through specialised tasks by deploying resources on motorways, the railway network, the water, and the air. Each regional unit has its separate control room, which has an overview of the locations and activities of the police units on the streets. In January 2020, the national control room collaboration was launched, coordinating the regional control rooms for all emergency services (Politie, n.d.-a) and thus creating a more centralised organisational structure. Lastly, the Police Service Centre (PCD) provides services regarding management, finance, ICT, communications, and human resources for all regional units.

2.2. Police decision-making chain during criminal pursuits

To understand the decision-making structure within an emergency call situation, Paoletti (2022) conducted interviews with police officers and a dispatcher that gave an overview of the process. In this section, her results are summarised to show the context of operations set in motion when an emergency call occurs where a crime is committed and the offender has fled the crime scene.

Calls for the assistance of the police come in through either the national emergency number 112 or the general police number 0900-8844. The call is transferred to the most nearby control room, where it is coordinated by a team of dispatchers, often consisting of two persons, where one manages the actual call and one person manages the communication with the police units. In the case of an incident where a crime was committed, and the offender has fled the crime scene, the dispatcher will create a profile of the situation that includes the following information, if available:

- Type of crime committed
- Information about the specific situation
- Urgency of assistance

- Description of the people involved in the incident
- Possible travel direction of the suspect
- Time of day
- Possibility of a suspect attempting to cross national borders

The dispatcher uses this information to determine the urgency of an incident (Low, Medium, High) and which units must be involved. At this moment, the decision to include the national police units is also made. Depending on the urgency and the needed reaction time, the dispatchers will directly transfer the information to the police officers or, if there is more time, develop a strategy for positioning the police units. With this, two tools are used that can further help in decision-making. Firstly, the information can be forwarded to the intelligence centre, which will collaborate by using the information on their servers to find data to help identify the suspect. This data can include connections to past similar crimes and give indications of escape routes. Secondly, the dispatchers have software available to suggest which police units to utilise, given their location and the location of the initial crime based on availability and proximity. The standard strategy is to divide the units between the crime location and the surroundings, where one or two units are sent to the crime scene and between 6 and 10 units to the surroundings for high-urgency incidents to attempt to encircle the suspect. In lower urgency situations, only between 2 and 3 units are sent to the surroundings. Positioning of these units can then be updated if more relevant information is gathered through, for example, new incoming calls.

This current process relies highly on the experience and intuition of the dispatchers handling the call. Initial decisions are required to be taken quickly, as soon as within 30 seconds. According to some experts, the efficiency of the decision-making is highly linked to the familiarity of the dispatcher with the area where the crime was committed. It was seen that the time needed to make decisions is higher, and the efficiency of the chosen strategy is lower if the dispatcher is unfamiliar with the area. The unit placement software is currently useful for determining which units to send to a location, but no advice is available on where these units should be positioned. Sometimes, characteristics from the crime can help suggest possible route directions. An example is that if the crime is a robbery, there is a higher chance of the fugitive criminal using main roads and highways to reach their situation, which is often their home. Alternatively, information from the intelligence centre can help identify possible escape routes. There is, however, no systematic way of achieving this kind of advice.

Because of the large amount of data that the dispatchers handle and the time pressure in high-urgency situations, creating good strategies for positioning police units can be challenging. Next to this, dispatchers often do not have expert knowledge of the best locations and strategies of interception because of both lacking experience and unfamiliarity with the characteristics of streets in the network. It was seen that though the police officers on the roads might have more experience, the dispatchers are the only ones with enough of an overall overview of the location and situation at hand and are crucial for determining the positioning strategy. To support dispatchers in this process, Paoletti (2022) suggest using Decision Support Systems (DSSs) that determine possible escape routes to establish a positioning strategy. This DSS is currently in the progress of implementation by researchers of the Dutch National Police and uses a mathematical optimisation algorithm based on both the crime location and the locations of the police units on the streets. Using this sort of system could improve the quality of the decision-making of the dispatchers. However, in general, it is widely debated whether DSSs improve the timing and quality of decision-making. While Skinner and Parrey (2019) argues this is not the case because they found a higher decision-making time, Bharati and Chaudhury (2004) claim that a DSS's effectiveness depends on the quality of the information, by assessing relevance, accuracy, completeness and timeliness of their inputs. To still explore the usefulness of a DSS, it is thus important for the functionality to be efficient, transparent and useful if adopted in the actual decision-making process. This is another reason for improving the completeness of the knowledge of criminal fugitive route decision-making that would be used in such a system to help increase the quality of the suggested positioning strategies. Next to this theoretical perspective, experts also indicated that less experienced dispatchers could benefit from software like this, assuming that the system's run time is low enough to be included in the decision-making (e.g. less than 30 seconds).

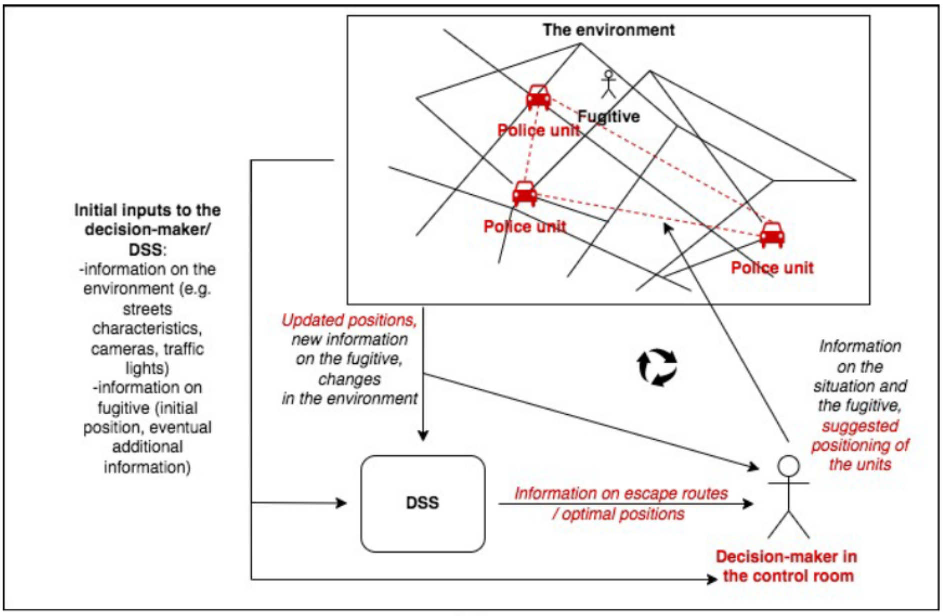


Figure 2.1: Overview of the organisational structure of decision making of police during a high-speed chase as adapted from Paoletti (2022, Figure 5.2)

An overview of the decision process as described by Paoletti (2022) can be seen in Figure 2.1.

3
Theoretical background

In this chapter, the theoretical background in the field of criminal fugitive escape route decision-making will be reviewed. Initially, in Section 3.1, the method and data sources used for this literature review are described. Then, in Section 3.2, the current route choice modelling for high-stress situations is explored to find the relevant topics and research fields. This was done because of a lack of literature on the criminal escape situation. This exploratory literature review resulted in the research field of criminal decision-making, rationality in decision making and route-choice decision-making, which is divided into route-choice behavioural factors and route-choice decision-making factors, Each of these fields is further discussed in separate sections. Lastly, the overall findings of the literature review will be discussed and concluded.

3.1. Method and data sources

To create the theoretical background for this study, two methods are used: a literature review and expert interviews. These are combined to create an overview of the relevant theory while validating this theory with expert interviews. Next to this, expert opinion is used to support literature when it does not encompass the fugitive escape situation or when literature is not specific to the fugitive escape situation. These methods require their own data collection and processing methods.

Firstly, the data used for the literature review is gathered by using the search engine Scopus. A set of queries was inserted to find the relevant literature, and the resulting papers were assessed for relevance. The relevance was determined based on whether the literature is in the context of behavioural route-choice modelling, criminal decision-making, or both. Criteria that were additionally used in the search were that the papers were required to be written or translated into English. There was no time demarcation used. In Appendix A, an overview of the queries and the resulting number of papers can be found. Next to this search engine, some other sources of information were used. Firstly, the research repository of the TUDelft and of the Dutch national police in which previously executed research is published concerning police structure and decision making. For the literature that was found during these searches, when relevant, forward snowballing was used to find the encompassing relevant literature. These methods and data sources ensure the available literature is gathered to find the theory relevant to the fugitive escape situation.

Secondly, expert interviews were performed with members of teams concerning the work of either the Dutch national police or one of the regional control rooms. From these interviews, some information and assumptions have been included in forming the theoretical background. It is indicated in a chapter if interviews are used to find the information provided. Because of the confidentiality of information provided by the experts, it is not possible to give specifics on the identity of the interviewed experts or to provide transcripts of the conducted interviews. The method and summaries of these interviews can be found in Appendix B. The interview results guide and complement the theory found in the literature review forming the basis for the theoretical background described in the remainder of this chapter.

3.2. Exploration of relevant route choice topics

In this section, the results of an exploratory literature review are used to describe the different modelling practices and behavioural factors in route choice behaviour studies. This is used to find a concrete list of relevant topics in route decision-making. Because of the limited research on the criminal fugitive escape situation, the search for relevant theory needs to be expanded to similar situations. Therefore, the search queries were broadened to include all high-stress situations. The literature found during the search can be characterised differently, mainly based on the context in which the models or simulations created in the papers were based. This context is seen to highly influence the assumptions used during the conceptualisation of route-choice behaviour. The following subsections describe the contextual factors, and the specific behaviour factors used to describe route-choice behaviour are reviewed. Lastly, this exploration is used to find the relevant research fields that need further study to encompass all relevant topics for criminal fugitive situations. The results of this exploratory review are then used further in this chapter to guide which topics to study in further detail.

3.2.1. Contextual factors

Individual vs collective behaviour
The first contextual factor influencing route choice modelling is the assumption of individual choices or a collective group making individual choices. An example of an individual perspective on route choice can be seen in a study by Barbierato et al. (2020). They developed a Markovian Agent model for the scenario of a fire in a closed environment, which can be seen as a high-stress response situation. This model was created to show the effect of individuals' behaviour on the total behaviour of a crowd. In contrast, some studies use collective behaviour such as in the conceptualisation of Reynolds (1987). In the context of crowds during emergencies, these models often show phenomena such as herding and flocking behaviour. They are in a different scope than only the individual because the agents respond to each other's behaviour. Although these models' results are measured collectively, the behavioural factors can still be seen as relevant because the behaviour is modelled at an individual level. These studies show how different perspectives on the interdependence of behaviour can influence the extent to which response to other people's decisions is included in assumptions of conceptualised behaviour.

Social environment
The social context is another contextual factor that is often included during the conceptualisation of route-choice behaviour. The factor of having a common or individualised goal can be of interest. Carpio et al. (2022) gave such an example by investigating the influence of environmental factors on safety risk factors in construction sites. They argued that human behaviour is predictable by studying probabilities of actions influenced by social relationships and numerical environments. This determines individual and group-level movement, where the person's state of mind is included in the conceptualisation of the behaviour to influence the risk aversion levels. As seen from this study, the social environment can influence the extent to which the behaviour of individuals influences each other, and the choice between an individualised or collective goal is relevant to include when conceptualising route choice behaviour.

Personal and situational characteristics
Next to the previously mentioned environmental factors, personal factors were found to be relevant for route choice behaviour. Personal differences in preferences and strategies are sometimes specified to influence the resulting route decision-making behaviour. For example, Li et al. (2019) studied the route choices of pedestrians regarding obstacle avoidance. They used different route choice factors, such as always using the shortest path, to determine which personality traits most benefit an efficient route using virtual experiments. Other studies focus on the effect of psychological effects on the presence of certain behaviour. For example, Li and Guo (2021) study evacuations through different psychological behaviour effects such as the unadventurous effect, choosing familiar routes, inertia effects, staying on the same strategy rather than changing, and panic effects, including making bounded rational choices because of limited processing time. Other studies focus on stress in general (Bode et al., 2015; Bode & Codling, 2013) on choice quality and flexibility. In conclusion, the personal and situational traits in a route choice situation, such as stress resistance and the composition of groups, can influence a person's route choices and the level of rationality that these choices are based on.

3.2.2. Relevant route choice factors

The results of the initial literature exploration show that different factors can be identified that affect route-choice behaviour during a high-stress situation. A set of factors is chosen on which to focus a model or conceptualisation where many of the non-included factors are implicitly assumed. This differs based on the social, environmental, contextual and temporal environment consisting of relevant factors as described in Section 3.2.1. It is important to consider that these factors and environments are specifically used for a certain scenario and that not all can be directly mapped to the fugitive escape route situation. To find a set of behavioural factors relevant to this study, an initial list of relevant behavioural factors can be found in Table 3.1. The full list of factors found during the literature review, describing the remaining non-relevant factors and the reasoning behind this choice, can be found in Appendix C. This list of behavioural factors is a subset of the total behavioural influences based on the limited scope of the literature review. It is thus merely a representation of all the influences on route choice behaviour. This list will be used further in this study to determine the relevant research fields and to analyse how the behavioural factors found could influence route-choice behaviour in criminal fugitives.

Table 3.1: List of relevant behavioural route-choice factors from initial literature review

Factor	Sources	Description
Inter-individual differences	Kinateder et al. (2014)	The influence of personal and criminal characteristics on the choices made
Nervousness / stress / mood	Almeida et al. (2013), Bode et al. (2015), Bode and Codling (2013), Carpio et al. (2022), and Van Gelder (2013)	Influence on emotional state of a person on his choices
Rational decision making	Almeida et al. (2013) and Reynolds (1987)	Making assumptions based on maximum utility.
Bounded rationality based on information overload	Carpio et al. (2022) and Li and Guo (2021)	Limitation of computational capacity to include all different choice options into decision making
Inertia effect	Bode et al. (2015), Bode and Codling (2013), Li and Guo (2021), Meneguzzer (2023), Moussaïd et al. (2011), and Reynolds (1987)	Decision making where suboptimal choices are made based on that they reach a satisfaction threshold and changing choice may induce regret
Familiarity / unadventurous factor	Cao et al. (2018), Helbing et al. (2002a), Li et al. (2019), and Li and Guo (2021)	The level of knowledge and experience with the network layout and its characteristics
Asocial behaviour	Reynolds (1987)	Behaviour that can be characterised as risky or dangerous
Obstacle avoidance	Kinateder et al. (2014), Li et al. (2019), Moussaïd et al. (2011), and Ye et al. (2018)	Avoiding obstacles such as intersections and traffic lights to reduce lower speed
Route directness	Almeida et al. (2013), Haghani and Sarvi (2016), Li et al. (2019), Lovreglio et al. (2016), Reynolds (1987), and Zhu and Shi (2016)	Goal of reaching a destination as fast as possible using the most direct route

3.2.3. Relevant research fields

Various research topics can be identified after reviewing behavioural route-choice decision-making modelling space as outlined in Section 3.2. This will be divided into three topics requiring a more extensive theoretical background. Firstly, to study the effect of the contextual environment and personal traits of fugitives, the research field of criminal decision-making should be reviewed. Secondly, a more thorough review of rationality in general decision-making needs to be done to understand how rationality factors such as inertia and emotional state influence the decisions that a fugitive makes. Lastly, the literature on route-choice modelling needs to be reviewed to understand further how behavioural route-choice factors influence route choices. This can be divided into route choice strategies, with more detailed literature on the behavioural factors previously found, such as asocial behaviour, obstacle avoidance and familiarity. Next to this, it includes the strategies to make decisions. This will be based on previous studies that conceptualise and model route choice decision-making. The identified research fields are visualised in Figure 3.1 and will be discussed in the remainder of this chapter.

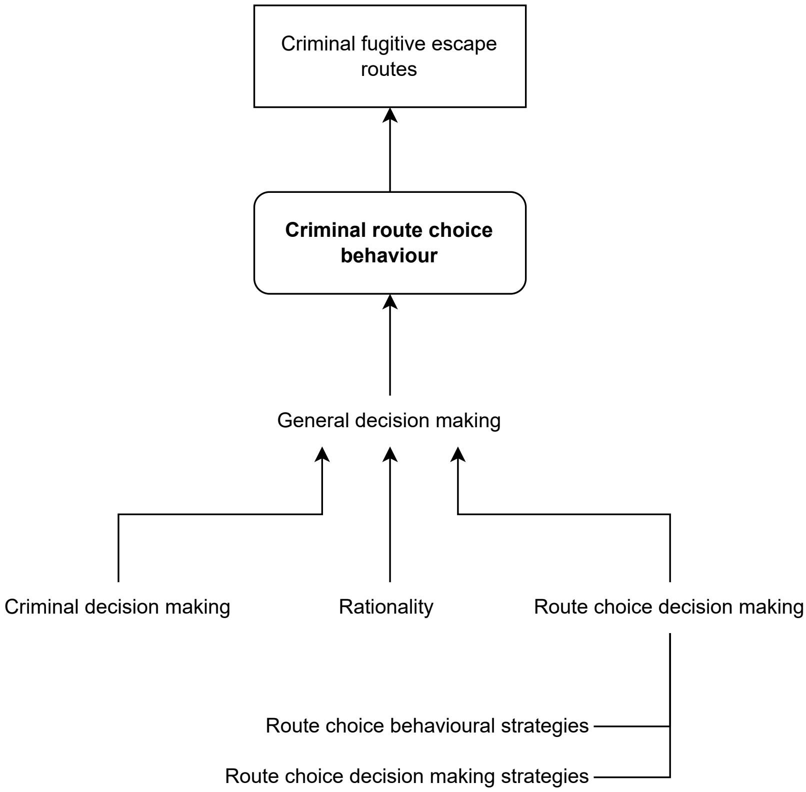


Figure 3.1: Overview of relevant research fields

3.3. Criminal decision making

As described in Section 3.2.1, personal traits can affect the route choice behaviour of people. In the criminal fugitive situation a specific type of person, namely someone suspected of a crime, is considered. Therefore, in this section, the relevant general assumptions from criminal decision-making are discussed to gain an understanding of the behaviour often found when a person is affiliated with a crime. Next to this, the specific characteristics of both fugitive suspects and the situational factors are discussed based on expert interviews. Lastly, the importance of camera surveillance and avoidance will be discussed in Section 3.3.4 because this was found to be a topic of interest based on the expert interviews.

3.3.1. Characteristics found in general criminal literature

In criminal decision-making research, studies often identify the characteristics of specific criminal situations and suspects. This overlaps with general decision-making based on whether rational behaviour can be assumed when considering a criminal situation and the extent to which criminal behaviour depends on heuristics (Pogarsky et al., 2018; Rossmo & Summers, 2022). Part of this is identifying the important norms and values of offenders, such as family disappointment and possible punishment. These are part of the deterrence theory (Apel & Nagin, 2011) often used in criminology stating that people refrain from committing crimes because of the negative consequences. These norms and values considered are often based on the characteristic of a suspect and their social environment.

Some characteristics that influence whether people are likely to participate in criminal behaviour are self-control, impulsivity, and sensation seeking (Burt et al., 2014, p 457). This is seen as based on adolescent development and childhood environment (Mamayek et al., 2015). Next to this, stress and risk have been seen within criminal research to be an important influence during criminal decision-making (Loewenstein et al., 2001; Pickett et al., 2018). A more detailed analysis of the correlation between personality traits and criminal behaviour was done by Levidi et al. (2022), who stated that distal characteristics (agreeableness, emotionality, honest-humility self-control and conscientiousness) affect the situational variables (negative affect and perceived risk), which in turn affect the outcome variable of criminal choice.

These different studies show that many different factors influence whether a person is likely to commit a crime and that there is no consensus on which factors are most important. This could be because situational factors (e.g. type of crime) have such an influence that the relevant factors considerably differ per situation. There is, however, no empirical research done on which personal characteristics influence criminal behaviour the most in the situation of fugitive route choices. Because of this lack of data, further detailed descriptions of suspect characteristics will be based on expert interviews.

3.3.2. Suspect characteristics in fugitive escape situations

To still get an idea of which characteristics are important, interviews with experts were used to determine which characteristics of both the crime and the suspect are seen as most relevant. The resulting topics from these interviews can be seen in Figure 3.2. The characteristics of suspects in fugitive escape situations can be categorised along 4 dimensions:

- **Premeditation**: from the police perspective, there is a clear distinction between the amount of planning that precedes a crime. This influences the amount of stress experienced and the specific strategies the suspect used during an escape. A distinction between three types of premeditation was made here: High premeditation crime, medium premeditation crime and low premeditation crime. This distinction can also be found in literature, where premeditation can result in more rational behaviour compared to non-premeditated crime (Shover & Hochstetler, 2005). In the justice system, this distinction is also made during punishment, where premeditation results in higher punishments (Van Gelder, 2013). There is, however, currently no empirical data to back this up and complete rational behaviour cannot be assumed because fear can still occur during premeditated crime (Akers & Sellers, 2009; Bouffard et al., 2000). Premeditation can, in some cases, be linked to whether a suspect is part of organised crime, where it is seen that organised criminals are often more prepared. But this does not mean that premeditation has a definite relation with organised crime. Therefore, premeditation and organisation should be seen as two separate characteristics.
- **Experience**: the experience of a person in committing a certain type of crime. Experts note that suspects that have high experience seem to experience lower levels of stress and rely on habits that they've created for escape. One strategy of suspects with low experience and high stress was to attempt to be as less predictable as possible by changing direction often and thus taking turns at every intersection.
- **Risk aversion**: Based on premeditation and experience, an influence on the risk aversion of criminals was determined. Low premeditation and low experience lead to higher risk-taking, while in the opposite situation, conformity with normal behaviour is seen more often. Another influence on risk aversion that is seen is the distance from the crime scene; where close to the crime scene and also closer to the final destination, the risks taken are higher. The risks taken are higher closer to the destination because it is believed that criminals tend to think that once they are at their final location, they can no longer be found.
- **Familiarity**: the extent to which a suspect is familiar with its surroundings. This determines how much a suspect knows the network layout and details, such as good escape routes.

3.3.3. Crime characteristics of fugitive escape situations

Next to the suspect characteristics, some contextual characteristics of the crime were also found to be relevant when discussing fugitive route choice behaviour. The relevant crime characteristics can be categorised in the following manner:

- **High/low impact crime**: a measurement of the impact that a crime has on society. High-impact crime is characterised by the fact that it impacts society on a larger scale. This sort of crime is often highly organised and involved high aggression and violence.
- **Time of day**: the time of day that a crime has been committed. This affects the amount of traffic, the number of incidents at the time, and the number of police units available.
- **Crime scene locations**: the location of the crime scene. This differs among the type of crime that is committed where organised high-impact burglaries are often in shopping centres of cities while low-organised crime is often closer to the suspect's home.

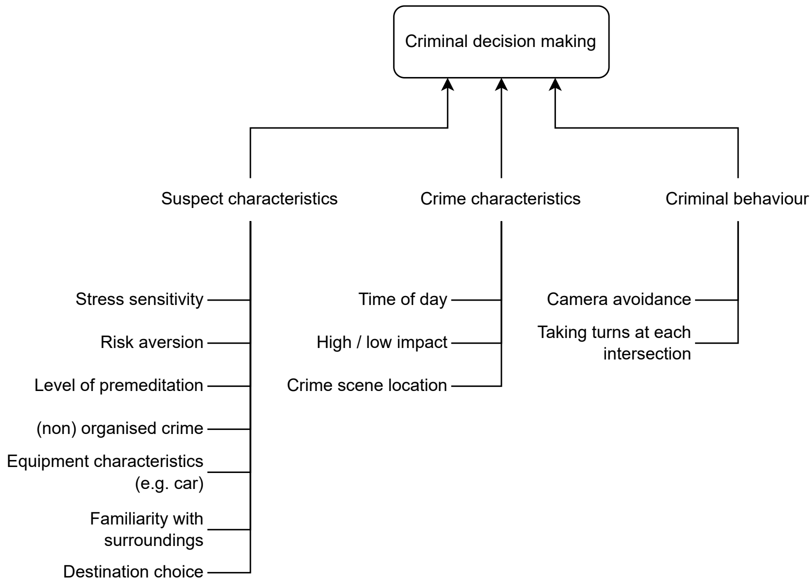


Figure 3.2: Overview of topics within criminal characteristics

3.3.4. Camera avoidance

From the expert interviews, the importance of camera surveillance became apparent. Camera surveillance is often used during emergency calls to gather information on the situation and possibly track suspects. Different types of cameras are used by law enforcement to find a suspect. For the specific situation of car-based escape, one type of camera is most relevant: Automatic Number Plate Recognition (ANPR) cameras. In this section, the use of ANPR cameras and the possible influence that cameras have on crime are discussed.

In 2011, the Dutch police started investigating the value of using ANPR cameras to aid in locating vehicles that are associated with certain felonies (e.g. outstanding traffic fines) to use for investigations and prosecution of criminal offences, in particular serious crimes (Flight & van Egmond, 2011; Politie, n.d.-c). ANPR cameras are often located near highways but can also be remotely used by police units either in the police vehicle or to be positioned on the side of a road (Politie, n.d.-b). ANPR cameras are used to take pictures of the vehicle and the license place and are not meant to include persons that are present in the vehicle (Politie, 2021).

Cameras can shape the environment of the road network in different ways. For instance, as Rubenstein (1980) mentions, cameras can reduce criminal opportunities by improving the ability to detect suspicious behaviour. This was also noted by Cusson (1993), who states that camera presence can influence the offender's emotional state by increasing fear. A reason for this is that some offenders perceive cameras as a warning of a potential punishment resulting from their actions. This is, however, not supported by all literature, as seen from research done by Taylor et al. (2012), who stated that although ANPR cameras can aid in recovering previously stolen cars, they do not influence the rate and routes of car theft in a certain area.

Even though the effects of cameras are not entirely certain, it can be assumed that criminals might avoid camera presence for both the reason of being tracked during the escape from a crime scene and as a means to protect themselves from being identified during prosecution. It is, however, not likely that a criminal will determine to avoid cameras during the escape process, but that this will be considered before the offence has been committed. This includes finding out the placement of the cameras and including this in the planned routes (van Schijndel et al., 2012). This assumption thus applies mainly to premeditated crime.

As can be read from the interviews in Appendix B, cameras are highly relied on in the operation of the control room. They are used for understanding the situation and identifying and following the suspect. City centres of big Dutch cities have a high camera coverage percentage which makes it easy to follow individuals through the streets and determine the direction they are moving towards. Experts note that because the coverage of a city centre can be high, suspects are seen not to take them into account anymore. Suspects assume that they are always visible and that avoiding cameras is not feasible. ANPR cameras are used in a different way than regular cameras. They are mainly useful when a suspect attempts to leave the city through one of the highways because these cameras will alert the police of their movement. Experts assume this type of camera avoidance to be more likely in the planning of organised crime. It is also noted that if a fugitive is stressed that they are seen to include risks of getting caught less and that they focus on getting as far away from the crime scene as fast as possible instead of focusing on camera avoidance. Camera avoidance is thus a behavioural factor that is used in different circumstances and will further be considered as a relevant behavioural factor although it is not always a priority for a criminal fugitive.

3.4. Rationality

As described in Section 3.2.3, the rationality of choices made is relevant when making assumptions on route choice behaviour. In previous research on human decision-making, there has been discussion on how exactly decision-making takes place. Different theories can be seen in this field, where there is a spectrum of models using different definitions of rationality or bounded rationality. The fact that there is so much discussion surrounding this indicates that there is no consensus on how decision-making exactly happens and that assumptions need to be made to conceptualise behaviour. In this section, the different perspectives within this discussion are shown to give some insight into the theoretical background of how decisions could be modelled. The overview of the categorisation within rationality can be found in Figure 3.3.

3.4.1. Rational decision making

Modelling of decision-making is often focused on describing the costs and benefits of options and assigning values to different choices. This method is based on utilitarianism, where choices are made depending on which options create the best utility value. The main method to do this is to determine the different costs and benefits relevant to a specific action. The costs and benefits are translated into (often monetary) comparable values, where the choice with the highest net worth is considered the optimal solution. In criminology, this perspective can also be found in rational choice models for criminal activity, where criminal decision-making is seen as purposive and rational (Clarke & Felson, 2004; Cornish & Clarke, 1986). The costs are hereby specified from the consequences of either being caught by law enforcement (e.g. fine, incarceration) or from reduced social status and negative emotions such as guilt and regret. They are translated into numerical values through mathematical equations (Becker, 1968). This assumption is the basis for the deterrence theory, which states that possible negative consequences of crime reduce both the initial chance of a crime occurring and the chance of

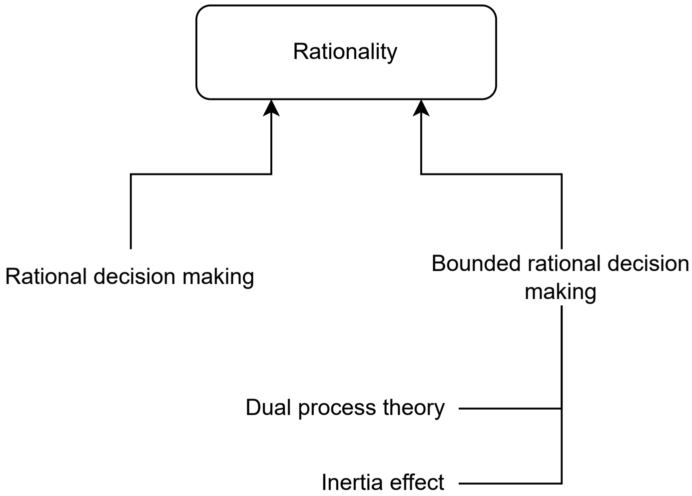


Figure 3.3: Overview of topics within rationality

happening a second time when a person has been punished for a previous crime (Apel & Nagin, 2011). As summarised by van Gelder and de Vries (2013), these models are based on the perspective that people will commit crimes if they perceive that the potential benefits outweigh the potential costs.

3.4.2. Bounded rationality

The mathematical calculation of consequences of decision options can be a very useful method when making decisions in a time and space where there is certainty about the completeness of the information and complete rationality of the decision maker. In real life, however, these two assumptions cannot be made without careful consideration. For this purpose, Simon (1990) defined the concept of bounded rationality, which was used to incorporate the cognitive limitations of the decision-maker into rational decision-making models. In his paper, he noted that bounded rationality could be showcased by relaxing the fundamental assumptions of the subjective expected utility theory. This theory states that choices are made based on three assumptions: (1) there is a bounded number of options to choose from; (2) the probability distributions of outcomes are subjectively known; and (3) a person always maximises their expected utility (Savage, 1954). To relax these constraints, one could assume estimated instead of known probability distributions that include uncertainty or utility satisficing instead of maximisation.

In practice, bounded rationality can be affected by different factors. Some examples are limitations of time and non-accurate calculations of probabilities and risks. On the other hand, informational limitations such as a non-complete knowledge base and non-optimal memory can affect the calculations of optimal solutions. Because of this, completely rational assumptions are often not applicable to human decision-making. Within bounded rational decision-making, there are many different theories on conceptualising decision-making. In this following subsections, two theories are further explained that were seen to be relevant to the given situational context.

Inertia effect

One effect seen within bounded rationality that is often included in the modelling of route choices is the factor of choice inertia. Choice inertia can be defined as ”the tendency to repeat previous choices independently of the outcome, which can give rise to perseveration in suboptimal choices” (Alós-Ferrer et al., 2016). In route choice research and modelling, this has been supported through behaviour such as taking a route with a lower utility because the current route is satisfactory instead of changing to a route with a higher utility (Avineri & Prashker, 2004; Meneguzzer, 2023; Sun, 2023; Zhang & Yang, 2015). Models that attempt to model this inertia effect often calculate the minimum satisfactory level of a route, and if the current route has a satisfactory level above this threshold, then it is assumed that the agent will stay on the current route. Some models are specifically focused on repeat routes which can suggest that inertia is more commonly found in travellers who are experienced drivers on the network (Frei & Gan, 2015). Choice inertia is thus used in every day route choice models to show how people make sub-optimal route choices because of the already perceived satisfaction of the current route.

Dual Process Theory
Dual process theory is a conceptualisation of bounded rationality meant to deal with limitations of including emotions and mood into the mathematical calculations of costs and benefits as used in rational decision making assumptions. One of these limitation is that rational choice models assume that decision-makers are merely responding to their immediate external environment and that this environment is the only factor that needs to be included in the decision-making. In criminal behaviour, it is seen that factors such as the emotions and mood of the offender are equally as important as any monetary value that could be gained when making decisions (De Haan & Vos, 2003). Emotions such as anger and shame should be seen to influence decisions during violent crimes (Athens, 2005). Next to this, the assumption that criminals have a thought-out plan for their behaviour during a crime cannot be assumed and that careful calculations of the situation are not always to be expected (Shover & Hochstetler, 2002; Shover & Honaker, 1992; Tunnell, 1990). These limitations reduce the ability of simply inserting emotions into rational cost benefit calculations.

To deal with these limitations, dual process theory suggests that in activities that include solving problems, evaluating risks or deciding between alternative actions, two mental processing modes operate simultaneously (Kahneman, 2003; Van Gelder et al., 2009). As a result, decision-making is seen as a process influenced by two modes that process information and risks in alternative ways. The most common assumption in models based on this theory is that behaviour is based on multiple processes and not merely on calculations (Strack & Deutsch, 2004). The two modes that the theory identifies can be described as cool and hot. The cool mode is based on rule-based information processing decision-making where rationality is expected through extensive consideration of options. Oppositely, the hot mode is described as automatic, impulsive and heuristic-based. Hot mode is seen as a triggered response which can lead to reduced self-control and is seen as correlated or even defining to criminal behaviour (Gottfredson & Hirschi, 1990). Because the hot mode results from reactions to external stimuli, it is relatively independent of (long-term) goals, resulting in reduced risk identification because the capacity to represent the future and consequences is lacking. It is important to note that the hot and cool modes cannot be seen as entirely separate. They are modes that operate simultaneously, and the perspective still assumes a certain level of rational consideration when making decisions at all times. Both these modes are thus important to include in a behavioural model to explain the effect of emotions on decision making.

Specifically in criminal decision-making, the identified hot mode can explain why criminal behaviour can deviate or even contradict what would be found to be the most beneficial course of action if calculated purely from a utilitarian calculation (Van Gelder, 2013). This hot mode can lead to rudimentary cognitive processing of pros and cons because of limited time and processing ability (Cornish & Clarke, 1986) and is not represented by rational decision-making models. Therefore Van Gelder (2013) created the hot-cool framework for criminal decision-making. He argues that the one-off discrete choices between alternatives do not adequately represent the flow of events during a crime.

3.4.3. Police perspective on rationality in decision making

From expert interviews, it was seen that when observing fugitive escape behaviour, choices cannot always be explained using known rational decision-making rules. The experts describe this behaviour as irrational decision-making. From experience, experts see that when the stress levels of a suspect are very high, for example, when they think they are likely to be caught, they start making decisions that seem almost random. In this case, the experts think that the suspect no longer follows a chosen strategy but acts instinctively on the first idea that comes to mind. This experience can also be found in literature, through, for example Walters (2015) who suggests that during criminal activity, people sometimes respond to a situation with a disproportionate amount of stress and fear, which makes them completely unable to reason the risks and consequences of their actions rationally. This can go even as far as to say that during panicked responses, people no longer have full voluntary action on their decisions (Dimitrov, 1999). During this type of decision-making, suspects can be assumed to have no goal but to get away from the police as fast as possible. Although experts perceive this type of behaviour as irrational, there is always a certain level of decision-making structure in the choices made, even if stress levels are very high. The police are simply no longer able to distinguish the rules used to make the decisions. This shows the different goals and decision-making priorities that a fugitive could have and that interpreting the exact definition of patterns within the choices is difficult.

3.5. Route choice decision making strategies

In this subsection, we will look at the current different methods of modelling used to model behavioural route choices. This can be divided into the current rational view on route-choice modelling and the view of including bounded rationality in the behaviour. An overview of the relevant factors described in this section can be found in Figure 3.4.

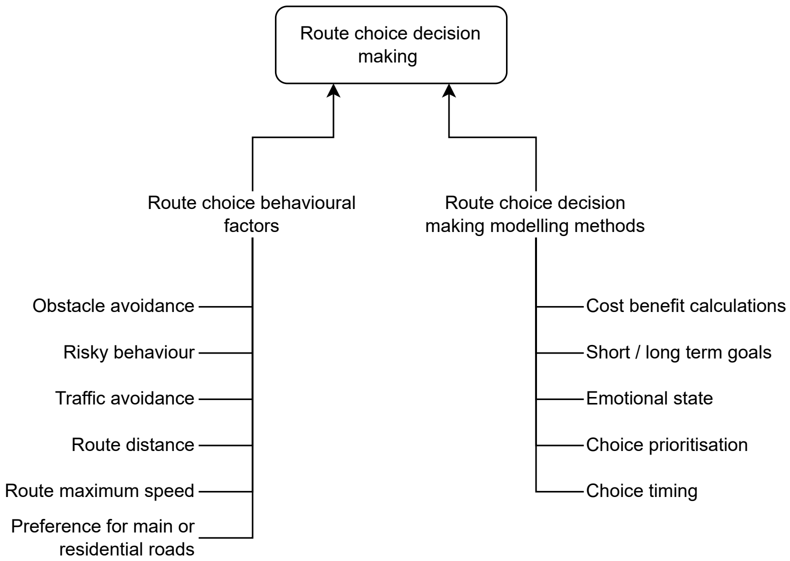


Figure 3.4: Overview of topics within route-choice decision making

3.5.1. Rational route-choice modelling

When considering rational route-choice modelling, strict assumptions of maximizing utility are used. This simplifies the decision-making because the focus is only on the fastest or shortest routes (e.g. Li et al., 2019; Wongsai & Pawgasame, 2016). These rational models are based on situations where an individual has a set origin and destination and has options within the path space between these two points. Shortest path algorithms, such as Dijkstra (1959), are often used, which includes factors such as route length, maximum speed and traffic to determine the costs of different paths. Using this method, a choice must be made regarding the frequency of route choices. The first option is that an agent chooses a route at t=0 and follows this until the destination is reached. The other possible option is to dynamically choose the route, where an agent can change the planned route throughout the time of the commute. The decisions can then be dynamically updated through the stream of continuously changing environmental information. This choice already showcases that bounded rationality is always partly included in modelling through the amount of network and traffic information available.

3.5.2. Bounded rational route-choice modelling

To model bounded rationality in route decision-making models, different methods can be used. These methods often are based on an interaction between the different mental processes, such as the hot-cool mode of dual process theory (Kahneman, 2003; Sloman, 1996; Slovic et al., 2004). Different conceptualisation and model formalisations are based on different assumptions. An overview of these different types of assumptions is given here.

Adjusted costs and benefit calculation
In current path choice modelling, the most straightforward way of including the effect of the internal state of an agent into a model is to include a calculation of the psychological values directly in determining costs and benefits. This can be done by creating randomised choices or including preferences for certain road types in the cost-benefit calculations (Bode et al., 2015; Helbing et al., 2002b; Li et al., 2019). This is argued to be valid by Loewenstein et al. (2001) because emotions, such as regret or relief, are only felt after the decision has been made and thus can be seen as anticipated costs or benefits. During high-angry-emotional arousal, both formal and informal consequences of actions can be included in offenders' decision-making (Carmicheal & Piquero, 2004). These two methods can then be used separately or combined to include emotions in calculating the costs and benefits of choices.

Short term vs long term goals
Another method can be seen from Tawfik et al. (2010), who concluded that route choice behaviour is not always rational and that drivers sometimes make decisions based on their short-term goals and short-term information. For example, making decisions on travel speeds instead of travel time, where higher travel speed is preferred even though the route takes more time. Environmental factors such as stop signs and traffic signals are included to model this. They note that drivers tend to make decisions based on short-term goals for the next short part of their journey instead of the whole journey. This is also consistent with the findings of Golledge and Gärling (2004). This shows that there is a choice to model either long or short-term goals or a combination of both.

Calculation of emotional state
Including emotions and needs in decision-making can also be done by disrupting the cost and benefit calculations. An example of this is Danaf et al. (2015), who used the modelling of state-trait anger theory (Spielberger et al., 1983) in a discrete choice model where agents made choices between different anger-induced activities at each intersection. Their model described the incremental amplification of anger during the simulation. They used this to determine probabilities of certain anger-induced decision choices at each intersection. The State anger of an agent was based on their previously found anger (at time step t-1) and current environmental factors (e.g. blocked intersections). Their model shows an alternative way of including high emotion in the behavioural modelling during transit through separate decisions that can occur next to the regular cost-benefit calculations.

Similarly, another model of emotions in the route choice behaviour is the event-based evacuation model of Yuan et al. (2017). They include a complex model based on many different types of behaviour. Firstly, the behaviour of an agent is divided into strategic, cognitive, tactical and operational. An agent's specific route choice and behaviour patterns depend on their strategy and nervousness. They use different behavioural models (e.g. shortest path, car-following and lane-changing models), which form a set of behaviour patterns. These behaviour patterns are triggered by events that occur. The state of the model triggers these events. This state consists of an agent's static attributes, dynamic parameters and environmental parameters. The nervousness level of an agent is included in the dynamic parameter of an agent, which in this model is determined by using the model of Helbing et al. (2002b) and updated at each decision point. When a particular state causes an event, the agent will change from a non-panic state to a panic state, altering the agent's behaviour pattern. The emotional state in this model is thus intertwined with the regular route choice decision-making instead of being separate processes.

Choice prioritisation and timing
Lastly, a conceptualisation was specifically made for criminal fugitive escape routes by Kempenaar (2022) based on Dual Process Theory. In this conceptualisation, there is a categorisation based on organised and local crime, either in hot or cool mode. In modelling this conceptualisation, through a discrete event simulation, a prioritisation of choice options is used to determine an agent's choices. During hot mode, the different options of direction are analysed per intersection. The options are then prioritised based on a set of rules, which are dependent on whether the suspect is organised or local crime. In the case of cool mode, a shortest path algorithm is used. This shows the modelling method of including different prioritisation rules based on the contextual environment.

The behavioural factors that the prioritisation rules are based on are the characteristics of organised and local crime. Organised crime behaviour depends on avoidance of blind alleys, maximising the number of lanes and maximising speed. Both local and organised behaviour depends on avoiding blind alleys and maximising the number of lanes. The hot mode also includes a long-term goal of the shortest route because if a suspect is on a regional or highway road, it will follow the shortest path calculation. These assumptions create different behaviour based on the type of suspect.

The conceptualisation of Kempenaar (2022) showcases the difficulty in determining the timing of choices made during situations such as a fugitive escape. The choices range from one-time decisions, such as in some cost-benefit calculations or continuous decisions, such as in Kempenaars model. Next to these extremes is a wide range of options for the timing of decisions. The assumptions for choice timing and their affect on the resulting behaviour should be considered carefully.

3.6. Route choice behavioural strategies

In this section, a more detailed review will be done for the remaining route decision factors relevant to criminal fugitive behaviour, as described in Section 3.2.2. Based on previously described literature of route choice modelling, the route choice strategies of shortest paths through route distance and driving speed were found. These will be combined further with possible route choice behavioural strategies found when reviewing the route decision factors obstacle avoidance, familiarity effect and anti-social and risky behaviour. The list of behavioural strategies is displayed in Figure 3.4.

3.6.1. Obstacle avoidance

Obstacles in a route are seen in previous research as a contributor to the situational perception that a person has of their environment. Avoiding obstacles has been seen in both small-scale and larger-scale evacuation studies. There are different ways that studies interpret how obstacle avoidance, or barrier avoidance, influences route choices. On the one hand, the spatial room is preferred. This was seen from a preference for wider corridors in small-scale pedestrian in-door evacuations (Snopková et al., 2023) and a tendency to use wider roads in car-based evacuations by using roads with multiple lanes (Takabatake et al., 2020). Baxter and Warren (2020), on the other hand, notes that barrier avoidance causes participants to change their decision-making goals from longer to shorter-term goals and that obstacles influence a local route deviation rather than the global path length. An example of how obstacle avoidance can be implemented in a route choice algorithm can be seen from Jacob et al. (2014), who adjusted the general Dijkstra algorithm to include a preferred width of roads. This was included threefold through minimum width, preferred width and level of preference to take wider roads. The exact strategies for how people deal with obstacle avoidance may, however, not be consistent and can differ depending on individual factors (Fajen & Warren, 2003). From the literature, there is thus evidence of obstacle avoidance, but the exact method and effect on route choices is uncertain.

In practice, the environmental aspects that can influence decision-making in route choices can be divided into either part of the static road network or dynamic through time. Examples of static components include traffic lights, traffic signs such as stop signs, pedestrian crossings, roundabouts and priority roads. Some components can be seen as semi-static, such as construction places, opening times of bridges and accidents. Lastly, traffic can be seen as the dynamic part of the network. Including traffic is commonly seen in route recommendations because it can considerably impact travel time. From expert interviews, it is also interesting to note that larger road crossings with traffic lights can help intercept fugitive suspects. If organised crime is aware of this, they could thus attempt to avoid these types of road segments. In practice, objects can thus affect fugitive escape routes in different ways.

3.6.2. Familiarity effect

The familiarity in route decision-making can be seen as based on different characteristics of a person, such as the pre-event spatial experience, habitual path preferences and past traverse experiences (Syarlianti et al., 2023). The influence of familiarity with a network is seen in both high-stress situations such as evacuations and in every day commutes.

In evacuations, a correlation was found between familiarity and the evacuation time, the safety of driving and the actual route choices (Hu et al., 2022; Li & Guo, 2021; Stubenschrott et al., 2017). As seen by Sadri et al. (2014b), this can result in a preference for familiar routes over recommended routes. It is, however, important to note that this willingness to follow recommended routes can differ according to the area of evacuation (Sadri et al., 2014a). The influence of familiarity is thus mainly based on the characteristics of the driver and their knowledge of the network.

In normal circumstances of commute, familiarity has also been seen to influence the route choices that people make (Li et al., 2016; Nabijiang et al., 2019; Ouyang et al., 2014). Choosing the same route every time and relying on habit is seen to influence route choices (Chavis & Gayah, 2017). This preference for the habitual route is still seen if the route is less optimal based on the conditions of the road and the dynamic traffic environment compared to other routes (Dow & Cutter, 2002; Lindell & Prater, 2007). The reason for choosing the familiar routes may be the perceived directness and lower traffic that a familiar route may have (Payyanadan et al., 2019). The long-term effect is that travel time throughout repetition decreases (Colonna et al., 2016). Next to this, a lower influence of new information during a commute is found (Dia & Panwai, 2007; Gan & Chen, 2013). This could be because of the habits that a person forms when repeating the same route. This perspective is, however, not consistently seen through literature because other studies suggest that more familiar travellers respond more to the perceived traffic conditions (Lotan, 1997; Sadri et al., 2014b). In commute situations, characteristics of experience, habits and knowledge of the network are thus mainly influencing the routes chosen.

The main influence of familiarity on route choices is thus based on the characteristics of the suspect and their knowledge of the network. One way that familiarity affects behaviour directly is that it has been seen that people choose to utilise main roads over the shortest route along minor roads (Goto et al., 2012). When deriving behavioural factors from familiarity, there is a difference between the effect on the network knowledge as part of the suspect characteristics and possible behavioural factors. The behavioural route choice factors associated with familiarity are avoiding traffic, perceived directness and utilising main roads.

3.6.3. Anti-social and risky behaviour

Another behavioural factor influencing route choices is anti-social and risky behaviour through high emotional response. As described in Section 3.4.2, emotional arousal can influence people's decision-making. As a result, short-term benefits are weighed disproportionately to the long-term consequences and the trade-off of actions is not considered properly. An individual's mood can change the perception of risk in both positive or disruptive ways because of the reduced ability to adaptively react to the surroundings and problems (Ward & Nee, 2009). With this, there is a division based on the type of emotions. Firstly, anxious moods can cause cautious behaviour; thus, fewer risks are taken because of increased regret and risk aversion (Ahsanuzzaman & Messer, 2021; Schwarz & Clore, 1988). On the other hand, high anger emotions can cause sensation-seeking behaviour where higher risks are taken (Leith & Baumeister, 1996; Van Gelder et al., 2009). This can also be seen to be correlated with the familiarity that a person has with the network (Payyanadan et al., 2019). The emotional responses thus influence route choices through either more cautious or risky behaviour and can be seen in many different ways.

The level of risk that a person takes can depend on the information they receive during a commute (Ben-Elia et al., 2013). However, it was seen that people often persist in their initial choices and that risky choices are made more often if there is high-risk indication information at the beginning of the decision-making process (Ahsanuzzaman & Messer, 2021). The amount of risk taken can also vary depending on the characteristics of the person where age, ethnic background and temperamental control have been seen to correlate with risky route choices (Barton et al., 2012). Risky behaviour is thus highly dependent on the contextual environment and can affect the general driving style of a fugitive.

Studies on the situational characteristics affecting driving style showed different aspects that influence the probability of speeding as a form of risky behaviour. Firstly, the socioeconomic and personal characteristics of the driver and the vehicle are considered. Javid et al. (2022) showed that factors such as age, gender, employment, vehicle type, engine size and driving frequency are all factors that can be used to predict speeding. This was also confirmed by Rezapur-Shahkolai et al. (2020), who also added driving experience and educational level to show a correlation with the severity of road accidents. It is also seen that next to these types of factors, environmental factors such as spatial and temporal factors and even the driver's mental state are also of influence. Research specifically on these environmental factors has shown a correlation between dangerous driving events such as speeding and the type of road. Min and Ando (2020) showed that expressways, national highways and prefectural and municipal roads have a higher possibility of speeding as the road standard increases. Next to this, Auñón-Segura et al. (2021) showed that speeding is more common in residential areas and smaller roads during the morning hours, possibly caused by the morning rush hour. Finally, Afghari et al. (2018) showed that roads with high-speed limits (100 km/h or higher) have more medium-speed limit violations proportionally to the number of minor and major speed limits compared to roads with lower speed limits. However, the proportion of major speed limits was seen to correlate with the number of heavy vehicle traffic. In contrast, major speed limits are likely higher along rural highways than other road types. This shows the correlation of risky behaviour with certain route choices, such as the type of roads taken and the surrounding traffic situation.

From this, two factors are seen to be most influential on the occurrence of risky behaviour: the road quality in combination with the minimum number of traffic obstacles such as speed bumps and the remoteness of roads where residential and rural environments are seen as less risky. Another explanation for the different levels of speeding can be seen from the level of monitoring of a city and the lengths of straight roads (Uenk-Telgen, 2018). To conclude, the behavioural factors that can be extracted from the theory of risky behaviour are avoidance of traffic and obstacles and a preference for specific types of roads, such as main with high maximum speed or residential roads.

3.7. Summary of findings

In this chapter, the relevant theoretical background required to describe criminal fugitive route-choice behaviour is outlined. Because of the lack of direct research, an exploratory literature review was performed on route-choice behaviour in high-stress situations. This review was used to find a list of relevant factors to be considered when discussing criminal fugitive route-choice behaviour. From this list, three research fields were identified that needed more detailed review: criminal decision-making, rationality in decision making and route-choice behavioural factors. These different fields add to the knowledge required to describe the behaviour of interest.

Firstly, from the literature on criminal decision-making, it was found that there is no specific knowledge on how decisions are made in fugitive situations. It was, however, found that specific criminal situations and behaviour are often correlated with certain personal and crime-related characteristics. To create an overview of these characteristics of the fugitive chase situation, expert interviews were used. This showed that many different suspect characteristics can influence the seen behaviour, but there is no consistent pattern in which characteristics lead to which behaviour. It is thus not possible to create overarching behavioural profiles based on these characteristics. From these interviews, it was found that there are three contextual, relevant crime-related characteristics: time of day, level of impact of a crime and the crime scene location. These all relate to the route choice behaviour after a crime. Still, because of a lack of data, there is no certainty on the relation between these characteristics and the suspects' behaviour. Overall, many different characteristics of both the suspect and the crime are seen as related to the suspect's behaviour. Still, there is no certainty on how this relation can be seen in practice. During these interviews, two behaviours that could directly be used to describe route-choice behaviour were found: the behaviour of camera avoidance and taking turns at each intersection. They should thus be seen as relevant behaviour in fugitive route-choice behaviour. The overview of the resulting relevant topics from criminal decision-making literature can be found in Figure 3.2.

Secondly, literature on rationality in decision-making was reviewed. This showed the complexity and uncertainty of human decision-making and the different perspectives and assumptions used in different theories of both rational and bounded rational decision-making. It was concluded that rational decision-making is not realistic in most human choices and that there is, therefore, a need to describe the bounded rationality found. This could be done by relaxing the three assumptions of rational decision-making as defined by Savage (1954): (1) there is a bounded number of options to choose from; (2) the probability distributions of outcomes are subjectively known; and (3) a person always maximises their utility. Two conceptualisations of this bounded rationality were further reviewed: inertia effect and dual process theory. The inertia effect is relevant for route choices because it is often seen in habitual commuting, where a sub-optimal choice is made based on the habits of experienced drivers. Dual process theory is relevant for criminal decision-making because it deals with the limitation of including emotions in rational decision-making by assuming a division of mental processing into two separate processes. This has been theorised to be effective during high-stress criminal cases, but there is high uncertainty on how these two processes work. This review showed high uncertainty on which assumptions to use when describing how humans make decisions and that there is no consensus on the optimal way of doing this.

Lastly, previous studies of conceptualisation and modelling of route-choice behaviour were reviewed to find the different relevant modelling methods and behavioural factors that should be considered when describing criminal fugitive route-choice behaviour. This review showed that the factors in these models can be decomposed into a list of behaviours often found in route-choice decision-making. Several considerations need to be made when creating a model of how these behaviours are used to make route choices showing the complexity of route-choice modelling. This resulted in the list of different perspectives and behavioural factors in Figure 3.4.

To conclude, many contextual, personal and behavioural factors were identified to relate to or influence criminal fugitive route-choice behaviour. These factors are often seen to be interdependent or overlapping and this dependence needs to be carefully considered when describing a specific behavioural pattern in route choice behaviour. This shows the complexity of how humans make decisions and the difficulty of making concrete assumptions that describe general route-choice behaviour.

4 Conceptualisation

In this chapter, a conceptualisation for criminal fugitive route decision-making is developed. This is based on the theoretical background in Chapter 3. This starts with explaining the difficulty of conceptualising route choice behaviour based on fugitive characteristics and profiles in Section 4.1. Additionally, in this subsection, the relevance of the crime characteristics is discussed and conceptualised when necessary. Based on this knowledge, an alternative method of conceptualisation is proposed through the conceptualisation of separate route choice behavioural factors. These specific behavioural factors are further elaborated in Section 4.2, based on the list of behavioural factors constructed in Figure 3.4. Finally, to be able to use test these behavioural factors on the influence of the route choices made, a conceptualisation of the general process of decision-making is explained in Section 4.3. These steps in the conceptualisation form the assumptions on which the model formalisation, as described in Chapter 5, is based.

4.1. Suspect and crime characteristics

From the theoretical background in criminal fugitive decision-making, based on both literature and expert interviews, it became clear that no specific personal characteristics distinguish a fugitive. Every fugitive suspect has its own profile of many different characteristics. Although some assumptions could be made based on suspected premeditation and background, these assumptions do not apply to all fugitive suspects and are highly uncertain. Additionally, overlap in premeditation, stress sensitivity and other characteristics with route choice behaviour makes it difficult to make clear profiles distinguishing specific fugitive types. More research needs to be done on profiling fugitive suspects before concrete assumptions can be drawn. Therefore it is chosen not to conceptualise specific behavioural profiles to reduce the number of assumptions of the fugitives characteristics. Instead, separate behavioural route choice factors will be combined to create a strategy that a fugitive suspect could use. These behavioural route choice factors are further discussed in Section 4.2.

Regarding crime characteristics defined in Figure 3.2, three situational factors require conceptualisation. Firstly, the time of day can affect the route choices of a fugitive by changing the dynamic environment, such as traffic and traffic light operations. To reduce the variety of the conceptualisation based on this difference in the environment, this conceptualisation will assume a situation with non-rush hour traffic during the daytime. Secondly, the crime scene and destination locations are not defined but are considered unknown. This was chosen because there is currently no data evaluation that indicates characteristics of possible crime scenes and destination locations which can be used to demarcate this set. Lastly, the characteristic of high or low-impact crime will not be conceptualised. This is done because there is much unknown about the difference in suspect characteristics and behaviour based on whether a crime has a low or high impact.

The conceptualisation of the crime characteristics can be found in Table 4.1.

Table 4.1: Conceptualisation of crime characteristics

Behavioural factor	Description
Time of day	Time during the day during non-rush hour traffic and regular road operation.
Crime scene and destination locations	Assumed to be unknown

4.2. Behavioural factors

As explained in Section 4.1 there were no specific behavioural profiles found for fugitive suspects. Because of this, it is chosen to conceptualise separate behavioural factors influencing route choices. To do this, behavioural concepts from route decision-making and criminal behaviour are combined to conceptualise behavioural route choice factors. The conceptualisation of these factors is mainly based on the factors' relevance on the criminal fugitive escape route situation, which was determined in Section 3.2. The conceptualisation is solely based on route choice decision-making. It does not consider all general driving decision-making, including asocial behaviour towards other road users and violating the law by speeding.

The specific behavioural factors to be conceptualised are based on the route-seeking strategies defined in Figure 3.4. These strategies include the basis assumptions of route choices with a preference for a short path based on the length of roads and the maximum speed to reduce the travel time between an origin and destination location. These strategies will be used directly in conceptualising route choice behavioural factors. The remaining behavioural factors can then be conceptualised as a preference or avoidance of a road characteristic. For traffic avoidance, this is conceptualised as an avoidance of roads with high traffic. For obstacle avoidance and risky behaviour, this can be done in the following manner:

- Obstacle avoidance is conceptualised as avoiding roads with obstacles and preferring higher-lane roads.
- Risky behaviour was conceptualised as a preference or avoidance for more risky streets. Risk seeking is conceptualised through a preference for roads with higher speeds. Risk aversion is conceptualised through avoidance of one-way roads and a preference for residential roads.

Lastly, from the identified criminal behaviours, two were chosen to include in the conceptualisation. Firstly, camera avoidance is directly included. Secondly, the preference for shorter roads, and therefore more often options of changing direction is included. In conceptualising these behavioural factors, the preference of avoidance of some road characteristics may correlate. Still, every behavioural factor can be seen in different situations, and all combinations are plausible. Therefore, the factors are assumed to be orthogonal and that they can influence the behaviour separately.

The overview of behavioural factors can be found in Table 4.2.

4.3. Concept of a route decision

To be able to use the behavioural factors conceptualised in Section 4.2, a route choice must be defined. To conceptualise how a decision is made, we need to determine what the outcome of the decision is. A route decision outcome can be conceptualised based on two interdependent assumptions: the assumption of long or short-term goals and familiarity with the environment.

A decision based on short-term goals can be conceptualised as making a route decision at every intersection. In this case, the choice consists of a single road that a fugitive follows until it arrives at the next intersection. This choice is made based on only the direct environment. Short-term goals are probable in two situations. Firstly, short-term goals are seen if a fugitive is unfamiliar with the road network and thus unfamiliar with the route options outside the direct environment. Secondly, short-term goals are

Table 4.2: Conceptualisation of behavioural route seeking factors

Factor	Description
Camera avoidance	The avoidance of roads where there is an ANPR camera located
Obstacle avoidance	The avoidance of roads that lead to an obstacle (e.g. traffic lights, roundabouts, bridges, tunnels)
One-way road avoidance	The evaluation of the risk of driving on a one-way road. This can be seen as lower when a suspect is seen as showing risky behaviour to drive the correct way into a one-way road or as seen as higher when a suspect drives into a one-way road from the wrong direction.
Traffic avoidance	The lower preference for roads with high traffic.
Higher number of lanes preference	Preferring roads that have more than 1 lane, so a suspect can overtake other vehicles
Residential road preference	The preference of roads that are in residential areas. Either higher because there is less police surveillance in residential areas. Or lower because of unfamiliarity with the area.
High maximum speed preference	Preferring roads with a higher maximum speed because these can bring the suspect away from the crime scene as fast as possible.
Short road preference	Preferring roads that are shorter to allow for more options of turning. In contrast, a lower preference because many intersections can lead to a lower speed.

seen if a fugitive has a high emotional state and behaviour becomes radical. The choices are then perceived as random. From the expert interviews, this is seen from route choice behaviour, such as changing direction at every intersection.

A decision based on long-term goals can be conceptualised as a choice for multiple consecutive roads, creating a route from a start to a destination location. This decision is based on the environmental information of the road network between this start and destination location. How far a fugitive makes decisions into the future, and thus how far away the destination location is, could depend on the familiarity with different regions in the road network. This can further be divided into medium and long-term goals. The long-term goal is defined as the eventual final destination of a fugitive, while the medium goal is defined as the direction of the next x number of roads. For long-term goals, the familiarity used to make a decision is for the whole network, while for medium-term goals, only regional knowledge surrounding the current position is required.

When looking at previous research for route decision-making, many conceptualisations use long-term goals by creating routes between an origin and destination location. This conceptualisation is valid in transportation situations because the destination is known, and the driver is familiar with the road network. For criminal fugitive escapes, both the destination and the familiarity with the network are unknown. Kempenaar (2022) attempted to conceptualise this through different familiarity and goal timing for different situations. In his conceptualisation, full familiarity and long-term goals are assumed during low emotional situations (‘cool’ mode). During high emotional situations (‘hot’ mode), short-term decisions based on direct environmental information are made except if a fugitive is on a regional or highway road, in which case full familiarity long-term decisions are made. The different options to conceptualise the familiarity and goal timing can be found in Table 4.3

There are different limitations to consider when conceptualising short-term goals. Firstly, based on the common characteristics of fugitives, it is unlikely that a fugitive is unfamiliar with the road network in which the incident happens. For planned crime, familiarity is found in the preparation of the crime. For non-planned crime, the crime location is often close to the fugitive’s residence, thus implying a certain level of familiarity. Additionally, the reasoning and environmental information used during the choices made during high-emotional decision-making is unknown. Lastly, it is not known when fugitives rely on short-term goals and when they rely on long-term goals. Because of these limitations, it is chosen not to use short-term goal choices for this conceptualisation.

Table 4.3: Possible conceptualisation for goal timing and network familiarity

	Short-term	Medium-term	Kempenaar (2022)	Long-term
Goal length	For the single next road	For the next x number of roads	Depending on the emotional state: long term for cool mode and hot mode on main roads, otherwise short term	For all road between start and destination location
Level of familiarity	Only direct environment	Regional familiarity with certain radius or for certain neighbourhood	Depending on the emotional state: full familiarity for cool mode and hot mode on main roads, otherwise only direct environment,	Full familiarity

For medium-term goals, the familiarity with the network and the extent to which a fugitive makes decisions in the future can differ highly based on the characteristics of the fugitive. Regional familiarity required to conceptualise medium-term goals can be defined in many ways, for example, as a specific familiarity radius or familiarity with specific types of roads. Medium-term goals can also be defined differently, for example, for a specific distance from a start location or a goal of reaching a specific neighbourhood in a network. This shows that the definition of both familiarity and the level of medium-term goals is complex and ambiguous. The alternative is to use the full familiarity of the network, which could be seen as unlikely for the average fugitive. Still, because of the ambiguity of regional familiarity, it is chosen to include full familiarity with a whole road network in this conceptualisation. No assumption is made for the number of consecutive route decisions to be included in a decision, as it is seen as dependent on the chosen destination location.

4.4. Decision making rationality

Knowing how a possible decision outcome is structured, the process of coming to this decision must be considered. As discussed in the theoretical background, the decision-making process of fugitive suspects is complex, and full rationality cannot be assumed. To conceptualise rationality in the choices made, the three assumptions of rationality are considered. In this section, a conceptualisation is made, which can be used to describe how a fugitive makes a route choice concretely. The overview of the conceptualisation can be found in Table 4.4.

4.4.1. Bounded number of options

The first factor in the rationality of decision-making is whether a fugitive can choose from a bounded number of choices. The starting location is the only information with high certainty in an escape situation. It is unknown what the destination location is or whether a fugitive even has a destination location in mind. From the expert interview, it was noted that during an incident, a fugitive has an initial movement direction and that this direction is used to predict where a fugitive will be going. This suggests that a fugitive does choose at least a local location to move towards, limiting the possible routes that the fugitive can take. In this conceptualisation, we, therefore, assume that there is a destination location that a fugitive has in mind and that the fugitive will take a path towards this destination. To conceptualise these routes, the term path is used from graph theory which refers to a route where the roads and intersections are distinct (Wilson, 1986). This reduces the outcome space by eliminating routes that have loops. A fugitive's bounded set of decision options is the set of possible paths between a start and destination location. The choice of destination location will not be further conceptualised.

4.4.2. Probability of outcomes is subjectively known

The second assumption of rationality is that the probabilities of outcomes are subjectively known. In the fugitive route choice situation, it is not possible to know exactly all the environmental information in a network. Therefore, we can use assumed knowledge instead of actual knowledge. This is the knowledge that a fugitive assumes about a network. Examples are that highways have a lot of traffic, or that driving is faster on roads with multiple lanes. This also applies to behavioural factors that might be chosen because of an assumed lower chance of getting caught, such as driving in residential areas. This is not knowledge that is known but knowledge that is assumed by the fugitive. Next to this, there is no updating of knowledge. If a fugitive knows the traffic situation at the start of an escape, he does not know whether there is a change in traffic or whether an accident happens on certain roads. Therefore, there is no dynamic adaptability to the environmental information, and there is a reliance on the initial information at the start of an escape attempt. This information basis affects the probability calculation that a fugitive would make and are subjective to the knowledge base and the strategy of the fugitive. This also eliminates the usage of the inertia effect, as described in Section 3.4, because a fugitive is not aware of the sub-optimality of its initial choices.

4.4.3. Maximisation of utility

A fugitive is assumed to prefer some routes over others within the bounded number of routes described in Section 4.4.1. This preference can be based on a calculated utility of a route. Which routes a specific fugitive prefers depends on the routes' characteristics and the fugitive's preferences. As previously stated, there is much uncertainty surrounding the specific characteristics of a fugitive, and there is currently no way to conceptualise a specific fugitive profile with specific behaviour. Therefore, the list of behavioural factors was conceptualised, describing separate behavioural factors influencing the strategy a fugitive uses to make decisions. A strategy is therefore seen as a set of behavioural factors that a fugitive uses and the level of importance that a fugitive gives each of these behavioural factors. The concept of having a strategy is thus assumed, but the exact composition of this strategy will not be conceptualised. A preference in the possible routes can be decided using this strategy with specific levels for behavioural factors. A behavioural factor will then decide whether a route is preferred based on the characteristics of a route.

4.4.4. Emotional state

From the theoretical framework, it was seen that the emotional state of a fugitive can influence their behaviour. This was seen as a period of time during an escape where the behaviour differs from the normal behaviour. Experts explain this through the stress level that a fugitive experiences. A conceptualisation considered is Dual Process Theory, with hot and cool mode of behaviour. This concept is complex because it describes two systems that are not operating completely separately. An alternative way that sudden stress, or panic, could be conceptualised is a sudden change in the goal of a suspect and, therefore, his strategy. In this conceptualisation, the stressed reaction is based on the behaviour found in route seeking instead of the unknown practical conceptualisation of the hot and cool mode framework as described by Van Gelder (2013).

Table 4.4: Conceptualisation of route choice decision making

	Conceptualisation
Goal length	A whole route between start and destination location
Level of familiarity	Full familiarity
Possible outcomes	Bounded set of paths from start to destination location
Utility	Utility value for all paths, higher utility is assumed to be more likely. The utility is based on a strategy of behavioural factors
Subjectively and probability of outcomes	Assumed instead of actual information, no updating of dynamic information
Change in emotional state	A sudden switch in strategy

5 Model Formalization

This chapter formalises a model that implements the conceptualised criminal fugitive route-choice behaviour. This includes the definition of the route cost model and the implementation of this model based on the road network of Rotterdam.

5.1. Network formalisation

For the formalisation of the behavioural factors, as defined in Section 4.2, a network with certain characteristics is needed. This network consists of vertices and edges. The vertices represent intersections and are linked by edges representing the roads. Based on the behavioural factors, the edge characteristics are defined in Table 5.1.

Table 5.1: Edge characteristics

Edge characteristic	Type
Camera	Boolean
Obstacle	Boolean
One way	Boolean
Number of lanes	Integer
Road type	Road type as defined by OSM
Maximum speed	Integer
Length	Integer

In this network, a sequence of edges can form a route using the path definition as defined in Section 4.4.1. This is defined as the following:

A route r is a sequence of edges e_{ij} between vertices i and j, which result in a path between the origin point o and the destination point d

To find the most likely routes that a fugitive takes based on their behaviour, a route cost model is defined to calculate the cost of a route given the preferences of a fugitive. This model is defined in Section 5.2.

5.2. Route cost model

5.2.1. Fugitive strategy

The behavioural factors defined in Section 4.2 are used to form the strategy of a fugitive. The strategy consists of the set of behavioural factors BF defined in Table 5.2 where each behavioural factor bf has a multiplication factor MF_{bf}. This multiplication factor is active for a condition $c_{bf}(e)$ based on the characteristics of an edge e. A strategy is defined as a set of values for the behavioural multiplication factors

$$S = \{MF_{bf} \mid bf \in BF\} \tag{5.1}$$

Table 5.2: Formalisation of behavioural factors

Behavioural factors (BF)	Condition $c_{bf}(e)$	Scale of multiplication factor MF_{bf}
Camera avoidance	$e_{camera} = True$	[1, ∞)
Obstacle avoidance	$e_{obstacle} = True$	[1, ∞)
One way avoidance	$e_{one\,way} = True$	[1, ∞)
Traffic avoidance	see Equation (5.4)	[1, ∞)
Lane preference	$e_{number\,of\,lanes} > 1$	(0, 1]
Residential preference	$e_{road\,type} = Residential$	(0, 1]
High speed preference	$e_{maximum\,speed} > 50km/h$	(0, 1]
Short road preference	$e_{length} < 100m$	(0, 1]

The behavioural factors can be divided into either a preference or an avoidance of edge characteristics. These two types of behaviour are processed differently in the model.

Edge avoidance
There are four avoidance-based behavioural factors: camera avoidance, obstacle avoidance, one-way road avoidance and traffic avoidance. When a fugitive wants to avoid an edge based on one of its characteristics, the cost of this edge increases. The multiplication factor of the avoidance-based factors can increase the costs of an edge by multiplying the multiplication factor MF_{bf} that is >= 1. The higher the avoidance level of the fugitive, the higher the multiplication factor and the cost of an edge. As explained in Section 5.2.3, when calculating the full costs of a route, the cost of routes with edges that are avoided following the strategy of a fugitive will be increased. Therefore, routes with edges that are avoided have a higher cost.

Edge preference
There are four preference-based behavioural factors: lane preference, residential preference, high-speed preference and short-road preference. When a fugitive prefers an edge based on one of its characteristics, the costs of this edge decrease. The multiplication factor of the preference-based factors can decrease the costs of an edge by multiplying the multiplication factor MF_{bf} that is on the scale (0, 1]. The higher the preference level of the fugitive, the lower the multiplication factor and the cost of an edge. As explained in Section 5.2.3, when calculating the full costs of a route, the cost of routes with edges that are preferred following the strategy of a fugitive will be decreased. Therefore, routes with edges that are preferred have a lower cost.

5.2.2. Edge cost calculation

The strategy of a fugitive is used to calculate the costs that a fugitive perceives for each edge in the network. The base costs of an edge are based on the perceived travel time of an edge calculated by dividing the length of an edge by the maximum speed. This base costs for an edge is then adjusted to represent the strategy of the fugitive by multiplying the base cost with the multiplication factors, given the conditions of the behavioural factors. This is calculated using the following formula:

$$cost(e) = \frac{e_{length}}{e_{maximum\,speed}} * \prod_{bf \in BF} v_{bf}(e), \tag{5.2}$$

The value of v_{bf} is dependent on the conditions of the behavioural factor. For all behaviour factors, except traffic avoidance, this is defined as follows:

$$v_{bf}(e) = \begin{cases} MF_{bf} & \text{if} \quad C_{bf}(e) \\ 1 & \text{else} \end{cases} \tag{5.3}$$

For traffic avoidance, different road types are distinguished that are assumed to have different traffic and, therefore, different cost values. This is defined as follows:

$$v_{traffic\ avoidance}(e) = \begin{cases} MF_{traffic\ avoidance} * TA_1 & \text{if} \quad e_{road\ type} \in road\_type\_category_1 \\ MF_{traffic\ avoidance} * TA_2 & \text{if} \quad e_{road\ type} \in road\_type\_category_2 \\ MF_{traffic\ avoidance} * TA_3 & \text{if} \quad e_{road\ type} \in road\_type\_category_3 \\ 1 & \text{else} \end{cases} \tag{5.4}$$

Table 5.3: Definition of road type categories

Road type category	OSMNX road types
Category 1	Motorway, motorway_link, trunk
Category 2	Primary, primary_link, secondary
Category 3	Tertiary

5.2.3. Route cost calculation

To model the route choice behaviour of criminal fugitives, calculations are made that determine the preference for specific roads and routes. This is based on the behavioural route choice and bounded rationality factors described in the Chapter 4. To find the likelihood of a route between an origin and destination point, a calculation based on the weight of edges in the network is used. The cost of a route is calculated by taking the sum of the weights of the edges in a route:

$$cost(route) = \sum_{e \in route} cost(e) \tag{5.5}$$

The model output is the set of all possible routes between an origin and destination location and the cost for these routes. The lower the route cost, the more likely it is to be taken.

5.2.4. Strategy switch

A strategy switch SW is defined as a mapping from one strategy to another, which happens at a specific decision time t

$$SW_t : S \mapsto S \tag{5.6}$$

The effect of the strategy change in the model is that a route is separated into two different strategies where a switch between these strategies occurs at a decision point t. The first t decisions in the route are based on the first strategy set, and the decisions in the route from t till the end of the route are based on the second strategy. The decision time step t is decided using a strategy change percentage of the original route using only the starting strategy.

5.3. Model implementation

In this section, the network implementation of the formalised model is explained. This includes the considerations taken for the choice of the network to implement and the data sources required to implement the model on this network.

5.3.1. Network

An important aspect of a route choice model is the network on which it is built. Different characteristics of this network should be considered since they can affect the representativeness of the problem and influence the results. The following model characteristics were identified to be relevant:

- **Size and density of a network**: Influencing the length and complexity of possible routes.

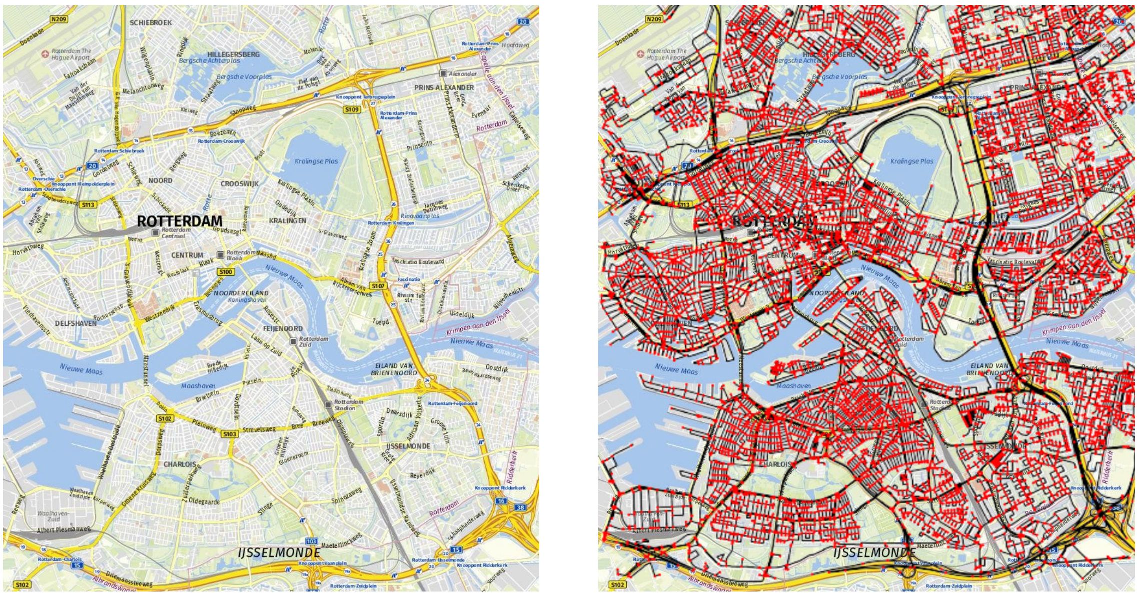
- **Complexity of network infrastructure**: defined as the complexity of the infrastructure of a network. This includes containing structures or obstacles such as cameras, bridges, roundabouts and traffic lights. Also, including different road types such as multi-lane roads, residential roads, and highways are relevant for the complexity of a network.

To fully incorporate the behavioural factors, as described in Section 4.2, these characteristics should be considered when choosing a network. This would imply using different network sizes and complexities to test the different influences that behavioural factors have in different situations. For the time span of this project, however, exploring this space of networks is not feasible. Next, when considering the validation of results based on certain network characteristics, only the networks should be included for which validation is possible.

Considering these criteria, the set of possible networks can be reduced. Firstly, when considering the inclusion of complex infrastructure, networks of large cities are most appropriate. These will include the complexities such as ANPR cameras and complex traffic junctions that smaller cities might not have. Next to this, when considering validation through contact with experts on criminal behaviour, the network of Rotterdam was chosen to be the most suitable. A bounding box was created to demarcate this network, of which the specific values can be found in Table 5.4. A visual representation of this bounding box can be found in Figure 5.1a.

Table 5.4: Latitude and longitude coordinates of used bounding box

	value
Latitude south	51.863171
Longitude west	4.427773
Latitude north	51.970486
Longitude east	4.580918



(a) Demarcated map of Rotterdam

(b) Vertices (red) and edges (black) from network

Figure 5.1: Visualisation of Rotterdam network

5.3.2. Data sources

The Python package OSMnx generates a graph of Rotterdam's car road network. This is a package which combines the Python package NetworkX with OpenStreetMaps. The bounding box from Table 5.4 generates the network of vertices and edges. The resulting map of edges and vertices can be found in Figure 5.1b.

Next to the road network, additional data is necessary to incorporate the behavioural factors. The relevant data types can be summarised in Table 5.5. For the edge-based data sources, the data is directly used. For the vertex or position-based data sources, the closest edge is calculated. For data sources based on vertices from OSM, this is done by calculating which vertex in the network is closest to the data point. For this vertex, the outgoing edges are marked for the specific data type. For the ANPR cameras, the positions are often in the middle of a road, and the edge must thus be calculated directly. This is done by calculating the perpendicular distance between the location of a camera and the edges. The closest edge is then marked as having a camera. Visualisations of the specific data sources embedded in the network can be found in Appendix D. Here it can be seen that there are no data sources that overlap enough to merge into one data source.

Table 5.5: Data sources

Characteristics	Source	Unit	Specification level
ANPR Cameras	Politie (n.d.-b)	Position	lat/lon coordinates
Traffic lights	OSM	Position	Vertex
Bridges	OSM	Position	Vertex
Roundabouts	OSM	Position	Vertex
Tunnels	OSM	Position	Vertex
Road one way	OSM	Boolean	Edge
Road type	OSM	Categorical	Edge
Road number of lanes	OSM	Integer	Edge
Road maximum speed	OSM	km/h	Edge
Road length	OSM	Meter	Edge

5.3.3. Tools

The model as described in this chapter, is implemented in Python. This implementation is based on the functionality of the NetworkX and OSMNX python package, which can be used to support graph-based spatial calculations (Boeing, 2017). The code for the model itself can be found in the following git repository: https://github.com/WillemijnTutu/EPA_thesis_WATutuarima

5.4. Model validation

Because of the lack of data to validate the model, expert opinion and resulting routes of the model are used to validate the model. The following list of assumption validation used to reason that the model is valid:

- **Assumptions of behavioural factors:** All behavioural factors are based on either theory or expert interviews. The resulting list of used behavioural factors and their conceptualisation as described in Chapter 4 were discussed with experts and seen as valid.
- **Assumption of destination location:** From the expert interviews, it became clear that it cannot be assumed that a fugitive has a single destination in mind. Therefore, in the model, different locations can be sampled, which gives a range of locations and directions that a fugitive can go towards. This thus reduces the influence of a single destination choice in the model.
- **Resulting routes from the model based on behavioural factors:** In the uncertainty analysis, as described in Chapter 7, the different route networks based on specific behavioural factors

are analysed. When these networks are compared to the characteristics of the network as can be seen in Appendix D, the routes are seen to avoid or prefer the correct roads. The only behavioural factor that was seen not to affect the resulting routes appropriately is the shortest path preference. This was thus chosen to not further include in the analysis. For all other behavioural factors included in the experimental design, the resulting routes are consistent with the expected behaviour.

- **Strategy change:** The concept of a strategy change given at a certain time after an incident is directly induced from expert interviews. It is therefore seen as valid.

6 Route metrics

The model output is a list of routes with a cost score based on the specific strategy of the fugitive. Using this list, we can extract the routes with the lowest costs to find the routes likely to be chosen by a suspect. In this study, we want to see the difference in these likely routes depending on the strategy.

6.1. Differences based on travel time

When looking at how the difference in routes is quantified in previous research, we can see that secondary metrics are often extracted. Examples of this are total travel time (Mainali et al., 2011; Yamamoto et al., 2002) or a metric derived from this travel time, such as evacuation rates (Haghani & Sarvi, 2016; Jacob et al., 2014). This travel time is based on the length of a route and the speed that is driven. In the implemented model, the maximum speed of a route is known, but the actual driven speed is not known. Other travel time-affecting factors, such as traffic and waiting for traffic lights, are not included. This makes it difficult to measure the travel time accurately. Therefore, it is chosen to base the travel time on the number of intersections that a route goes through. To define this route metric, the following definition of continuity is used as adapted from Marshall (2015):

Continuity represents the length of a route based on the number of vertices a route is made up of and represents the number of intersections a route is continuous through.

This continuity metric can be used to compare the travel time of routes with the same start and end point. To compare the travel time between two locations with the travel time between two other locations, we must normalise the metric to be independent of the origin and destination location. This can be done by dividing the continuity value of a route by the continuity value of a base case route between the specific origin and destination location (Croce et al., 2020). The base case that can be used is the likely route for the base case strategy. The base case strategy is the strategy with all MF_i set to 1. An example of possible routes and the base case route can be seen in Figure 6.1 where the yellow and orange routes represent the most likely routes based on two different strategies, and the black route is the base case route. The number of vertices in all the routes is calculated to determine the continuity of each route. This number of vertices per route is then divided by the number of vertices in the base case route. The continuity of the base case is always equal to 1.

Figure 6.1: Three routes where the black line represents the base case route and the orange and yellow lines represent routes using different strategies.

6.2. Differences based on route overlap

One metric of interest that became apparent from the expert interviews is whether intersections or parts of a network are often used during an escape. We can look at Figure 6.2 to further understand how this can be formalised. Here, the likely routes are shown from one origin location to several destinations. We can see that some routes to different destinations use the same roads and thus overlap. This is interesting for the police because this means that certain roads are more likely to be used by a fugitive to escape. The police could use this to determine which intersections could be used to intercept suspects. This metric can be formalised on two levels: the overlap of the routes and the frequency of the intersections in the routes.

Connectivity
To formalise the overlap of routes, the following definition of Marshall (2015) can be used:

Connectivity represents the number of routes with which a given route is connected

The connectivity measure is normally used to represent the extent to which the routes in a network are interconnected. The connectivity of route x is the number of routes that intersect with x. For the escape routes, we are not interested in the number of routes a route is connected to but the degree of this connectivity. Therefore, the calculation should be based on the number of times a route connects with other routes. To calculate the number of times two routes connect, the following formulas can be used:

$$vertices(route) = \{i \mid e_{ij} \in route \; or \; e_{ji} \in route\} \tag{6.1}$$

$$connectivity(route_i, route_j) = \{v \mid v \in vertices(route_i) \; and \; v \in vertices(route_i)\} \tag{6.2}$$

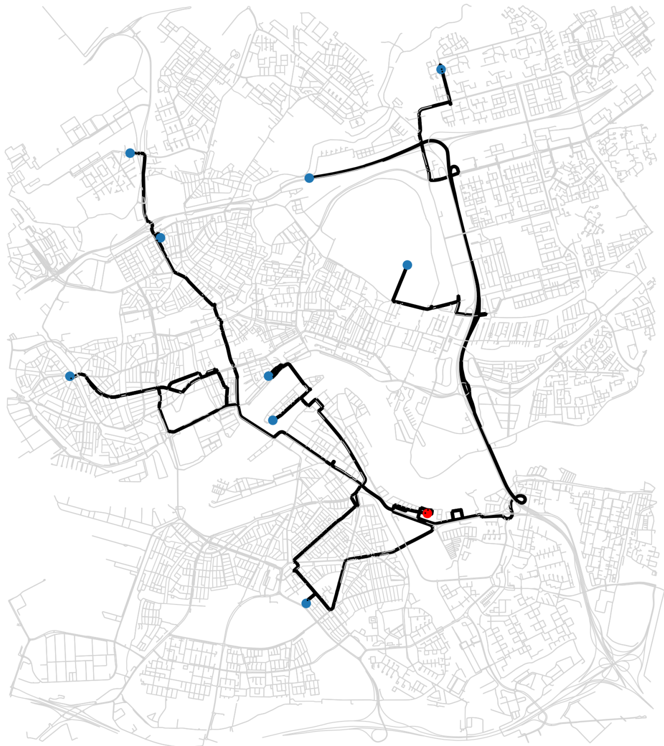


Figure 6.2: Example of routes from an origin location to several destination locations

When this connectivity is normalised based on the length of route i, the percentage of the length of route i connected with route j is measured. To measure the connectivity of a single route with all the routes from an origin location to several destinations, we can take the average connectivity of a route with all the other routes. This is calculated as follows:

$$connectivity(routes_i) = average_{routes}\left(\frac{|connectivity(routes_i, routes_j)|}{|routes_i|}\right) \quad for\, i, j \in |routes| \; and\, j \neq i \tag{6.3}$$

Vertex frequency
Another method to measure this overlap is to find the intersections used most often in the routes (Zimmermann & Frejinger, 2020). This can be determined by calculating the frequency of intersections used in the routes from a certain start location. To find a general measure of the vertex frequency of the routes from an origin location, the mean vertex frequency of all the vertices in the routes is used.

The three described metrics can measure the differences and similarities between routes based on characteristics relevant to the fugitive escape route situation and will thus be used in the experimental design. The overview of these measures can be found in Table 6.1.

Table 6.1: Relevant output characteristics of resulting route choices

Output indicator	Description	Unit	Measured on
Continuity	Length of routes	Number of intersections in a route	Route between single origin-destination pair
Connectivity	The extent to which routes are connected	Percentage of route i that overlaps with route j	Route from one origin location to several destination locations
Vertex frequency	Importance of intersections	Frequency of occurrence in routes	Intersection in route in one origin location to several destination locations

6.3. Alternative metrics

Other characteristics of routes considered are the type of roads in the route. This could include the type of neighbourhood a route goes through if it uses highways or residential roads (Dhulipala et al., 2020; Shin et al., 2023). These measures can depend on the input values of the behavioural factors. These are not included in the analysis to avoid direct dependence between input variables and outcomes of the model.

6.4. Summary of findings

In this chapter, two types of route metrics were defined that could be used to measure the differences in routes quantitatively: the length of routes and the overlap in routes. These can be measured using the continuity, connectivity and vertex frequency metrics. These metrics will be used in the experimental design described in chapter 7 to measure the differences of routes based on behavioural route-choice factors.

7

Experimental Design

This study aims to find the influence of behavioural factors on fugitive escape routes, as conceptualised in Chapter 4. To do this, a model is defined in Chapter 5. This model takes input values for the behavioural strategy of a fugitive and the start and end location. Using this input, the model creates a cost value for each possible route between the origin and destination point. From this list of routes with cost values, the most likely routes can be extracted. In Chapter 6, metrics were defined to quantify the difference in the likely routes. In this section, the method is discussed that is used to experimentally explore the input space of the behavioural strategies and their effect on the resulting route metrics.

7.1. Open exploration

As discussed in the theoretical background, there is much uncertainty surrounding the different factors influencing the route-choice decision-making of criminal fugitives. In this study, we attempted to create a conceptualisation and formalisation encompassing the most relevant factors. This showcases the deep uncertainty that can be found through the different steps, such as the choice of behavioural factors and the formalisation of the influence of these factors. Within the formalisation of the behavioural factors, the exact numerical values of the influence on decision-making are also uncertain and can currently not be supported by data or literature.

To find the role of these uncertainties in route choice behaviour, exploratory modelling can be used. Exploratory modelling focuses on different aspects of the modelling process: conceptualisation, formalisation or experimental design. In this study, the focus of the exploratory modelling will be the input values of the behaviour factors. The conceptualisation and formalisation will be constant.

Open exploration is suitable for this purpose because it is used to identify the bandwidth of outcomes based on different ranges of input variables. Additionally, it can be used to identify different types of behaviour. This process is, however, complex because the link between the model formalisation and the outcomes is uncertain, and the direction of this influence is unknown (see Figure 7.1). This creates an iterative process of adjustment of model and input ranges.

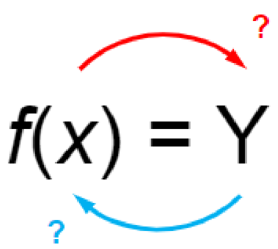


Figure 7.1: Iterative process of open exploration

Different techniques can be used to find different relations in a system. To find the most suitable methods, Maier et al. (2021) studied the different situations in which uncertainties are evaluated and the different methods to evaluate these uncertainties. They identified the following methods:

- **Uncertainty analysis**: this method describes the uncertainty in the outputs of a model based on the uncertainty of the inputs (Matott et al., 2009). Modellers can use it to quantify the variability caused by incomplete knowledge (Cariboni et al., 2007). The outcomes suggest the relative magnitude of system responses.
- **Sensitivity analysis**: Determine the effect of changes in the uncertain input space on the outputs. Describes how uncertainty can be apportioned to sources of uncertainty in inputs (Saltelli et al., 2008). The outcomes suggest probabilities of different system responses.
- **Scenario analysis**: Represent future scenarios by sampling values in input space (Maier et al., 2016). The outcomes suggest values for plausible system responses.

7.1.1. Uncertainty analysis

Uncertainty analysis is a method that can be used to describe the range of the output variables based on the uncertainty and variations of inputs (Mountford et al., 2017). One method for uncertainty analysis is proposed by Geffray et al. (2019), as follows:

Step 1: Describe the knowledge of the variables and the correlation between variables through probability density functions.

Step 2: Generate a sample of the distribution of step 1.

Step 3: Execute the model on the sample.

Step 4: Apply statistical methods to determine the value of each uncertainty.

This method can be performed in a very extensive way based on the knowledge and data in the given field. In fugitive route-choice behaviour, this data is unavailable, and the values used for the input sample can thus only be found in an exploratory way. This also suggests it can be used to determine the importance and influence that certain uncertainties have on a resulting route. Because there is so little data, uncertainty analysis is used in this study to find the ranges of which uncertainties cause differences in route choices. These ranges are then used in the following steps to find the importance and influence of each of the uncertainties. A more extensive explanation of the method used for the uncertainty analysis and the results can be found in Appendix F.

7.1.2. Sensitivity analysis

Sensitivity analysis is a method to determine the relationship between the inputs of a model and the sensitivity of the outputs. Different reasons to conduct sensitivity analysis are to find which input variables contribute most to the output of the model, which are insignificant, which variables interact with each other and how the output of the model could be explained through the input variation (Iooss & Lemaître, 2015). Different methods exist: determining correlation, regression-based techniques and variance-based techniques (Geffray et al., 2019; Saltelli et al., 2008).

One decision to make when choosing a sensitivity analysis method is how many uncertainties to include simultaneously. The different options are one-at-a-time (OAT) sensitivity analysis, regional sensitivity analysis or global sensitivity analysis. AOT sensitivity can have the limitation of not accurately describing the total influence of a single uncertainty on the outputs of a model and is not used during this study. Also, global sensitivity analysis might not be suitable for the described model because the model distinguishes between two types of influences: the behavioural factors and the bounded-rational factors. These cannot be directly combined because the behavioural factors are used as input for the bounded-rational strategies. Therefore, regional sensitivity analysis is most appropriate for this model.

As previously stated, there are correlation, regression and variance-based sensitivity analysis techniques. The direct relation between a model's inputs and outputs can be found using the correlation-based sensitivity analysis. In this method, the correlation is calculated based on each individual input variable. Other possible correlation calculations can be based on multiple or multivariate parameter choices. These methods have the limitation of overfitting when there are too many independent variables and when the independent variables correlate too much. Because there is a high number of independent variables and the extent of correlation is unknown, it is chosen only to use single-parameter correlation in the sensitivity analysis.

For the regression and variance based, several methods to find sensitivity can be used, which have different attributes. An overview of the different attributes of some of these methods can be found in Table 7.1. From these characteristics, linear regression is decided not to be included in the consideration because the linearity of the model cannot be assumed, and the accuracy of linear regression can, therefore, not be expected. When considering the desired outcomes, namely the singular influence of each behaviour factor and the combined influence, Sobol indices are the most suitable choice. A limitation of the Sobol indices method is that it cannot sample categorical uncertainties. The model parameter *One way possible* is a categorical uncertainty and thus cannot be used in this analysis. Lastly, the run time of Sobol indices is very high. Because the mode has many independent variables, this run time is too high for the scope of this project. Therefore, Extra-Tree Random Forest (ETRF) will be used to find the sensitivity of the variance of the outcomes. This method will be explained below.

Table 7.1: Overview of characteristics of different sensitivity analysis methods based on personal communication from J. Kwakkel on May 9th, 2022

	Linear regression	Sobol indices	(Extra-Trees) Random forests
Works with non-linear models?	No	Yes	Yes
Number of runs needed for k uncertainties	>50k	>1000(k+2)	>100k
Output for variable importance	β^2 coefficients	S1 index (effect of variable on its own) and ST index (effect of variable + interaction)	Variable importance (approximates relative values of Sobol ST)
Sampling type	LHS, MC	Sobol sequence	LHS, MC

Extra Trees Random Forest
Classification and Regression Trees (CART) are a greedy-based machine learning algorithm that can create decision trees representing a data set. In this method, the uncertainty space is split on certain conditions. The split conditions in this method are based on a specific uncertainty value and can be seen as a vertex in a tree to split the data set. Parts of the resulting output space that satisfy these conditions can then be seen as the leaves in the tree. A decision tree is setup up in a way that each leaf consists of only a certain specified data characteristic, which is called a pure leaf. This can be used to classify data points in a data set. To find the optimal decision rules to split the data set at each vertex to find pure leaves, each uncertainty is traversed to check which values produce the most information gain based on the resulting output split.

Decision trees can also be used for regression. In this case, decision trees are built up using variance reduction of the model outputs as the decider for the purity of a leaf. This method of splitting the data set based on the variance reduction is executed until the desired depth is reached.

The decision trees are highly sensitive to the used training data. This can create a high variance. To reduce this sensitivity, a forest could be created, a set of trees based on a bootstrapped set of samples. For each tree in the forest, only a random subset of the uncertainties is used to create the decision trees. The results of the trees in a forest are aggregated using majority votes. To reduce the reliance on the bootstrapped samples in Random Forest, the whole input data can be used. This method is called Extra Trees. Next to this, the Extra Trees method randomly chooses the decision split in data while Random Forest chooses the optimal split. These two features of Extra Trees can reduce the bias and variance in the resulting trees. Because of this, Extra Trees typically reduce the risk of type II error.

To find the sensitivity of uncertainties using the Extra Trees Random Forest method, feature importance can be used. This method uses the mean and standard deviation of the accumulation of the variance reduction that uncertainty causes for a specific output for all created trees. Extra Tree Random forest can be used for continuous, categorical, or switch-based uncertainties. This process is visualised in Figure 7.2. Although the outcome values of this method do not show actual feature impact but feature importance. However, the outcome values are seen as similar magnitude as the ST values found in the Sobol method and are used accordingly.

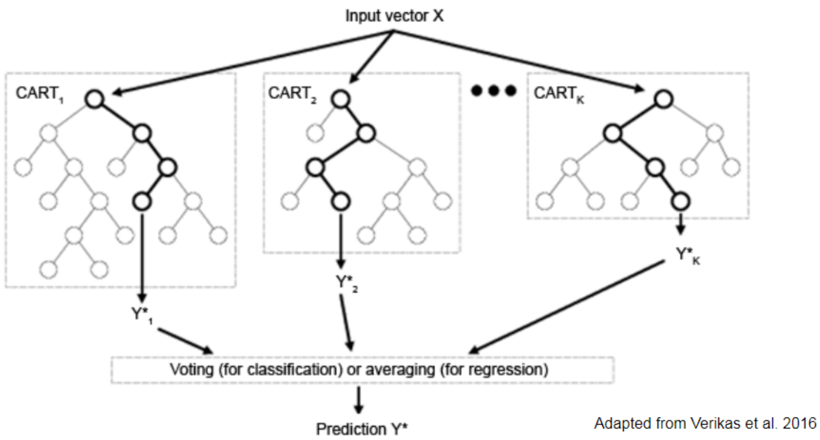


Figure 7.2: Overview of random forest method

Correlation calculations
One method to additionally be used in sensitivity analysis is to calculate the correlation between the input and output values of a model. This correlation can be calculated using different methods. These methods have different limitations regarding the accuracy of results. In the sensitivity analysis of this study, the normality of the distributions of the model output was tested using the Shapiro-Wilk Tests. When evaluating the p-values of these tests, it was found that there is no normality in the distributions of any of the model outputs. Because of this, it was chosen to use the Kendall correlation method (Kendall, 1938) to calculate the correlations in the sensitivity analysis.

When using correlations in sensitivity analysis, two limitations should be highlighted. From a correlation value between two variables, two pieces of information can be taken: the direction (+ or -) and the magnitude. The interpretation of the magnitude of a correlation is highly dependent on the context, and categorising a magnitude as high or low can be ambiguous. This correlation magnitude can also only show linear relations and does not show possible clustering of values. Because of these limitations, only the direction of the correlations will be used to add information about the direction of an influence while relying on the importance values of the ETRF analysis for the magnitude of the influence on a model input to a model output.

7.1.3. Scenario analysis: Patient Rule Induction Algorithm (PRIM)

Scenario analysis is a method to find scenario sets for values of output. To do this, subspace partitioning can be used. This method creates an (orthogonal) subspace for the model uncertainty space, for which a high concentration of cases of interest is found. Subspace partitioning can be implemented using regression and classification-based methods. An example of the classification-based method is the CART method, as described in Section 7.1.2. Because of the limited visualised results from the

CART method, a more visual method called the Patient Rule Induction Algorithm (PRIM) will be used.

The PRIM algorithm is a lenient hill-climbing optimisation algorithm in which each optimisation step is stored and creates a peeling trajectory. It identifies regions of uncertainty values that are highly predictive of the outcomes of a model. It can only be used for binary classification and struggles when uncertainty factors are of mixed data types (Kwakkel & Jaxa-Rozen, 2016). To compensate for this, a more lenient objective function can be used, increasing the mean offset by the loss of the number of data points inside a box. Especially when categorical data types are used, this can strongly increase the quality of the results. The PRIM method is similar to the CART method, creating boxes with uncertainty limitations with a certain concentration of target outcomes. The difference is that it works in a recursive way to slice data from the original uncertainty ranges. The best possible slice is determined through an objective function which results in the next box. PRIM is a method to visualise the boxes based on the decided target outcomes where the concentration and coverage of these target outcomes can be limited to find a suitable box.

7.2. Scenario input and output definition

To form a scenario, the different input values must be defined. A scenario is based on a set of origin and destination locations P. For each point in this set, the most likely routes to all the other points in P are extracted from the cost calculation based on the given behavioural strategy of the fugitive. These routes are used to calculate the route choice metrics described in Chapter 6.
The input values that need to be defined depend on whether there is a strategy switch. When there is no strategy switch, the input values are defined in Table 7.2. If there is a strategy switch, the input values are defined as in Table 7.3.

Table 7.2: Definition of scenario input for a scenario without strategy switch

Scenario input	Description
Strategy S	A multiplication factor MF_i for each behavioural factor
Traffic avoidance value set TA	A value TA_i for each road category
One way possible	A boolean value indicating whether one-way roads can be traversed in both directions.
Origin and destination set P	A set of locations in the network
Number of routes n	The number of routes that are extracted from the list of routes with the lowest cost

Table 7.3: Definition of scenario input for a scenario with strategy switch

Scenario input	Description
Start Strategy S_{start}	A multiplication factor MF_i for each behavioural factor
Start Strategy S_{end}	A multiplication factor MF_i for each behavioural factor
Traffic avoidance value set TA	A value TA_i for each road category
One way possible	A boolean value indicating whether one-way roads can be traversed in both directions.
Strategy switch time t	The time step for which the strategy switches from S_{start} to S_{end} expressed in the percentage of the total route
Origin and destination set P	A set of locations in the network
Number of routes n	The number of routes that are extracted from the list of routes with the lowest cost

The output of a scenario, as defined in Table 7.4, is a combination of the most likely routes in a route set R based on the input scenario independent variables and the route metrics calculated for these routes. This creates a value for the route metric continuity and connectivity for each route in R. The list of vertex frequencies is based on each intersection in the route set R.

Table 7.4: Definition of output values for a scenario

Scenario output	Description
Route set R	The n routes with the lowest costs between locations i and j in origin and the destination set P
Continuity of routes	A list of the continuity of all routes in R
Connectivity of routes	A list of connectivity of all routes in R, where the connectivity is based on the routes from the same origin location, as seen in Figure 6.2
Vertex frequency of intersections	A list of vertex frequency of intersections in routes in R

7.3. Sampling

Different sampling techniques are used for the input values for a scenario, as defined in Section 7.2. In this section, the general sampling for continuous numerical input variables is described, and the sampling of the origin-destination location set is explained.

7.3.1. Latin Hypercube Sampling

Different sampling techniques can be used for the continuous numerical input variables in the scenarios. The analysis methods described in Section 7.1 commonly use either monte carlo or Latin hypercube sampling. Monte carlo randomly selects N independent values within a range. Latin hypercube sampling initially divides the sampling space into N intervals and selects one sample from each interval. This results in an evenly spread distribution, while monte carlo sampling can contain clustering. Because of this, Latin hypercube sampling contains a smaller sampling error. Therefore, Latin hypercube sampling will be used.

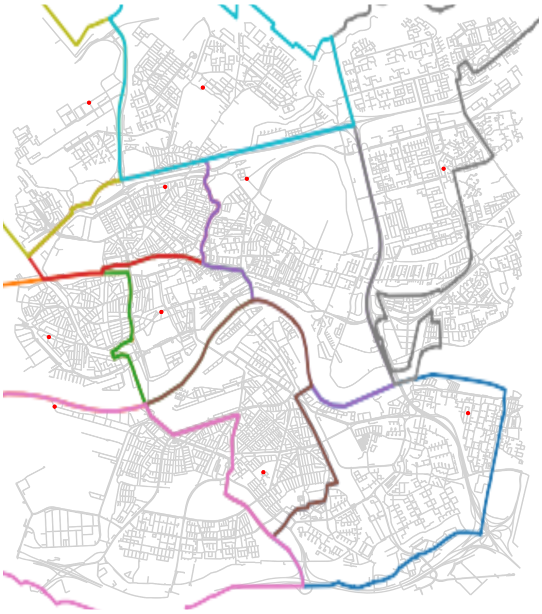
7.3.2. Origin-destination locations sampling

Random sampling is used to sample the origin and destination location set P. To sample random points in a map, different methods could be used. The following were identified:

- **Coordinate-based sampling**. In this method, a randomised choice is made based on the latitude and longitude coordinates grid. This sampling will then be mapped to the vertices in the network. A limitation that this method could cause is that if the vertex density of a part of the network is low, all the sampled points will be mapped to a small set of vertices. This will reduce the diversity in vertex selection.
- **Vertex-based sampling**. This method makes a randomised choice based directly on the vertices in the Networkx graph. A limitation of this method is that if a part of the network is vertex dense because of many intersections, it can be over-represented in the resulting set of locations.
- **Network characteristic based**. This method divides the network based on specific characteristics, such as population density or maximum travel time. This has the limitation that parts of the city that might be unlikely to be part of a route are included in the network.

Based on the limitations of these methods, it was chosen to use a network characteristics-based location sampling because this ensures the inclusion of the whole network while limiting over-representing any dense area. One way that the network of Rotterdam can be divided into parts is based on the divisions made by local authorities. For Rotterdam, this division is made through sub-areas and neighbourhoods. Rotterdam encompasses 14 sub-areas and 71 neighbourhoods of different sizes (Wonen in Rotterdam, n.d.). The number of origin and destination points will be used in full factorial against each other and can thus create a high number of combinations. It is chosen to start with a small initial set to prevent a rapidly increasing number of points. Therefore, the sub-area division within the bounding box of the network will be used. This results in 10 sub-areas. The resulting subareas can be seen in Figure 7.3. Within these sub-areas, the random choice of location is based on a coordinate-based random choice mapped to the vertices in the network. These areas are often divided by the large highway network in a city. This can support the choice of using the sub-areas for a car road network-based model.

(a) Sub-areas in Rotterdam, adapted from (Wonen in Rotterdam, n.d.)



(b) Neighbourhoods mapped over road network with example random points (red)

Figure 7.3: Visualisation of sub-areas Rotterdam network

7.4. Case study

Initially, a case study will be executed. This is done to provide a more controlled overview of the possible outcomes based on a small set of origin and destination locations. In this set, only one origin location is used to create routes to 3 destination locations to form the output route set R. The route set R will be visualised in a network map. The remaining scenario outputs, defined in Table 7.4, will be displayed in several ways. The continuity and vertex frequency will be averaged over the total route set and the intersections of these routes. The connectivity is averaged separately for each origin-destination location pair. The behavioural factors used in the experiment are tested separately, while the other factors MF_i are equal to 1. This shows the difference in routes caused by a specific behavioural factor in different location combinations. The behavioural factors included in this case study are high-speed preference, obstacle avoidance, residential preference and traffic avoidance. More details on the location set used can be found in Chapter 8.

7.5. Experiments with aggregation over origin destination locations

The remaining experiments will use an aggregation of output values over a set of origin and destination locations, sampled using the method described in Section 7.3.2. The most likely route set R will be created by running the model on the full factorial of this location set to create the origin and destination points between which the routes with lowest costs are calculated. The outputs that will be further analysed are the continuity, connectivity and vertex frequency. These will be averaged over the full set of routes R. The continuity and connectivity are averaged over all routes in the total route set R, and the vertex frequency is averaged over all the intersections in these routes.

7.5.1. Experiment 1: traffic avoidance factors TA_i

The first experiment is to measure the influence of the traffic avoidance factors TAi. For this experiment, the ranges for the factors can be found in Table 7.5. All of the factors have been given equal ranges to be able to compare their influence. All MF_i are defined as equal to 1, the number of paths equals 5, and the experiment is run for 5 different origin and destination sets. There is no strategy switch. There are 3 uncertainties in this experiment, which are randomly sampled for 300 different values per origin and destination set.

Table 7.5: Values for experimental design run 1

Scenario input	Values
MF_i	1
TA_1	[1, 10]
TA_2	[1, 10]
TA_3	[1, 10]
$One\_way\_possible$	False
Origin and destination set P	5 different location sets using the sampling method described in Section 7.3.2
Number of routes n	5

7.5.2. Experiment 2 and 3: Behavioural multiplication factors MF_i

For the behavioural multiplication factors MF_i, two runs are defined based on the outcomes of the uncertainty analysis. Firstly, in experiment 2, the full ranges of the multiplication factors are explored. The ranges are based on the maximum value where a change in routes is seen, as found in the uncertainty analysis in Appendix F. In this run, the one-way possible factor is included. Secondly, in experiment 3, all factors with similar influence in the model (avoidance or preference) are given an equal range. In this run, one way possible is not included because it has a different effect in the model and excluding it increases comparability between the behavioural factors because there are no categorical input values in the model. In both experiments, it is assumed that the strategy is constant throughout the run with 5 paths between an origin and destination point. Experiment 2 is run on 3 origin and destination sets, and experiment 4 is run on 5 origin and destination sets. This was done because of the increased run time length caused by the one-way possible factor. For the values of the traffic avoidance factors per category TA_i, it was chosen to include constant values where there are higher values for higher assumed traffic based on the traffic categories. There are 8 uncertainties in experiment 3 and 7 uncertainties in experiment 4, respectively randomly sampled for 800 and 700 different values per origin and destination set.

7.5.3. Experiment 4 and 5: strategy change and number of paths

For the experiments to test the influence of strategy changes and the number of paths, two strategy profiles are defined. This is divided into a risky and a cautious profile. For the risky profile, high-speed preference, lane preference and traffic avoidance are set to the maximum value. For the cautious profile, obstacle avoidance, one-way avoidance and residential preference were set to a maximum value. These profiles attempt to create the maximum difference between the two route choice behaviour and represent the switches in stressed responses as found during the conceptualisation phase, as can be read in Chapter 4. These profiles are not based on the scenario analysis because there were no conclusive results for experiments 2 and 3. The values for the behavioural factors for the profiles can be found in Table 7.7.

Table 7.6: Values for experimental design run 2 and 3

Variable	Values experiment 2	Values experiment 3
$MF_{camera\_avoidance}$	[1, 5.0]	[1, 5.0]
$MF_{obstacle\_avoidance}$	[1, 200.0]	[1, 5.0]
$MF_{one\_way\_avoidance}$	[1, 600]	[1, 5]
$MF_{traffic\_avoidance}$	[1, 5]	[1, 5]
$MF_{lane\_preference}$	[0.1, 1]	[0.1, 1]
$MF_{residential\_preference}$	[0.1, 1]	[0.1, 1]
$MF_{high\_speed\_preference}$	[0.1, 1]	[0.1, 1]
TA_1	2.0	2.0
TA_2	1.7	1.7
TA_3	1.3	1.3
$One\_way\_possible$	{True, False}	False
Origin and destination set P	3 different location sets using the sampling method described in Section 7.3.2	3 different location sets using the sampling method described in Section 7.3.2
Number of routes n	5	5

Table 7.7: Values for behaviour strategies used in experiment 4 and 5

Variable	Risky strategy	Cautious strategy
$MF_{camera\_avoidance}$	1	1
$MF_{obstacle\_avoidance}$	1	5
$MF_{one\_way\_avoidance}$	1	5
$MF_{traffic\_avoidance}$	5	1
$MF_{lane\_preference}$	5	1
$MF_{residential\_preference}$	1	0.1
$MF_{high\_speed\_preference}$	0.1	1

Using these profiles, two experiments are defined. In these experiments, the start and end strategy are either of the strategy profiles. In experiment 4, the strategy is switched from cautious to risky, and in experiment 5, the strategy is switched from risky to cautious. For these runs, values for the number of paths and the strategy switch time t given as a percentage of the total number of decision steps are variated. The experiments are run for 5 origin and destination sets. There are 2 uncertainties in both experiments, which are randomly sampled for 200 different values per origin and destination set.

Table 7.8: Values for experimental design run 4 and 5

Scenario input	Experiment 4	Experiment 5
Start strategy	cautious	risky
End strategy	risky	cautious
TA_1	2.0	2.0
TA_2	1.7	1.7
TA_3	1.3	1.3
$One\_way\_possible$	False	False
Strategy switch time t	[0.01, 0.99]	[0.01, 0.99]
Origin and destination set P	3 different location sets using the sampling method described in Section 7.3.2	3 different location sets using the sampling method described in Section 7.3.2
Number of routes n	[1, 25]	[1, 25]

7.6. Tools

The method used to perform the analysis methods described is the Exploratory Modeling and Analysis research methodology (Bankes, 1993), which is implemented in the EMA workbench (Kwakkel, 2017). This workbench includes the necessary analytical tools to perform the previously described methods and can be used for different sampling methods. Because of the high number of model iterations in the different experiments, the computational sources of the DelftBlue supercomputer of the TUDelft are used (Delft High Performance Computing Centre (DHPC), 2022).

8
Case study

In this chapter, the results from a case study are shown. This case study is used to understand the effect of behavioural factors in a controlled setting with specific start and destination locations. For the case study, one start location at the town hall in Rotterdam is used. For the destination location, three locations are chosen. These are a location towards the highway to the north, towards a highway to the east and to a residential area in the south of Rotterdam. The routes are shown for different strategies for each destination location. In these strategies, individual behavioural factors are tested, and the remaining factors are assumed to equal 1. The number of routes used per location pair is 5. The start and destination locations are visualised in Figure 8.1.

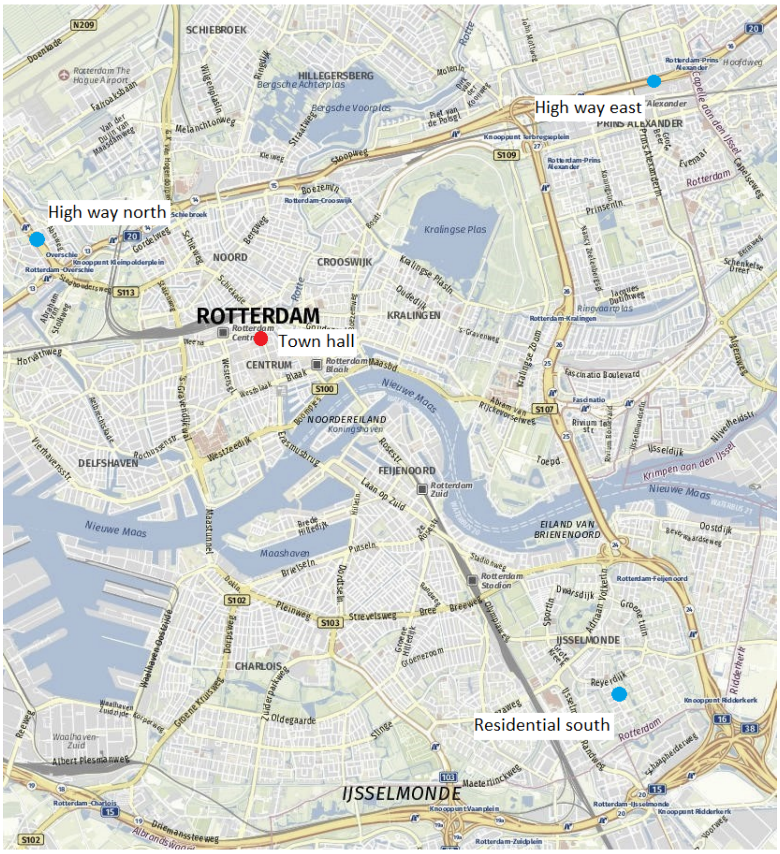


Figure 8.1: Origin destination at town hall (red), destination locations (blue) at highway east, highway north and residential south location

8.1. High speed preference

In Figure 8.4, it can be seen that for lower values of $MF_{high\_speed\_preference}$, the routes change to routes that make more use of the highways. This can be most clearly seen in the route towards the residential south location. For the route to the highway in the east, there is no difference, and for the route to the highway in the north, the difference is small. These differences per destination location are visible in the continuity values as seen in Figure 8.2. This shows that the correlation between $MF_{high\_speed\_preference}$ and the continuity mean differs strongly depending on the destination location in both strength and direction. For the routes combined, the connectivity increases as the high-speed preference increases and $MF_{high\_speed\_preference}$ decreases as seen in Figure 8.3. This increase in connectivity can be seen through the increasing overlap in routes to the highway east and residential south locations as $MF_{high\_speed\_preference}$ decreases. Lastly, the node frequency mean might be expected to increase because of an increase in overlap. The node frequency, however, decreases as seen in Figure 8.3. This could be explained by the way that node frequency is calculated. In this calculation, the mean node frequency of a route is calculated by dividing over the route length (equal to the continuity). As seen in Figure 8.2, the continuity increases more strongly for the residential south location than it decreases for the highway north location. This would mean that, in general, the continuity and, thus, route length increases. Therefore, despite a higher overlap in routes, the continuity increase would cause the node frequency to decrease.

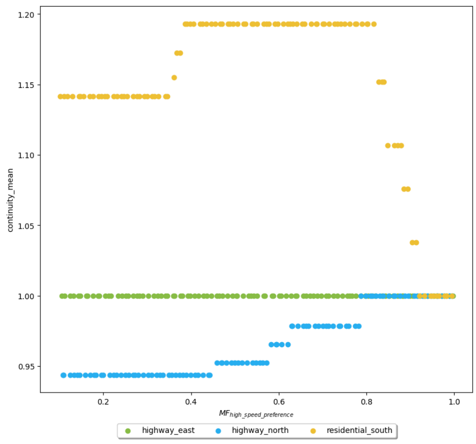
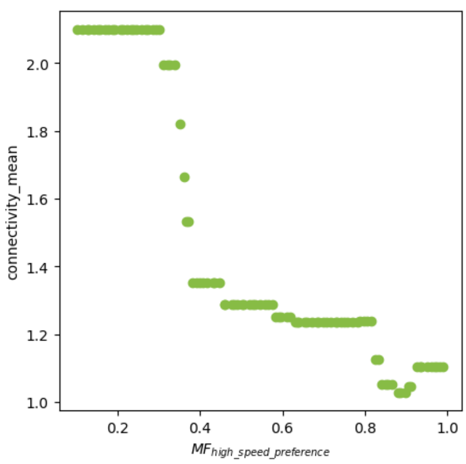
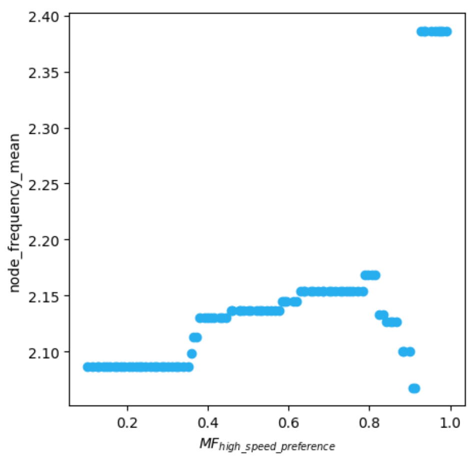


Figure 8.2: continuity mean

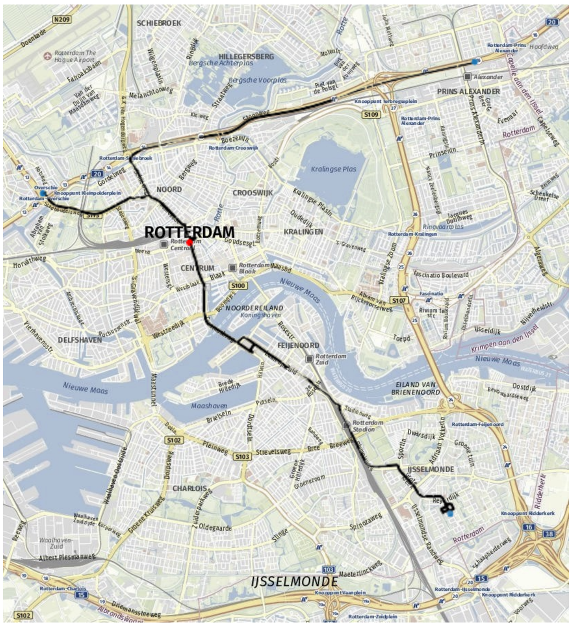


(a) Connectivity

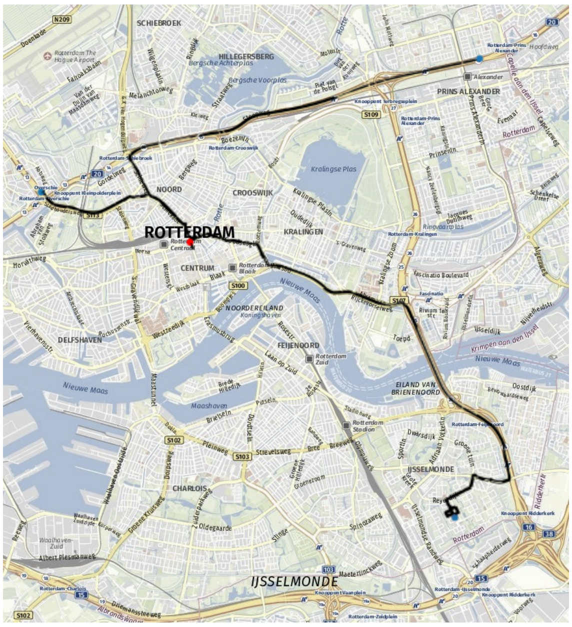


(b) Node frequency

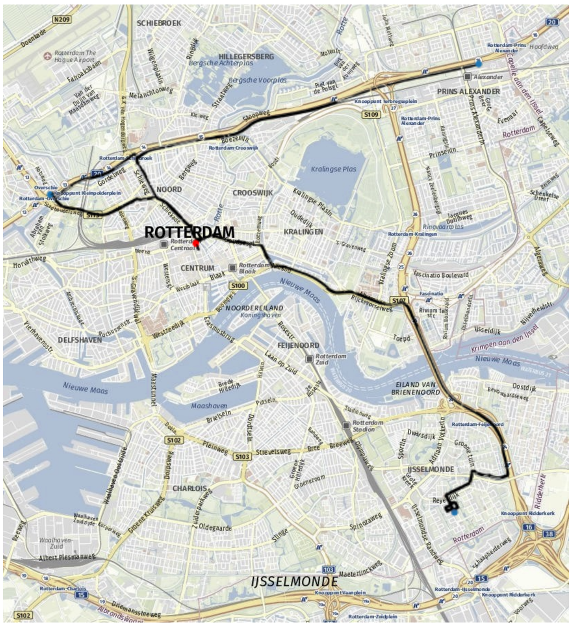
Figure 8.3: Scatter plots of model outcomes for case study high-speed preference



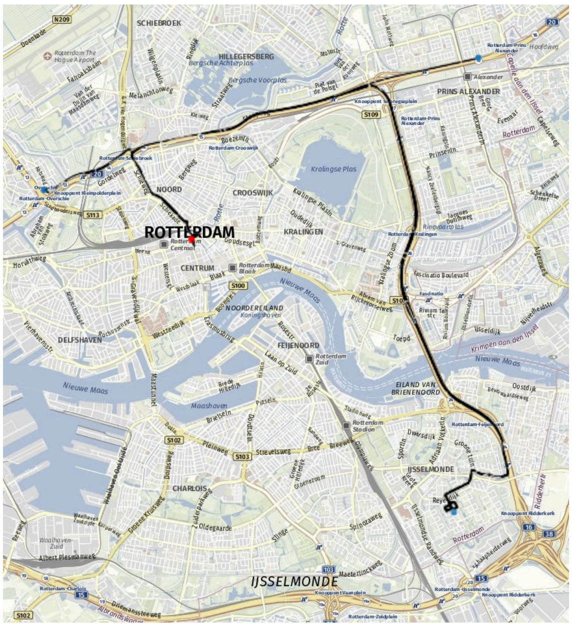
(a) Base case, $MF_{high\_speed\_preference} = 1.0$



(b) $MF_{high\_speed\_preference} = 0.8$



(c) $MF_{high\_speed\_preference} = 0.6$



(d) $MF_{high\_speed\_preference} = 0.1$

Figure 8.4: Route visualisation high-speed preference

8.2. Obstacle avoidance

In Figure 8.7, the routes for different levels of $MF_{obstacle\_avoidance}$ can be seen. The difference in routes is caused by different road characteristics, which can make the preference of roads complex. For the routes to the residential south location, there is always a bridge or tunnel that needs to be crossed. When looking at the bridges and tunnels with other obstacles, such as traffic lights and roundabouts, as seen in Appendix D, the Brienenoord bridge is the bridge with the least obstacles. This is the bridge located in the east of the network. It can also be seen in the routes that this is the most preferred bridge. Another way that obstacle avoidance can be seen is that highways often are connected to large crossings and bridges and are thus avoided.

For all the destination locations, the continuity increases when the $MF_{obstacle\_avoidance}$ increases. The strength of this increase differs strongly per destination location. There is no clear correlation over the whole range of input values for the connectivity and node frequency means.

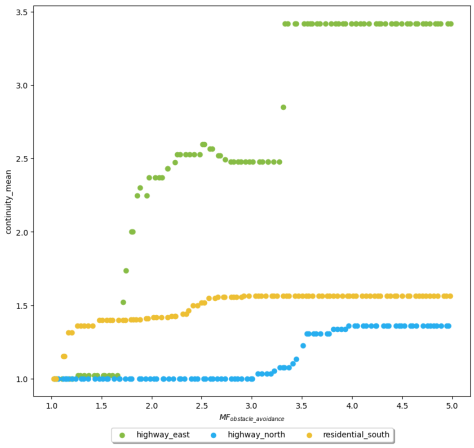
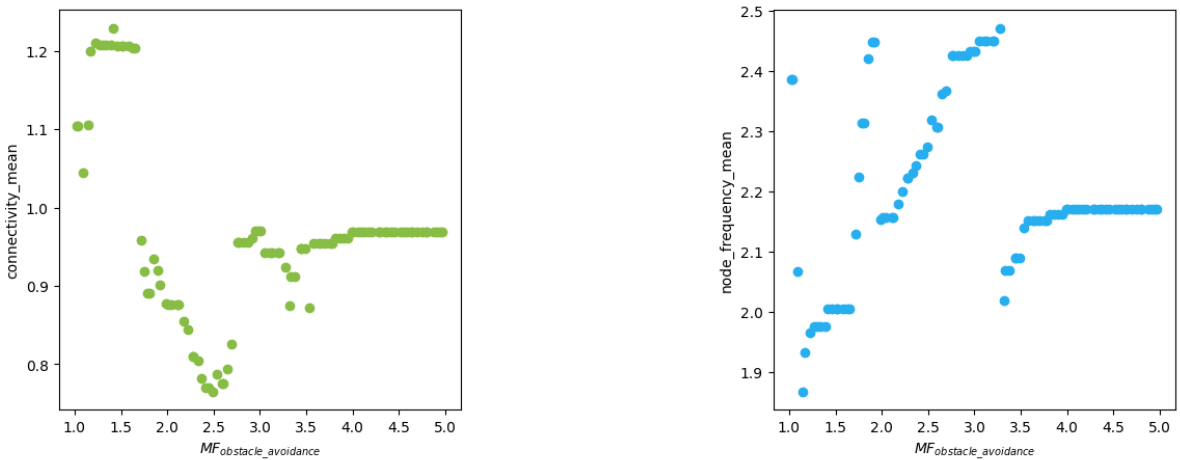


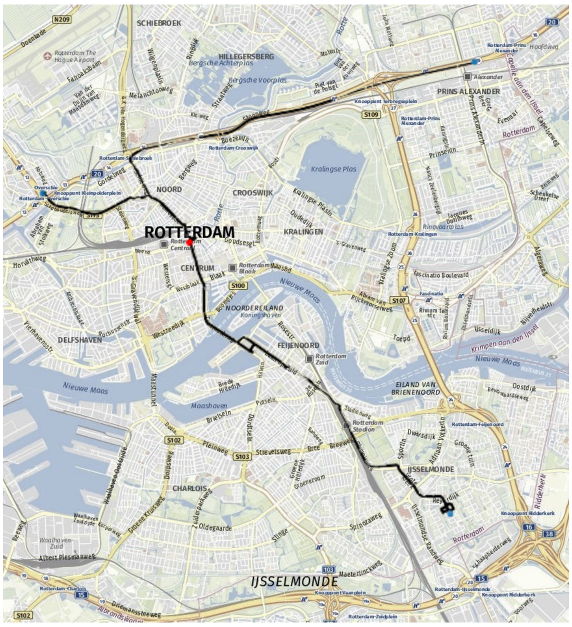
Figure 8.5: Continuity mean



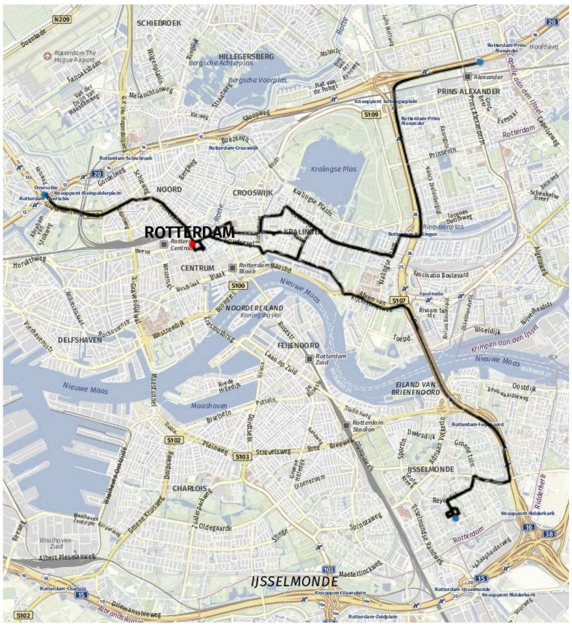
(a) Connectivity

(b) Node frequency

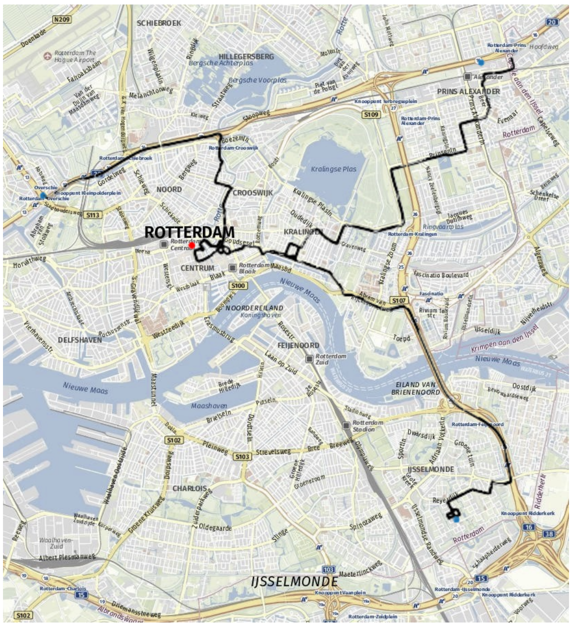
Figure 8.6: Scatter plots of model outcomes for case study obstacle avoidance



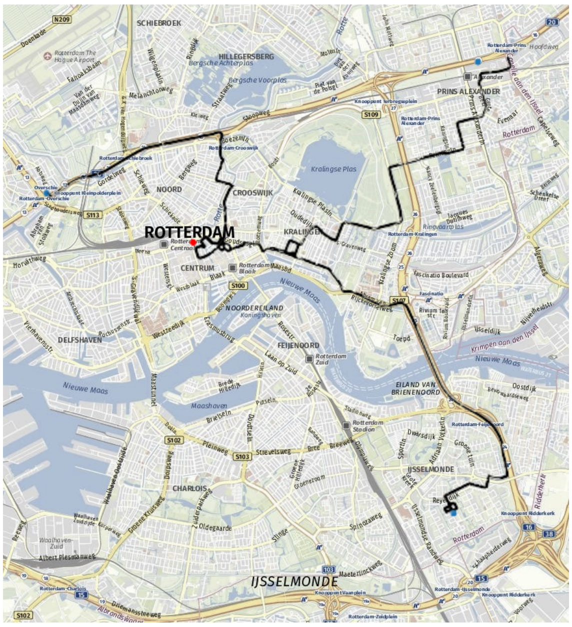
(a) Base case, $MF_{obstacle\_avoidance} = 1.0$



(b) $MF_{obstacle\_avoidance} = 2$



(c) $MF_{obstacle\_avoidance} = 4$



(d) $MF_{obstacle\_avoidance} = 5$

Figure 8.7: Route visualisation obstacle avoidance

8.3. Residential preference

As seen in Figure 8.10, when residential preference increases and the value of $MF_{residential\_preference}$ decreases, the likely routes go through more of the residential roads. Here it can be seen that the routes towards the highway east location change strongly while the routes towards the highway north and residential south locations change less strongly. The routes only change for lower $MF_{residential\_preference}$ values. This can also be seen in the value of the route metrics in Figure 8.8 and Figure 8.9. The continuity mean increases for all destination locations, but there is a difference in the strength of this correlation. The connectivity of the routes decreases for lower values of $MF_{residential\_preference}$ as can also be seen from the routes as the overlap in the routes decreases. For the node frequency, no correlation is found.

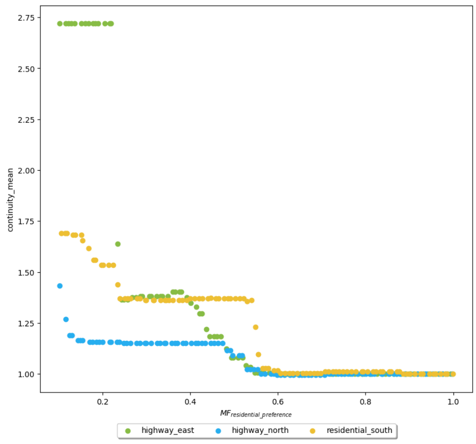
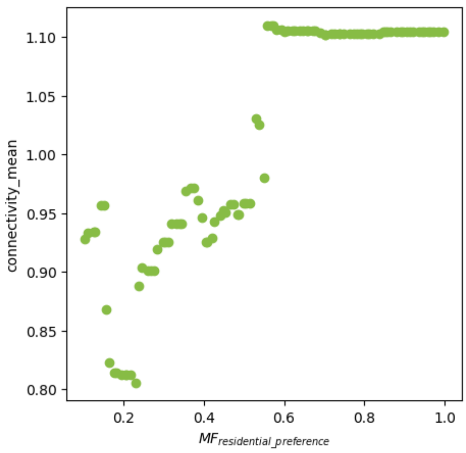
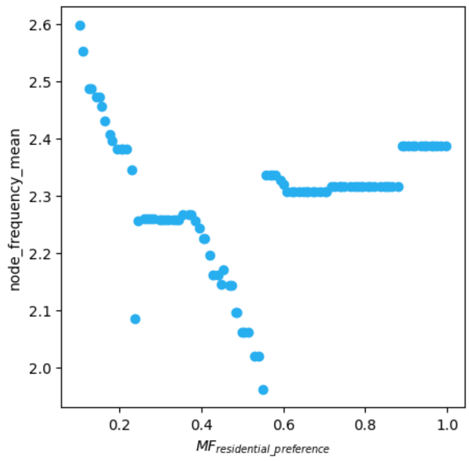


Figure 8.8: continuity mean

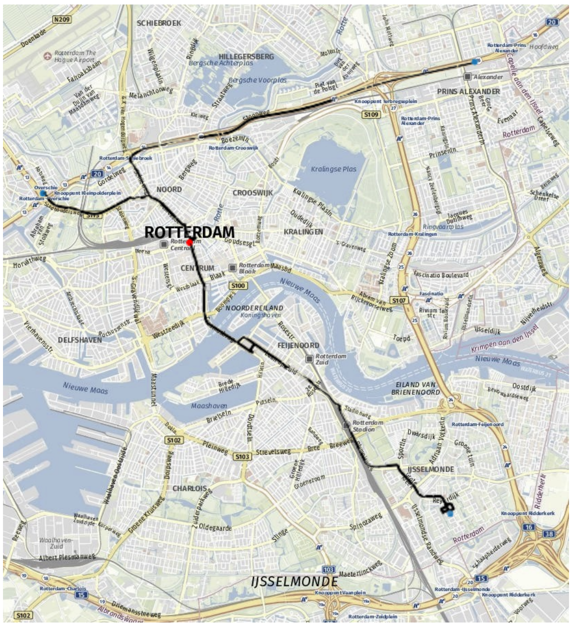


(a) Connectivity

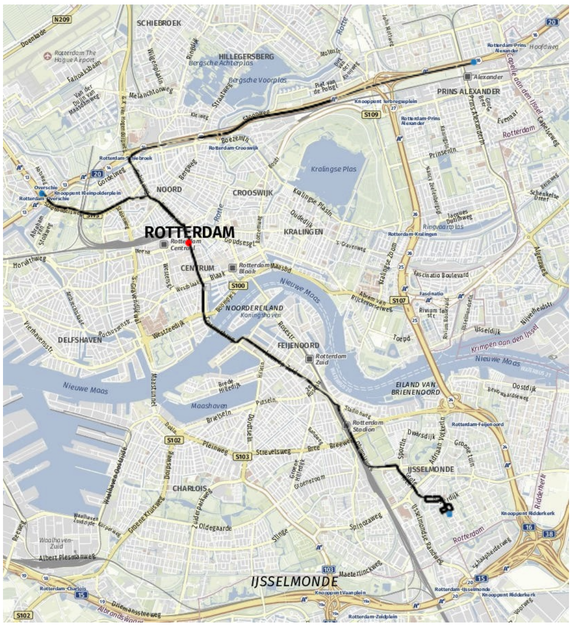


(b) Node frequency

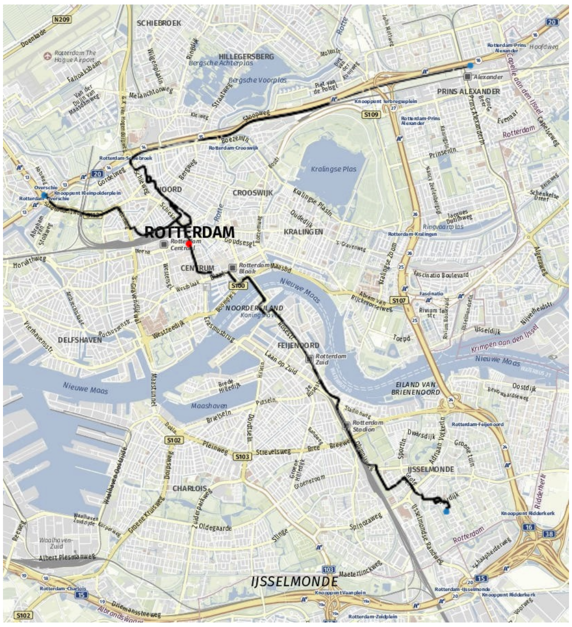
Figure 8.9: Scatter plots of model outcomes for case study residential preference



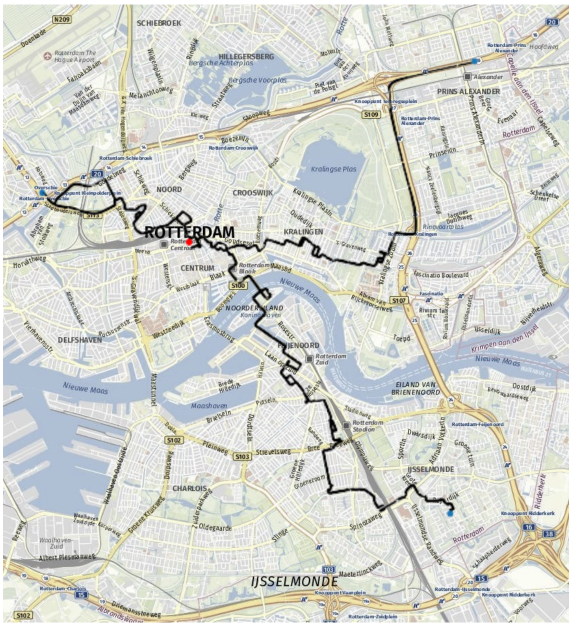
(a) Base case, $MF_{residential\_preference} = 1.0$



(b) $MF_{residential\_preference} = 0.6$



(c) $MF_{residential\_preference} = 0.3$



(d) $MF_{residential\_preference} = 0.1$

Figure 8.10: Route visualisation residential preference

8.4. Traffic avoidance

In Figure 8.13, the routes can be seen for different values of $MF_{traffic\_avoidance}$, where for higher values, highways and other main roads are avoided. This causes the routes to go through more residential neighbourhoods. For the routes to all the destination locations, there is a difference in the routes. From the continuity values as seen in Figure 8.11, it can be seen that the routes to highway east differ the most regarding route length. The connectivity values decrease for higher levels of $MF_{traffic\_avoidance}$ can be seen through the lower overlap of the routes. For the node frequency mean, increases are seen in specific $MF_{traffic\_avoidance}$ ranges, but there is no clear correlation on the full range.

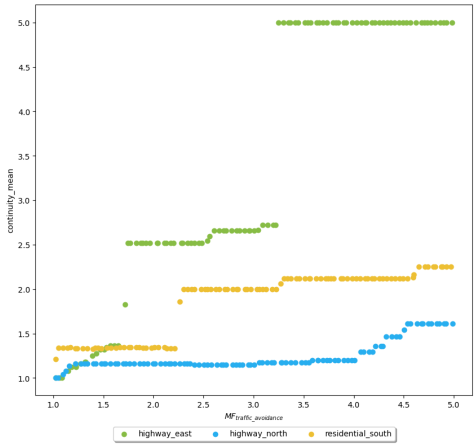
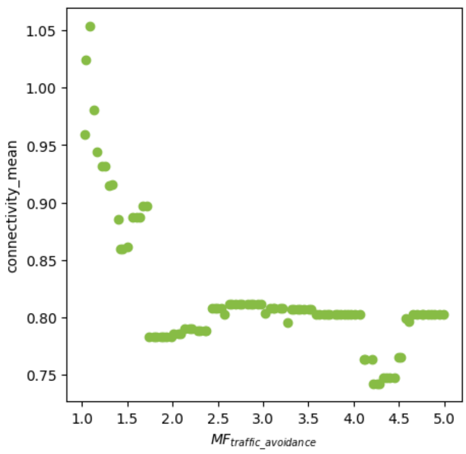
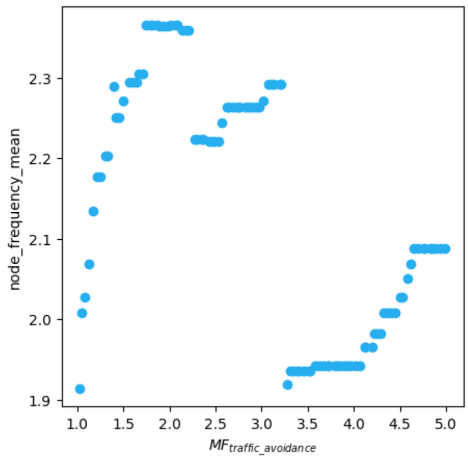


Figure 8.11: Continuity mean

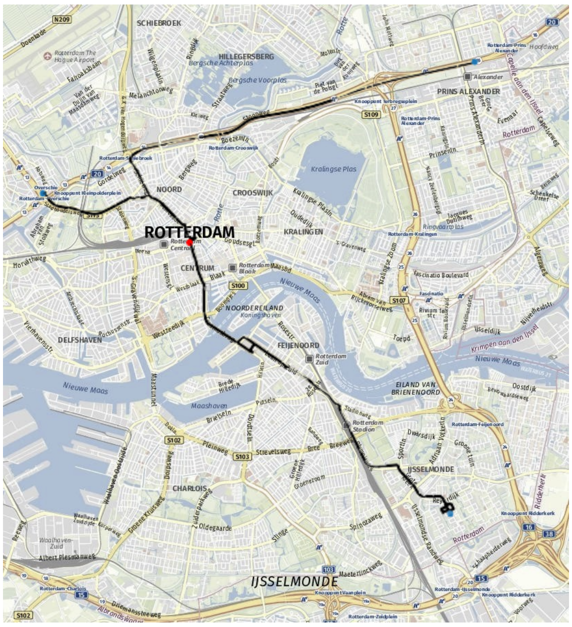


(a) Connectivity

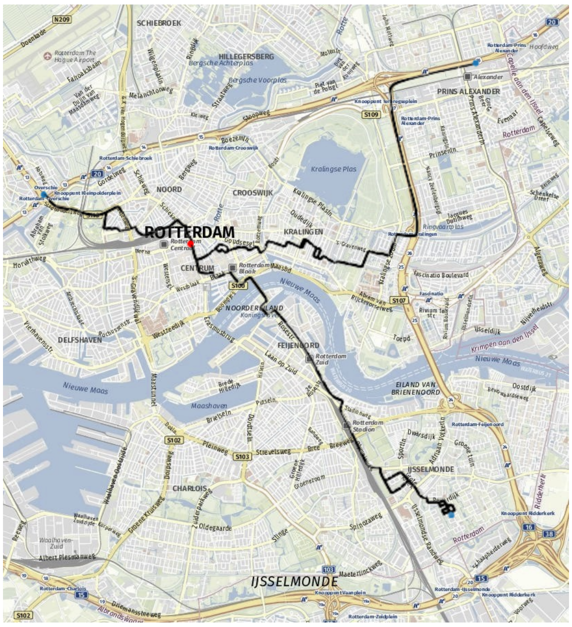


(b) Node frequency

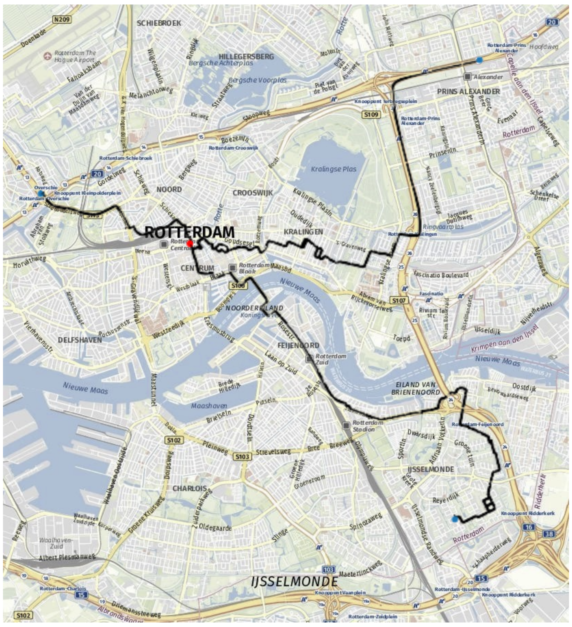
Figure 8.12: Scatter plots of model outcomes for case study traffic avoidance



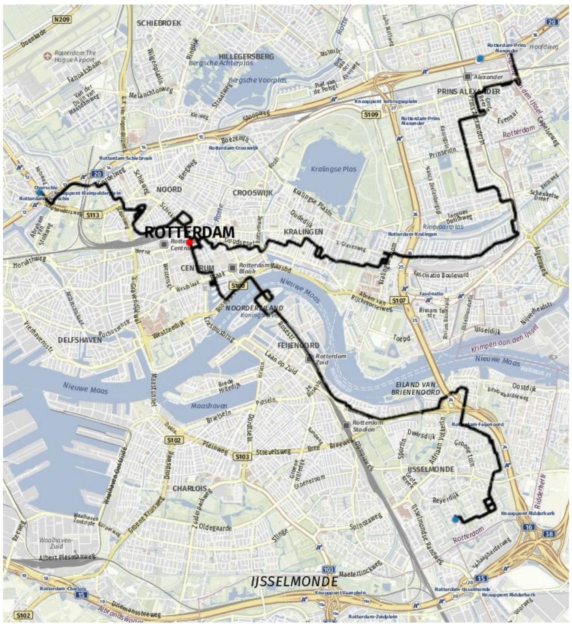
(a) Base case, $MF_{traffic\_avoidance} = 1.0$



(b) $MF_{traffic\_avoidance} = 2$



(c) $MF_{traffic\_avoidance} = 3$



(d) $MF_{traffic\_avoidance} = 5$

Figure 8.13: Route visualisation traffic avoidance

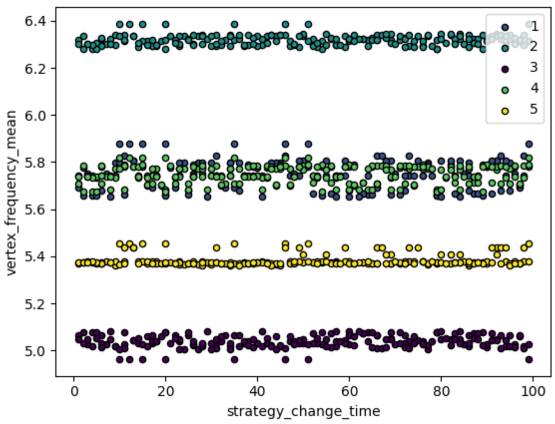
9 Results

In this chapter, the results from the experiments with aggregation over the origin and destination (OD) location set are shown. Initially, the resulting dependence of the model output on the OD location sets is explained in Section 9.1. Because of this, a choice must be made on how to format the remaining results to show whether there are consistent relations between the independent and dependent variables regardless of chosen OD location set. This is further explained in Section 9.2. Using this result formatting, the remaining results found from the experiments are shown. Firstly, in Section 9.6.3, the correlation between the model outputs is discussed. Then the results of the performed scenario analysis are explained in Section 9.3. Lastly, in the remaining sections, the results of the sensitivity analysis are shown for each of the experiments.

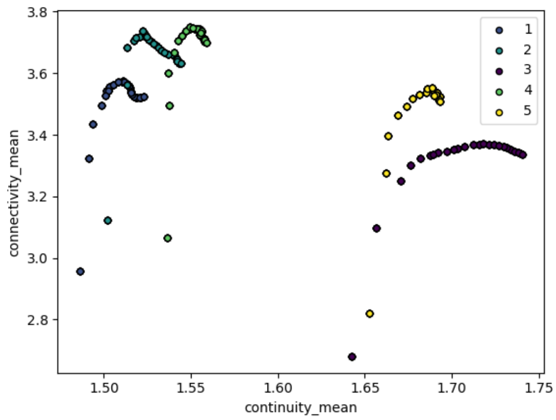
9.1. Dependence on the origin and destination location set

In all the experiments, a strong influence was found of the sampled OD location sets on the model's outcomes. This high impact of the OD location sets on the model output can be seen in the ETRF importance values assigned to the model inputs throughout the different experiments, as seen in Figure 9.2. For every experiment, it is seen that the OD location set has high importance values. Because of this, we conclude that the outcomes of the model are dependent on the OD location set.

When looking at specific distributions of outcomes, clustering based on the OD location set is found. To illustrate this, we can look at the examples from experiment 4 in Figure 9.1. This figure shows two examples of clustering of model output values dependent on the OD location set. Figure 9.1a shows how the vertex frequency mean values are separated based on the OD location set. In Figure 9.1b, clustering is seen when looking at the distributions of the outcomes of continuity and connectivity mean. These clustering patterns are consistent when looking at different pairings of outcomes throughout both experiments 4 and 5. For experiments 1, 2 and 3, this difference in outcome values based on the OD location set is also found, although less apparent when looking at the distributions directly. The full overview of the distributions of outcomes of different experiments showing these dependencies can be found in Appendix H.1. These results highlight the clustering of specific outcome ranges based on the OD location set and that the influence of the OD location sets needs to be considered when analysing the influences of the model inputs on the model outputs.

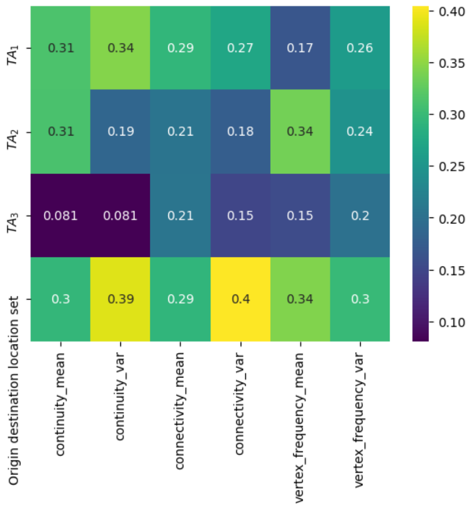


(a) Scatter plot of vertex frequency mean with strategy change time

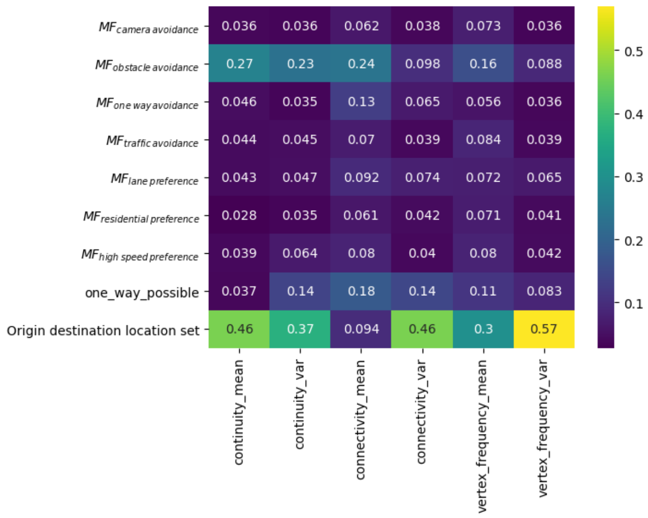


(b) Scatter plot of connectivity mean with continuity mean

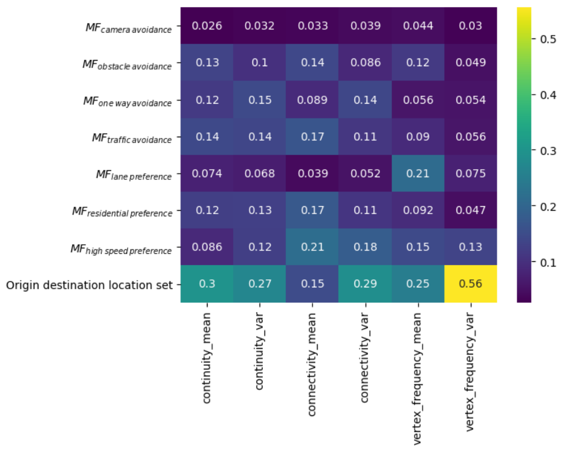
Figure 9.1: Examples of clustering of model output based on OD location set in experiment 4



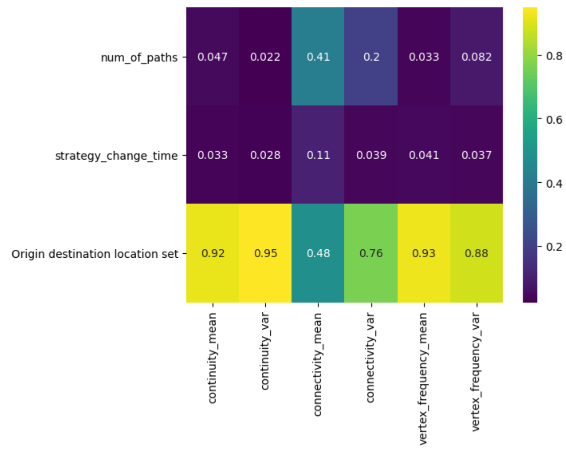
(a) Experiment 1



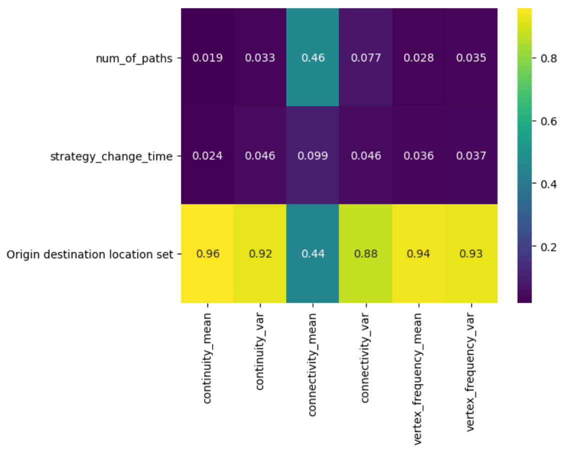
(b) Experiment 2



(c) Experiment 3



(d) Experiment 4



(e) Experiment 5

Figure 9.2: The ETRF importance value of all experiments

9.2. Result formatting based on origin and destination location set

As seen in Section 9.1, there is a strong influence between the OD location set and the model output values. This influence can affect how the relations between model inputs and outputs are represented depending on the aggregation over the OD location sets. Because it is uncertain how this can affect the interpretation of the results, we will look at the differences in data distributions based on two different aggregation levels. It is important to keep in mind that for the purpose of this study, we are looking for consistencies in model input-output relations independent of external factors such as the OD location sets. Therefore, the level of aggregation should thus be considered before further details of the results are displayed.

To illustrate what effect aggregation over OD location set has on the outcomes, we can look at the combined and separated distributions of model output. An example of this is shown in Figure 9.3 where the separate and aggregated continuity variance of the output of experiment 2 are shown. Figure 9.3a, Figure 9.3b and Figure 9.3c show the separate distributions of different OD location sets from which it can be seen that there is a multimodal distribution for each set. When these data sets are combined to create Figure 9.3a, this multi-modularity is no longer visible and a unimodal distribution is found. An analysis of the combined data set could, therefore, not show the multi-modularity of the outcomes of separate OD location sets and could misrepresent the relation between the input and output values of the model.

Next to this, the range of the outcomes differs between the OD location sets. This can be seen in Figure 9.3 where the distribution of OD location set 1 ranges up to 14 while the distribution of OD location set 3 ranges up to 20. When these distribution sets are aggregated, the information on these differences in ranges is lost, and data points in the combined set can mean different things in their original data set.

There is thus information loss on the distribution of the separate OD location sets when the data is aggregated. This might indicate that location cannot be aggregated and that origin-destination pairs must be studied separately. However, because we still want to study whether there is a consistent relation between the input and outputs of the model regardless of the origin and destination locations, the further displayed results will be shown separately per OD location set.

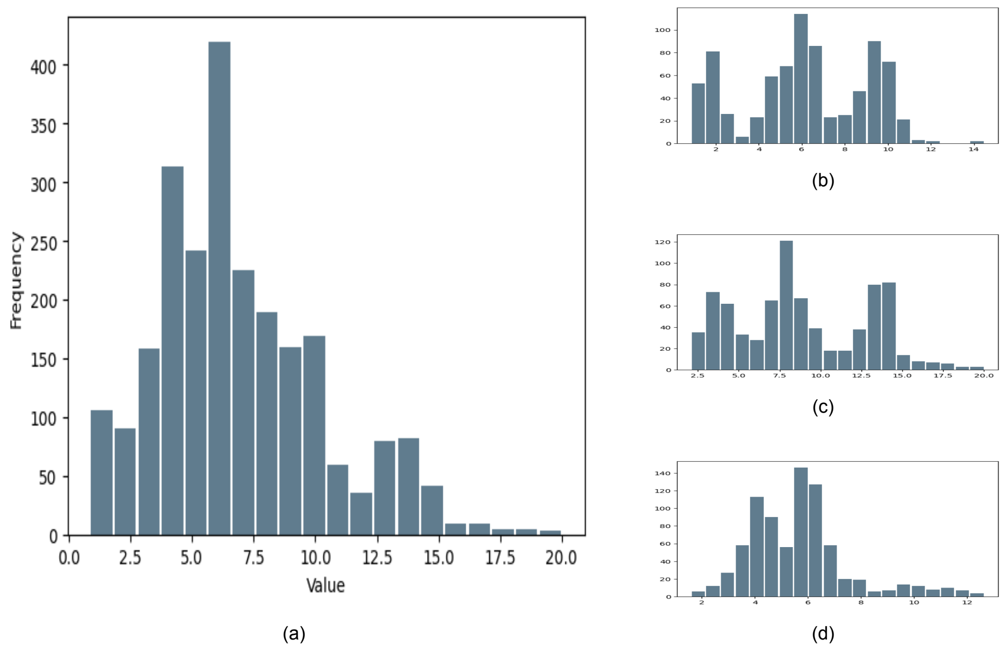


Figure 9.3: Histograms of the values of continuity variance in experiment 3. (a) is the histogram for all OD location sets combined, (b) is the histogram for OD location set 1, (c) is the histogram for OD location set 3 and (c) is the histogram for OD location set 5

9.3. Results scenario analysis

For the scenario analysis of the outcomes of experiment 3, it was found that there are no usable results to base scenarios. There are two reasons for this. Firstly, for target output ranges with high coverage and density PRIM boxes, the included data points are up to 75% of the original data set. This reduced the usefulness of the scenario because the set of model output is not restricted much. Secondly, as previously stated in Section 9.2, when the resulting outcome data sets are aggregated over the OD location sets, the original separate data sets are not well represented. When deciding a threshold value for the combined data set, the value can be represented differently among the different location sets separations. Because of these reasons, the scenario analysis results are not further considered. Further explanation and visualisation of the limitations of the scenario analysis can be found in Appendix H.5.

9.4. Results sensitivity analysis: TA_i

In experiment 1, the influence of the traffic avoidance factors TA_i for different road type categories was determined. From the coefficients of variation in Table 9.1, it can be seen that there is a difference in variance in the route metric depending on the OD location set. Here it can be seen that for the continuity mean, the coefficients of variation range between 11% and 18% while for the connectivity and vertex frequency mean, these coefficients of variation are between 5% and 7%. The influence of traffic avoidance of the road categories on this variation in model's outcomes can be seen from the ETRF importance values in Figure 9.4. These values show that TA_1 and TA_2 are more influential than TA_3. To further understand the influence of the TA_i values on the model outcomes, we will look at the specific ETRF values and the correlation matrices. The full overview of the correlation matrices, including p-values, can be found in Appendix H.2. When further interpreting correlation values, if the p-value of a correlation value is lower than 0.05 and thus not significant, it is marked with a - in the tables. In the next subsections, we will look at the specific importance and correlation found between the TA_i values and the route metrics.

Table 9.1: Mean (μ), standard deviation (σ) and coefficient of variation (COV) of model output of experiment 1

OD Location set		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	μ	1.45	0.3	2.88	1.56	5.54	8.97
	σ	0.16	0.12	0.16	0.31	0.26	0.67
	COV	0.11	0.4	0.06	0.2	0.05	0.08
2	μ	1.44	0.25	2.96	1.31	5.64	8.88
	σ	0.19	0.12	0.2	0.14	0.23	0.47
	COV	0.13	0.5	0.07	0.11	0.04	0.05
3	μ	1.81	0.69	2.79	1.17	5.17	9.28
	σ	0.3	0.38	0.2	0.24	0.3	0.55
	COV	0.17	0.56	0.07	0.14	0.06	0.06
4	μ	1.52	0.34	2.68	1.11	5.45	9.13
	σ	0.22	0.17	0.18	0.23	0.33	0.74
	COV	0.14	0.5	0.07	0.2	0.06	0.08
5	μ	1.74	0.59	2.73	1.16	5.36	9.26
	σ	0.31	0.34	0.2	0.31	0.31	0.7
	COV	0.18	0.57	0.07	0.27	0.06	0.08

9.4.1. Results sensitivity analysis: TA_1

From the ETRF values of TA_1 in Figure 9.4 and the correlation values in Table 9.2, the importance and direction of the influence of TA_1 on the route metrics can be deduced. Firstly, for the mean of the continuity metric, TA_1 has an importance value between 0.23 and 0.53 which shows a high variability of this importance depending on OD location set. According to the correlation values for the continuity mean, there is a positive relation between TA_1 and the continuity mean for all location sets. The same pattern is found for the continuity variance. Secondly, for the mean of the connectivity metric, TA_1 has an importance value between 0.4 and 0.49 which shows a considerable influence on the variability. According to the correlation, this influence is consistent over the location sets and is positive. Thus, a higher avoidance of edges with road type in road category 1 correlates with higher connectivity of routes. This consistency is also seen for the variability of the route connectivity. Lastly, for the vertex frequency mean, there are importance values found between 0.18 and 0.36. When looking at the correlation directions and significance, it is seen that there is no consistency on how this influence of the importance is found in the data. It can thus be assumed that there is non-consistent relation between TA_1 and the vertex frequency in routes. Overall, there was a positive consistent relation found between TA_1 and the route connectivity and a less consistent but positive relation between TA_1 and route continuity.

Table 9.2: Correlation between TA_1 and model output of experiment 1

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	0.539	0.653	0.368	0.300	0.061	-0.072
2	0.247	0.213	0.399	0.258	-	0.106
3	0.477	0.564	0.345	0.317	-0.326	0.261
4	0.522	0.667	0.324	0.381	-	-0.422
5	0.539	0.653	0.368	0.300	-	-

9.4.2. Results sensitivity analysis: TA_2

From the ETRF values for TA_2 in Figure 9.4 and the correlations in Table 9.3, the influence of TA_2 on the route metrics can be determined. Firstly, for continuity mean, there are importance values found between 0.36 and 0.65 which shows a considerable impact but a high difference in this impact depending on OD location set. The same results are seen when looking at the correlations where for most OD location sets, there is a positive correlation except for location set 5, where the correlation is close to 0. This same pattern is seen for continuity variance. Secondly, for the connectivity mean, there are importance values found between 0.27 and 0.32. The range of these values is small and consistent. However, as seen from the correlation values, there are inconsistencies in the significance and direction of this possible influence. The same is seen for the connectivity variance. Lastly, for the vertex frequency mean, there are importance values found between 0.41 and 0.58. This suggests a strong relationship. According to the correlation values, the direction of this relation is negative. A high avoidance of edges with road type in road category 2 thus leads to a lower vertex frequency in the resulting routes. This significant relation was not found for the vertex frequency variance. Overall, there is a considerable positive relation found between TA_2 and the continuity mean, and a considerable negative relation between TA_2 and the vertex frequency mean, where there was also a high variance found depending on the OD location set.

Table 9.3: Correlation between TA_2 and model output of experiment 1

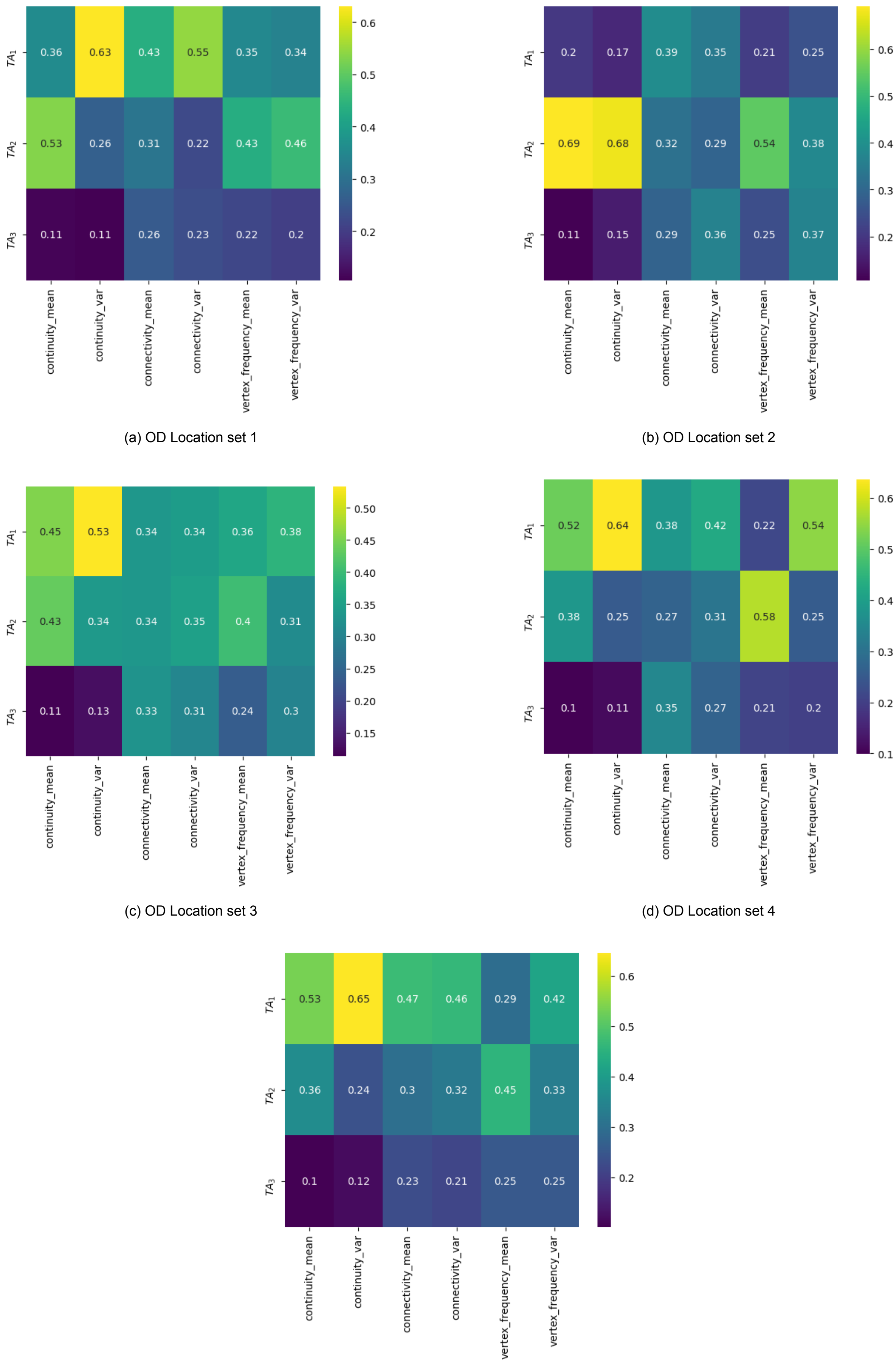
OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	0.559	0.343	0.127	-	-0.182	-0.122
2	0.720	0.707	-0.128	0.132	-0.377	-
3	0.501	0.359	0.173	0.060	-0.265	0.050
4	0.469	0.288	-	0.091	-0.511	-
5	0.058	0.037	-	-	-0.183	-

9.4.3. Results sensitivity analysis: TA_3

From the ETRF values for TA_3 in Figure 9.4 and the correlations in Table 9.4, the influence of TA_3 on the route metrics can be determined. Firstly, for the continuity mean, ETRF values between 0.11 and 0.12 are found and can thus be seen as negligible. This is consistent with the insignificance found in the correlation calculations. Secondly, for the connectivity mean, ETRF values between 0.22 and 0.35 were found, which are seen as low but consistent. This consistency is also seen through the correlation values where the relation between TA_3 and the connectivity mean is positive. The ETRF values of the connectivity variance are even lower and less consistent when looking at the correlations. Lastly, the ETRF values for the vertex frequency mean are between 0.2 and 0.25 which are low but consistent. Consistency in the correlation values is found for some of the OD location sets while there is insignificance found for others. Overall, TA_3 is seen to have a low influence on the route metrics, with only a low significant positive influence found on the connectivity mean.

Table 9.4: Correlation between TA_3 and model output of experiment 1

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	-	-	-	-0.118	-	-
2	0.086	0.099	0.213	0.148	-	0.179
3	-	-	0.271	0.155	-0.106	0.103
4	-	-	0.322	0.207	-0.183	0.125
5	-	-	0.168	-	-0.194	0.120



(a) OD Location set 1

(b) OD Location set 2

(c) OD Location set 3

(d) OD Location set 4

(e) OD Location set 5

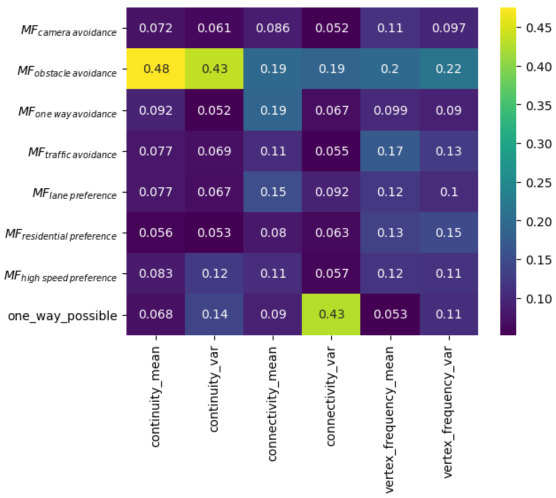
Figure 9.4: The ETRF importance value of experiment 1 for separated OD location sets

9.5. Results sensitivity analysis: MF_i in experiment 2

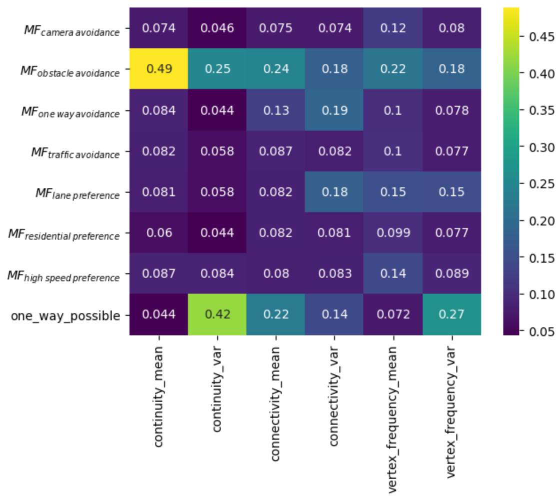
In experiment 2, large range of values for the multiplication factors MF_i of the behavioural factors are used. In Table 9.5, it can be seen that for the model outcomes, there are considerable differences in absolute values while the relative differences in variances are similar. The coefficients of variation show that for continuity, there is a coefficient of variation of between 9% and 13% of the mean and lower coefficient of variation for connectivity and vertex frequency, which range around 6%. The ETRF analysis on this variation can be found in Figure 9.5. These results show that in all OD location sets, only the multiplication factor of obstacle avoidance and the model input factor one-way possible show large importance. This shows that only these factors largely influence the variance in the route metrics that result from this experiment and that the influence of the remaining factors could be not determined.

Table 9.5: Mean (μ), standard deviation (σ) and coefficient of variation (COV) of model output of experiment 2

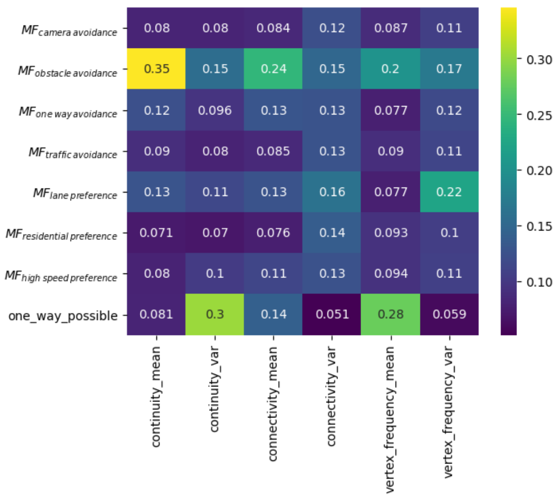
OD Location set		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	μ	3.92	6.14	4.38	2.35	5.19	9.03
	σ	0.52	2.9	0.2	0.37	0.29	0.66
	COV	0.13	0.47	0.05	0.16	0.06	0.07
3	μ	5.03	8.87	4.43	1.91	5.56	7.53
	σ	0.64	4.01	0.27	0.3	0.27	0.79
	COV	0.13	0.45	0.06	0.16	0.05	0.1
5	μ	4.37	5.65	4.28	2.44	5.38	8.92
	σ	0.39	1.9	0.27	0.25	0.3	0.66
	COV	0.09	0.34	0.06	0.1	0.06	0.07



(a) OD Location set 1



(b) OD Location set 3



(c) OD Location set 5

Figure 9.5: ETRF importance values of MF_i input of experiment 2

9.6. Results sensitivity analysis: MF_i in experiment 3

In this section, the results of the sensitivity analysis for the MF_i in experiment 3 are discussed. From the summarising statistics of the model outcomes, as seen in Table 9.6, it can be seen that although the absolute mean and standard differ per OD location set, the relative coefficients of variation are similar for the continuity and connectivity. The coefficients of variation for the continuity mean range between 12% and 16%, for connectivity mean between 7% and 12%. For the vertex frequency mean, the coefficient of variation is very low for location set 1 with only 1%, while the other OD location sets have a coefficient of variation between 4% and 7%. In general, the coefficients of variance of the route metrics are seen as consistent over the different location sets.

To find the influence of the behavioural factors on the variance in outcome values of the model, the ETRF importance values per location set can be used, as seen in Figure 9.6. These figures show how there are different patterns of importance per OD location set and that for each set, there are different behavioural factors that influence the variance of the outcomes the most. The only constant pattern throughout the different location sets is that camera avoidance does not have a strong influence on the variance of the model outcomes.

To find the influence of the multiplication factors MF_i on the model output in more detail, we will look at the ETRF importance values combined with correlation matrices of each multiplication factors MF_i for each OD location set. This is used to determine whether there is consistent and considerable influence among the OD location sets and what the strength of the influence is on the model outputs. In this analysis, an ETRF importance value is seen as considerable if it has a value higher than 0.2. The factor of camera avoidance is not further evaluated because, in addition to the low influence in the ETRF analysis, there was also no significant correlation found with any of the outcomes for the different OD location sets. The overview of all the correlations of the behavioural factors with the model outcomes, including p-values, based on the location set, can be found in Appendix H.3.

Table 9.6: Mean (μ), standard deviation (σ) and coefficient of variation (COV) of model output of experiment 3

OD Location set		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	μ	2.27	0.97	3.67	2.19	5.3	9.5
	σ	0.28	0.25	0.33	0.35	0.2	0.46
	COV	0.12	0.26	0.09	0.16	0.01	0.05
2	μ	2.45	1.79	3.87	1.87	5.58	9.47
	σ	0.3	0.57	0.28	0.26	0.21	0.6
	COV	0.12	0.32	0.07	0.14	0.04	0.06
3	μ	2.89	1.68	3.76	1.64	5.73	7.58
	σ	0.42	0.51	0.36	0.28	0.35	0.84
	COV	0.15	0.31	0.1	0.17	0.06	0.11
4	μ	2.36	1.45	3.42	2.01	5.45	8.54
	σ	0.38	0.74	0.36	0.42	0.3	0.93
	COV	0.16	0.51	0.11	0.21	0.06	0.11
5	μ	2.85	1.85	3.6	2.03	5.55	8.84
	σ	0.46	0.71	0.42	0.39	0.37	0.63
	COV	0.16	0.38	0.12	0.19	0.07	0.07

9.6.1. Results sensitivity analysis: Edge avoidance

Firstly, the results for the multiplication factors MF_i related to edge avoidance are discussed. With these factors, the input ranges are between 1 and 5 and thus a higher avoidance means a higher multiplication factor MF_i.

Results sensitivity analysis: $MF_{obstacle\ avoidance}$

For the multiplication factor of obstacle avoidance $MF_{obstacle\ avoidance}$, it can be seen that it has a different influence on the variance of the model output depending on the OD location set. For each of these model outcomes, this influence ranges between 0.09 and 0.27. The notable influences are to the continuity mean in the OD location set 1, the connectivity variance in the OD location set 2 and the vertex frequency mean in the OD location set 3. These influences are however not consistently considerable among the OD location sets.

The direction of influence can be seen in the correlation matrix, in Table 9.7. This table shows that there is a positive relation with the continuity mean, continuity variance and the connectivity mean. For the connectivity variance, vertex frequency mean and vertex frequency variance, the correlation relation is not consistent in one direction.

Table 9.7: Correlation between $MF_{obstacle\ avoidance}$ and model output of experiment 3

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	0.391	0.214	0.295	-0.081	0.220	0.089
2	0.280	0.266	0.267	0.296	-0.020	0.128
3	0.241	0.104	0.184	-0.101	0.320	-0.264
4	0.195	0.164	0.234	0.143	0.120	0.015
5	0.258	0.236	0.249	0.177	0.223	0.075

Results sensitivity analysis: $MF_{one\ way\ avoidance}$

For the multiplication factor of obstacle avoidance $MF_{one\ way\ avoidance}$, it can be seen that it has a different influence on the variance of the model output depending on the OD location set. From the ETRF values, only a considerable influence is seen for the connectivity variance in OD location set 2.

To determine the direction of influence for $MF_{one\ way\ avoidance}$ the correlation matrix in Table 9.8 can be used. This shows that there is a positive relation between the continuity mean, continuity variance, connectivity mean and connectivity variance. For the vertex frequency mean and variance, there is an inconsistent relation.

Table 9.8: Correlation between $MF_{one\ way\ avoidance}$ and model output of experiment 3

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	0.248	0.235	0.203	0.282	-0.047	0.064
2	0.235	0.254	0.224	0.351	-0.124	0.052
3	0.219	0.286	0.135	0.116	-0.154	0.221
4	0.259	0.254	0.129	0.287	0.045	-0.109
5	0.277	0.332	0.135	0.151	0.016	-0.089

Results sensitivity analysis: $MF_{traffic\ avoidance}$

For the multiplication factor of obstacle avoidance $MF_{traffic\ avoidance}$, it can be seen that it has a different influence on the variance of the model output depending on the OD location set. The cases where traffic avoidance explains a high percentage of the mode output variance is for the continuity mean and variance in OD location set 2 and 3 and for the connectivity mean in OD location set 4.

To determine the direction of influence for $MF_{traffic\ avoidance}$ the correlation matrix in Table 9.9 can be used. This shows that there is a positive relation with the continuity mean and variance, connectivity mean and variance and vertex frequency mean. There is a negative relation with the vertex frequency variance.

Table 9.9: Correlation between $MF_{traffic\ avoidance}$ and model output of experiment 3

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	0.267	0.306	0.247	0.150	0.126	-0.077
2	0.356	0.310	0.288	0.059	0.172	-0.145
3	0.341	0.361	0.298	0.157	0.109	-0.086
4	0.307	0.261	0.319	0.273	0.241	-0.258
5	0.304	0.241	0.321	0.272	0.190	-0.066

9.6.2. Results sensitivity analysis: Edge preferences

In this subsection, the results for the multiplication factors related to edge preferences are discussed. With these factors, the input ranges are between 0.1 and 1 and thus a higher preference means a lower multiplication factor MF_i. When evaluating correlation values, this means that a positive correlation with the MF_i is translated to a negative relation with the preference.

Results sensitivity analysis: $MF_{lane\ preference}$

For the multiplication factor of obstacle avoidance $MF_{lane\ preference}$, it can be seen that it has a different influence on the variance of the model output depending on the OD location set. Overall the multiplication factor has a high influence on the variance of the vertex frequency mean in OD location set 3, 4 and 5.

To determine the direction of influence for $MF_{lane\ preference}$ on the model output, the correlation matrix in Table 9.10 can be used. Here it can be seen that there is a positive relation with the continuity mean and variance and the vertex frequency mean. There is a negative relation with the connectivity mean and variance. For the vertex frequency variance, an inconsistent relation is found.

Table 9.10: Correlation between $MF_{lane\ preference}$ and model output of experiment 3

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	0.106	0.112	-0.036	-0.042	0.160	-0.055
2	0.137	0.173	-0.049	0.042	0.130	-
3	0.221	0.083	-0.138	-0.103	0.291	-0.144
4	0.173	0.148	0.070	-0.073	0.341	-0.289
5	0.186	0.171	-0.011	-0.097	0.430	-0.326

Results sensitivity analysis: $MF_{residential\ preference}$

For the multiplication factor of obstacle avoidance $MF_{residential\ preference}$, it can be seen that it has a different influence on the variance of the model output depending on the OD location set. It can be seen that there is a considerable influence on the variance of continuity mean and variance in OD location set 2 and 3 and of the connectivity mean and variance in location set 3, 4 and 5.

To determine the direction of influence for $MF_{residential\ preference}$ the correlation matrix in Table 9.11 can be used. This shows that there is a negative relation with the continuity mean and variance, the connectivity mean and variance and the vertex frequency mean. There is an inconsistent direction in relation to the vertex frequency variance.

Table 9.11: Correlation between $MF_{residential\ preference}$ and model output of experiment 3

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	-0.231	-0.285	-0.211	-0.129	-0.103	-0.043
2	-0.325	-0.300	-0.265	-0.111	-0.228	0.164
3	-0.317	-0.308	-0.294	-0.087	-0.170	0.071
4	-0.243	-0.209	-0.296	-0.294	-0.125	0.142
5	-0.277	-0.180	-0.309	-0.150	-0.171	-0.123

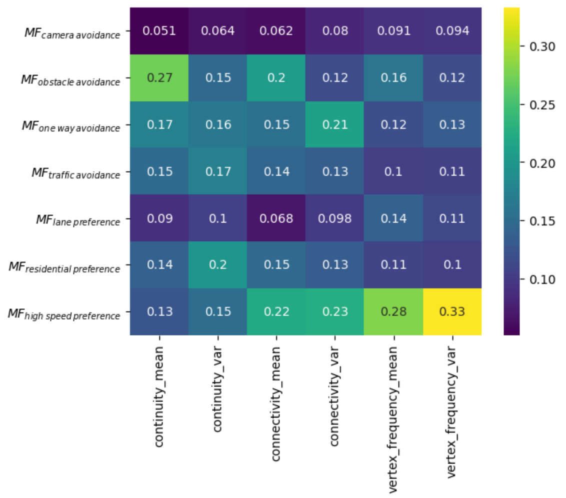
Results sensitivity analysis: $MF_{High\ speed\ preference}$

For the multiplication factor of obstacle avoidance $MF_{High\ speed\ preference}$, it can be seen that it has a different influence on the variance of the model output depending on the OD location set. There is a considerable influence on the variance of model output continuity mean and variance in OD location set 4, on the connectivity mean and variance in location set 1, 3, 4 and 5 and on the vertex mean and variance in OD location set 1, 2, 4 and 5.

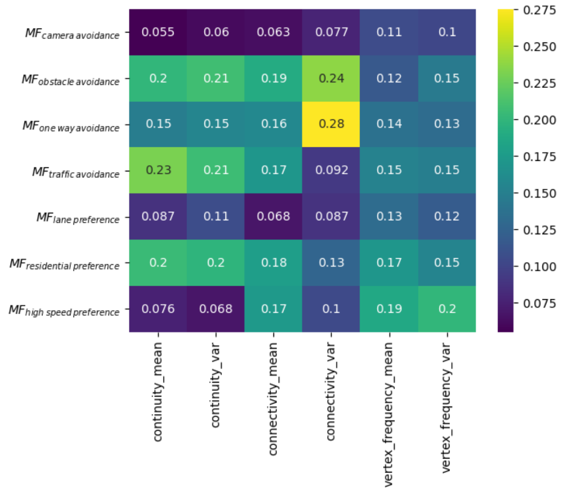
To determine the direction of influence for $MF_{High\ speed\ preference}$ the correlation matrix in Table 9.12 can be used. This shows that there is a positive relation with the continuity mean and variance, the connectivity mean and the vertex frequency mean. There is an inconsistent relation with the connectivity variance.

Table 9.12: Correlation between $MF_{high\ speed\ preference}$ and model outputs of experiment 3

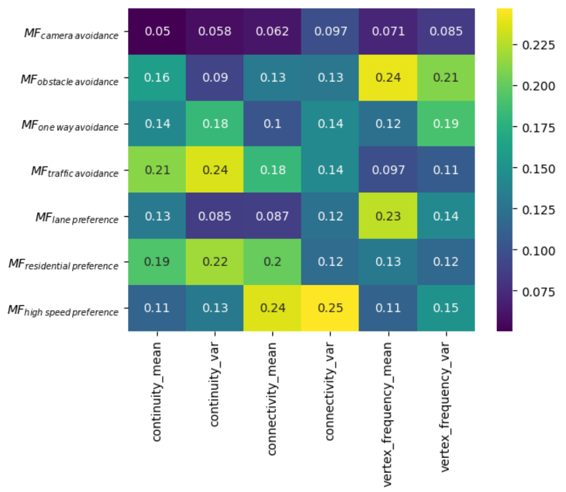
OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	0.207	0.187	0.276	0.231	0.320	-0.318
2	0.114	0.074	0.208	-	0.200	-0.207
3	0.161	0.171	0.265	0.180	0.158	-0.157
4	0.324	0.383	0.319	0.174	0.341	-0.384
5	0.193	0.236	0.294	0.312	0.189	-0.169



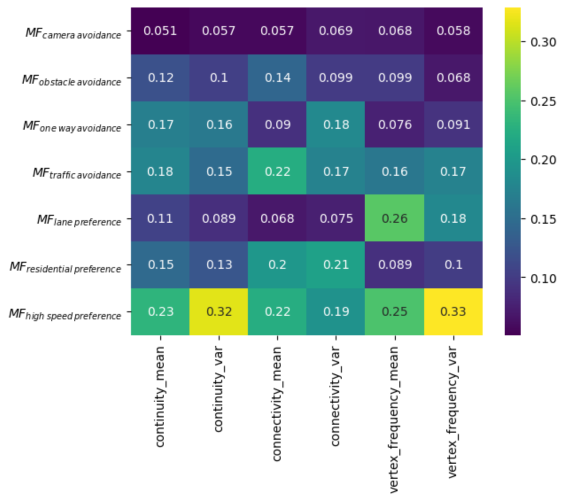
(a) OD Location set 1



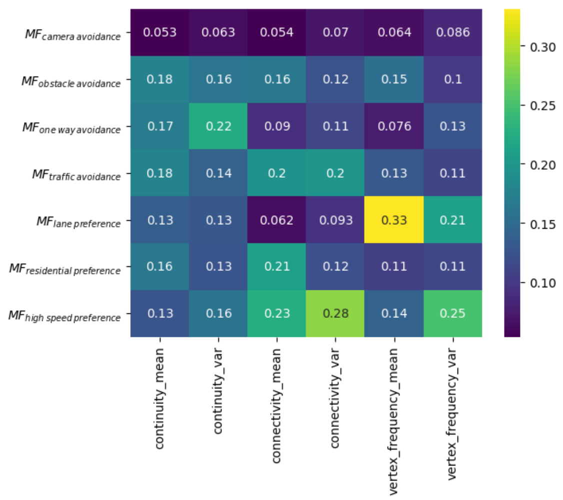
(b) OD Location set 2



(c) OD Location set 3



(d) OD Location set 4



(e) OD Location set 5

Figure 9.6: The ETRF importance value of experiment 3 for separated OD location sets

9.6.3. Correlation between model outputs

In Table 9.13, the correlations between model outputs can be found. The correlations show a positive significant correlation between all route metric mean variables. From the other correlations, it is seen that there is a significant correlation between a route metric mean and its variance. This correlation is positive for continuity and connectivity and negative for vertex frequency.

Table 9.13: Correlation between model outputs of experiment 3

	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
continuity mean	1.000					
continuity variance	0.676	1.000				
connectivity mean	0.461	0.480	1.000			
connectivity variance	0.131	0.181	0.273	1.000		
vertex frequency mean	0.488	0.403	0.318	-0.027	1.000	
vertex frequency variance	-0.358	-0.231	-0.073	0.069	-0.483	1.000

9.7. Results sensitivity analysis: number of paths and strategy change time

In this section, the results from the sensitivity analysis of experiments 4 and 5 are discussed. Both of these experiments showed very similar behaviour, and although the absolute outcome values differ, almost equal resulting coefficients of variation and ETRF importance values were found. It is therefore chosen to focus this explanation on the outcomes of experiment 4 in this section. The detailed outcomes of experiment 5 can be found in Appendix H.8 and Appendix H.10.

From the summarising statistics of the model outcomes, as seen in Table 9.14, it can be seen that although the absolute mean and standard deviation of the model outputs differ per OD location set, the relative coefficients of variation are similar and low for all route metrics. There is, thus, low variance in the model outputs based on the number of paths and the strategy change time. When looking at the ETRF importance values of experiment 4 for the different OD location sets, it can be seen that for all OD location sets, the variance of the model output is mainly explained by the number of paths model input. An example of this can be seen in Figure 9.7. The remaining ETRF tables can be found in Appendix H.6. For the OD location sets, this same high ETRF importance values of the number of paths and low ETRF importance values of the strategy change time is seen. Therefore, we assume an insignificant influence of the strategy change time on the model route metrics.

To determine the direction of influence for the number of paths, the correlation matrix in Table 9.15 can be used. This shows a positive correlation between the number of paths and the continuity mean and vertex frequency variance. A negative relation with the continuity mean, connectivity variance and vertex frequency mean is found. There was an inconsistent relation with the connectivity mean.

Table 9.14: Mean (μ), standard deviation (σ) and coefficient of variation (COV) of model output of experiment 4

OD Location set		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	μ	1.51	0.37	3.51	2.01	5.75	9.45
	σ	0.01	0.0	0.12	0.16	0.06	0.25
	COV	0.01	0.01	0.04	0.08	0.01	0.03
2	μ	1.53	0.29	3.66	1.56	6.32	8.4
	σ	0.01	0.0	0.12	0.04	0.02	0.16
	COV	0.01	0.01	0.03	0.03	0.0	0.02
3	μ	1.71	0.59	3.31	1.44	5.04	10.26
	σ	0.03	0.01	0.14	0.08	0.03	0.07
	COV	0.02	0.02	0.04	0.06	0.01	0.01
4	μ	1.55	0.59	3.69	1.65	5.75	9.45
	σ	0.01	0.0	0.14	0.12	0.04	0.2
	COV	0.0	0.0	0.04	0.07	0.01	0.02
5	μ	1.68	0.52	3.48	1.56	5.38	9.9
	σ	0.01	0.01	0.15	0.07	0.02	0.14
	COV	0.01	0.01	0.04	0.04	0.0	0.01

Table 9.15: Correlation between num_of_paths and model output of experiment 4

OD Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	-0.653	-	-0.987	-0.880	0.913
2	1.000	-0.793	-0.513	-0.853	-0.367	0.620
3	1.000	-0.593	0.360	-0.920	0.720	0.353
4	0.913	-	-	-0.793	-0.707	0.860
5	0.853	-0.840	-	-0.973	-0.187	0.933

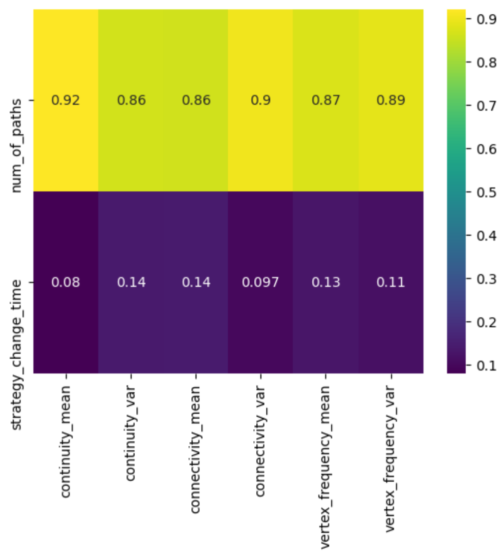


Figure 9.7: The ETRF importance values experiment 4 for OD location set 1

10 Discussion

In this chapter, the results from the experiments performed and their relevance to answering the research question are determined. This is firstly done by discussing the main findings from the case studies and sensitivity analysis and interpreting these findings in the context of finding the influence of behavioural factors on criminal fugitive escape routes. Next to this, the limitations of the research design on the findings are discussed and how these impact the practical usability of the results.

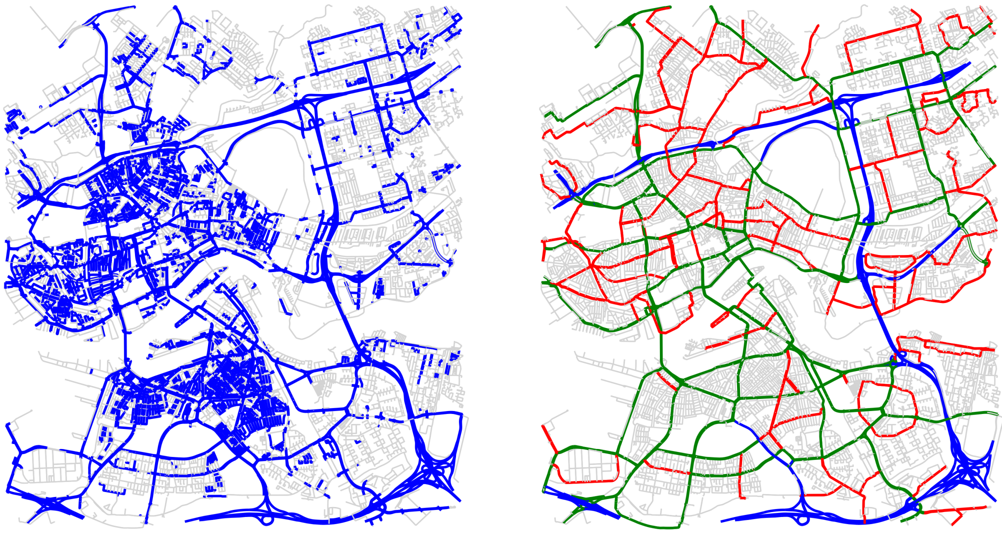
10.1. Dependence on origin and destination locations

The results from the case studies and the sensitivity analysis of the different experiments showed that the chosen locations for the crime scene and destination highly influence the model's outcomes. This is seen from the absolute values of the route metrics in both the case studies and sensitivity analysis and the different influences of the behavioural multiplication factors MF_i for different origin and destination locations in the case studies.

From the results of the case studies, it can be seen that the influence of behavioural multiplication factors MF_i can differ in direction and strength. An example of how the direction of the influence differs can be seen in the relation between $MF_{high\,speed\,preference}$ and the continuity metric of the resulting routes as visualised in Figure 8.2. An example of how the strength of influence differs, even if the direction is the same, can be seen in the relation between $MF_{obstacle\,avoidance}$ and the continuity metric of the resulting routes as visualised in Figure 8.5.

This impact of the OD locations on the strength of the influence shows the relevance of the distribution of edge characteristics in the road network on how behavioural multiplication factors influence routes. Examples of these distributions over the road network can be seen in Figure 10.1. This implies that routes going through some region of the network are more affected by a behavioural preference or avoidance in the region that is dense in the edge characteristic to which this preference or avoidance is relevant.

The impact of the OD locations on the direction of the influence shows the reliance on the base case behaviour on comparison of route metrics. The base case is the behaviour where a fugitive takes the shortest route between OD locations based on the route length and maximum speed. The maximum speed characteristics of the edges between OD locations thus strongly influence which route is included in the base case. To illustrate this, the scenario of a route with OD locations close to a highway can be used. In this scenario, the base case will likely use the highways because they have a high maximum speed. An additional preference for roads with high maximum speed will not influence this route much. If the OD locations are further from a highway and the base case route only goes through a residential area, a preference for high maximum speeds will more strongly affect the routes.



(a) Locations of one-way roads (blue)

(b) Locations of roads in road categories

Figure 10.1: Visualisation of one-way roads and roads of road categories 1, 2 and 3 in the Rotterdam network

10.2. Influence of traffic avoidance factors TA_i

For the different factors for traffic avoidance, it was found that the avoidance of road categories 1 and 2 was more influential on the resulting route indicators than traffic avoidance of roads in road category 3. When looking at the density of the different road categories in Table 10.1, it can be seen that the number of edges and total length of edges in road category 1 is considerably lower than those in road categories 2 and 3. Thus, the density of these road characteristics cannot explain the difference. What can explain the difference in influence is the maximum speed that is commonly found on the different road categories. The most common 100 km/h speed for road category 1 is considerably higher than the maximum 50 km/h for road categories 2 and 3. Because of this, roads in road category 1 would more often be part of routes in the base case because the cost of the routes would be lower due to the high maximum speed. This effect can also be explained for road category 2 because these roads still have higher speeds than road category 3. This explains why the influence of road categories 1 and 2 is higher than that of road category 3. This result shows the impact of the correlation between road characteristics such as road type and maximum speed on the likely routes.

Table 10.1: Densities of network characteristics of the Rotterdam road network

Network characteristic	Number of edges	Total length of edges (m)	Common maximum speeds (in order of frequency)
Roads category 1	257	144 257	100, 80
Roads category 2	2296	263 682	50, 80
Roads category 3	2842	244 750	50, 30

10.3. Influence of multiplication factors MF_i

10.3.1. Results sensitivity analysis

From the sensitivity analysis of the multiplication factors MF_i, it was found that there is a variation in values of the model output and the influence of the MF_i on these values depending on the OD location set. Because of a difference in absolute values of the model output depending on the OD location set, the relative variance was calculated using the coefficients of variance. This showed that there is consistency in the variance of the route metrics. It is, however, difficult to give meaning to these coefficients of variance because it is uncertain what the impact of a certain variance is on the routes. Therefore, we will first look at the separate influences of the multiplication factors on the variance in model outputs.

To determine the influence of a multiplication factor MF_i on a route metric for an OD location set, we can multiply the coefficients of variation, indicating the relative variance, with the ETRF importance factor found in the sensitivity analysis, indicating the influence of a MF_i on the variance of a model output. The resulting value gives the percentage of the relative variance of a route metric that a MF_i can explain. Because this differs per OD location set, Table 10.2 shows the minimum and maximum value for this percentage over the OD location sets. From the resulting percentages of influence, we can see that the percentages are low and have a large range within the percentages depending on the OD location set.

Table 10.2: Percentages to indicate the influence of MF_i on the route metrics in experiment 3

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
$MF_{camera\ avoidance}$	min	0.61%	1.66%	0.44%	1.08%	0.09%	0.47%
	max	0.85%	2.91%	0.65%	1.65%	0.45%	0.94%
$MF_{obstacle\ avoidance}$	min	1.92%	2.79%	1.30%	1.92%	0.16%	0.60%
	max	3.24%	6.72%	1.92%	3.36%	1.44%	2.31%
$MF_{one\ way\ avoidance}$	min	1.80%	4.16%	0.99%	2.09%	0.12%	0.65%
	max	2.72%	8.36%	1.35%	3.92%	0.72%	2.09%
$MF_{traffic\ avoidance}$	min	1.80%	4.42%	1.19%	1.29%	0.10%	0.55%
	max	3.15%	7.65%	2.42%	3.80%	0.96%	1.87%
$MF_{lane\ preference}$	min	1.04%	2.60%	0.48%	1.22%	0.14%	0.55%
	max	2.08%	4.94%	0.87%	2.04%	2.31%	1.98%
$MF_{residential\ preference}$	min	1.68%	4.94%	1.26%	1.82%	0.11%	0.50%
	max	2.85%	6.82%	2.52%	4.41%	0.78%	1.32%
$MF_{high\ speed\ preference}$	min	0.91%	2.18%	1.19%	1.40%	0.28%	1.20%
	max	3.68%	16.32%	2.76%	5.32%	1.50%	3.63%

When looking at the percentages, it can be seen that there are no large differences in influence over most of the MF_i. The only MF_i that has considerably lower influence on the results is $MF_{camera\ avoidance}$. This is unexpected when considering that from the theoretical background, camera presence was seen as an important factor that affects criminal fugitive routes. The distribution of the cameras in the formalised route network could explain the low influence found. As seen from Table 10.3, the number of cameras in comparison to the other edge characteristics is low. Next to this, as seen in Figure 10.2, the distribution of cameras is sparse and concentrated on the highways in the network. Because of the number of cameras and the distribution of cameras of the network of Rotterdam, camera avoidance is not seen as influential on routes within the city. This shows how the distribution of the edge characteristics within a formalised network can affect how strong the influence is of tested behaviour.

Table 10.3: Densities of network characteristics of the Rotterdam road network

Edge characteristic	Number of edges	Total length of edges (m)
ANPR cameras	101	18 338
Obstacles	2461	346 166
High speed roads	430	165 503
Residential roads	16713	1 393 332
Roads category 1	257	144 257
Roads category 2	2296	263 682
Roads category 3	2842	244 750
Roads category 1, 2 and 3 total	5395	652.689
Roads with > 1 lane	2509	371 028
Roads with one way	7556	827 700

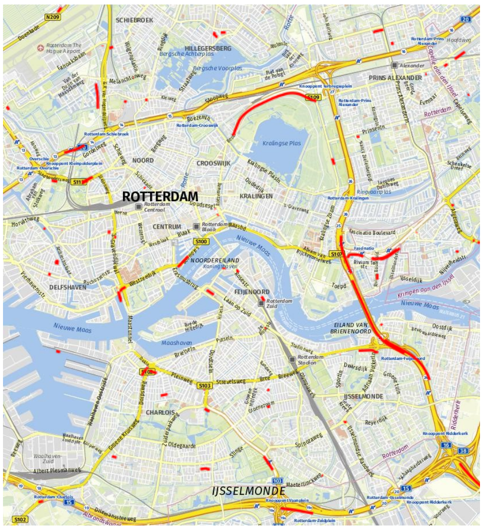


Figure 10.2: Visualisation of camera distribution in road network Rotterdam

10.3.2. Interpretation of findings

The findings from the sensitivity analysis on the MF_i show the difficulty of determining the influence of MF_i values on the routes through the route metrics. This is seen through different inconsistencies in the results. This is shown by the low percentile influences of the multiplication factors on the route metrics while seeing a large difference in the actual routes in the case studies. Next to this, it is seen in the difference in correlation between model output for different location sets. Next to this, the influence is also difficult to interpret because of the dual conceptualisation of the route-choice factors: either a preference or avoidance of edge characteristics causing edge costs to either increase or decrease. Because of this difference in formalisation, limitations can be found in interpreting how much a multiplication factor influences a route metric.

These limitations indicate that this method can only show which factors influence the routes through the route metrics and how strong this influence is. However, it cannot be used to determine how the factors influence the routes qualitatively. Two specific routes generated through behaviour would need to be compared to find this qualitative difference in routes and route metrics. This shows the general limitations of sensitivity analysis on a model with routes as the output format. In this method, it is necessary to find metrics that represent the routes so that these can be used to calculate sensitivity. The representation of the routes by the route metrics is, however, uncertain and, as seen from the findings of the sensitivity analysis in this study, can make it difficult to determine the meaning of the found sensitivity qualitatively.

This limited interpretability of the relation between the MF_i and the routes based on route metrics also explains why no conclusive data was found to show the influence of a strategy switch on the routes. Yet, the findings do suggest that many defined route-choice factors influence the routes. Additionally, both the sensitivity analysis and the inconclusivity of scenario analysis showed that no behavioural profiles lead to routes with specific characteristics. This suggests that routes based on a specific behaviour cannot be used to describe the general behaviour of fugitive suspects. These findings thus have limited interpretability for specific behavioural factors but can indicate findings for a complete description of route-choice behaviour.

10.4. Implication of research design

As stated in Chapter 1, this study focuses on the quantitative influence of behavioural route-choice factors on general criminal fugitive route-choice behaviour. Throughout the study, different limitations were found that show the difference between this quantitative perspective and the qualitative research method used to compare a specific behavioural factor, such as done by Kempenaar (2022) for the route-choice factor of the emotional state of a fugitive through dual process theory.

Firstly, a quantitative method attempts to determine an influence of a certain factor on the routes. Because of this, it is necessary to find a continuous measurement method to assess the influences of a continuous input factor. In comparison, in qualitative methods, the difference between two sets of individual routes and their characteristics can be compared directly. This affects the way that differences in routes are represented.

Secondly, a qualitative approach focuses on an entire behavioural profile, while quantitative focuses on aspects within possible behavioural profiles. Because of this, in the quantitative method, the number of assumptions in the modelling space needs to be reduced so that their effect on the resulting behaviour is limited, and the number of degrees of freedom is reduced. In a qualitative approach, more assumptions can be made within the specific behavioural profiles because these do not affect the comparability of the outcomes.

These differences in approach have implications for the interpretation of results. Where the qualitative approach can identify differences in routes without measuring what causes these differences, the quantitative approach can identify which factors cause these differences but is limited in showing how these differences affect the resulting routes.

For route-choice behavioural modelling specifically, the differences in assumptions can be seen in the conceptualisation phase of the behaviour. For this study, the specific type of long-term goal with full familiarity is chosen, and the influence of behavioural route-choice factors is assessed. Because of this assumption, some short-term behaviour, such as taking a turn at each intersection, could not be represented. In comparison, the study of Kempenaar (2022) has a more diverse conceptualisation of the goal length by combining short and long-term goals within specific behavioural profiles. However, because the research approaches assess the resulting routes differently, determining how these conceptualisations affect the resulting routes is not possible. To find how these differences in conceptualisation affect routes, a quantitative approach to measure the differences in long and short-term goals will need to be used.

These differences in assessing routes in either quantitative or qualitative approaches can explain the difficulty of determining how routes are affected by route-choice factors through a sensitivity analysis. While this method can find which route-choice factors influence the resulting routes and which environmental factors affect differences in these influences, a more qualitative approach is necessary to describe in more detail how these influences of route-choice factors can be seen in resulting routes.

10.5. Validation of findings

This study focuses on finding a conceptualisation of general criminal fugitive route-choice behaviour. While the assumptions that this conceptualisation is based on have been validated, the validation of resulting routes and the influence of behavioural factors on these routes has been found to be difficult. When attempting to do this, it is seen that experts cannot easily interpret individual behavioural factors. This is because, for experts, behaviour is always viewed within a specific context, and routes could thus only be validated when perceived within a specific behaviour profile. Because there were no behavioural profiles found within the results of the model, it was not possible to directly validate the routes based on only the separate behavioural factors. To validate the resulting routes and the influence of behavioural factors on these routes, behavioural profiles will need to be defined beforehand so that routes resulting from the model can be validated within the context of these profiles.

10.6. Implication on practical application

As stated in Chapter 1, this study focuses on the societal problem of determining locations in road networks to help position police units. To do this, the question needs to be answered of whether it is possible to plot escape routes to find important locations around a crime scene with a high probability of a fugitive passing. The findings of this study suggest that because of the inability to demarcate types of routes through behavioural profiles, a more inclusive approach to different strategies is needed. Because many different strategies are possible based on the separate behavioural route-choice factors, plotting these routes by themselves (as seen in Figure 10.3a) can lead to many roads being included. Therefore, an alternative approach needs to be taken that reduces the number of locations considered important.

(a) Aggregated routes (b) Heatmap based on frequency

Figure 10.3: Heatmap visualisation

To do this, the method of heat mapping can be used, as also used by Kempenaar (2022). This method demarcates the set of positions by filtering roads by the frequency that they are present within routes for different strategies. When a set of destination locations is chosen, this can show the roads with the highest likelihood of being in an escape route, as seen in Figure 10.3b.

In this method, the destination locations and the number of routes considered to these locations need to be defined. Because of the limited assumptions in the model, this method is flexible to different sets of destination locations. This can be seen in Figure 10.4, where a different number of destination locations are used. Also, for the uncertainty of whether a fugitive will take likely roads, the model is flexible through the possibility of inserting different numbers of paths considered between the crime scene and the destination locations, as seen in Figure 10.5. The effect of these inputs on the resulting heat maps is uncertain, and more analysis needs to be done to find the effect of using different values for this.

(a) Using 20 locations (b) Using 30 locations

Figure 10.4: Differences in heatmaps based on the number of destination locations used

When considering how this method of using different strategies applies to a practical situation, it can be seen that there is high applicability in many different situations. This is practically relevant because, as seen in the context chapter, there is much uncertainty about the characteristics of suspects and their strategies. Because of this, routes for specific behaviour are not wanted, but general routes should be considered. The limited number of assumptions in the method developed in this study means that the method can be used for this purpose.

(a) Number of paths = 1 (b) Number of paths = 10

Figure 10.5: Differences in heatmaps based on the number of paths used

10.7. Generalisation of findings

As stated in Chapter 1, the results of this study are focused on car-based fugitive escape routes within the road network of Rotterdam. When considering the generalisation of the findings within fugitive route-choice decision-making in different transportation types, the applicability of the chosen route-choice factors needs to be assessed. These factors were assumed based on a preference or avoidance of a road characteristic relevant to cars. This assumption might not be applicable to other transportation methods, such as walking or public transport, because broader contextual and environmental factors need to be considered when describing route-choice behaviour. Therefore, to generalise over the transportation types, these factors need to be assessed for relevance.

Next to this, the findings of the results indicate that the distribution of road characteristics over a network can affect how behavioural factors influence routes. When applying these findings to a different network, it should be assessed whether this network is similar enough to the road network of Rotterdam to lead to the same resulting influences. Therefore, the generalisation over different network types can be seen as limited and careful consideration of the characteristics of these networks needs to be made when doing so.

11 Conclusion

In this chapter, the conclusions from the results of the performed research method will be discussed. This is done by firstly answering the sub-questions defined in chapter 1. Then the overall research question is answered. Lastly, the societal and scientific relevance of the conclusions are discussed, and recommendations are made for future research.

11.1. Answers to sub-question 1

To answer the research question, two sub-questions were defined. To answer these, there is a distinction between the theoretical and conceptualisation part of the study and the results from experiments using a model based on this conceptualisation. Firstly, the following sub-question will be answered:

Sub-question 1: *What are the main factors influencing criminal fugitive route-choice decision-making?*

To answer this question, a literature review and expert interviews were performed. This formed a theoretical background for criminal fugitive route-choice behaviour. This was used to form a conceptualisation of the route-choice behaviour.

11.1.1. Conclusions from theoretical background

Because of a lack of research on criminal fugitive route-choice behaviour, it was necessary to use literature from other research fields to find relevant topics. The following research fields were found to be relevant: criminal decision-making, rationality in decision making and route-choice decision-making. These all add to the knowledge required to understand what factors influence criminal fugitive route-choice decision-making. Many different contextual and personal factors were found to influence the decisions that a criminal suspect makes. Regarding route-choice behaviour, it is not known which factors are most important, and no suspect and crime characteristics are associated with a specific behavioural profile. However, two relevant criminal behaviours affect route choices: camera avoidance and taking a turn at each intersection.

From the literature on rationality in decision-making, it was found that rational decision-making cannot be assumed for the criminal situation. Bounded rationality can be used instead to describe behaviour found in high-stress situations. Two conceptualisations of this bounded rationality were found to be relevant for criminal fugitive route choices: inertia effect and dual process theory. The inertia effect was seen to influence route choices in day-to-day commutes and lead to a reliance on habits when making route choices. Dual process theory has been used to conceptualise criminal decision-making through the influence of the ”hot” and ”cool” mode. These processes were seen not to be independent of each other and there is no concrete conceptualisation on how they affect decision-making. These results show that decision-making is complex and that rationality cannot be assumed but that there is much ambiguity in the definition of how people make decisions.

Lastly, from the route-choice decision-making literature, it was found that many different route-choice factors influence route-choice decision-making. These were assessed for relevance for the criminal fugitive situation to create a list of the relevant route-choice behaviour and decision-making modelling methods. The following list of route-choice behavioural factors was found: obstacle avoidance, risky behaviour, traffic avoidance, route distance and maximum speed, and preference for main or residential roads. For the route choice decision-making modelling methods, the following topics were found: cost-benefit calculations, short or long-term goals, emotional state, choice prioritisation and timing. These two lists of factors should be considered when conceptualising criminal fugitive route-choice behaviour.

11.1.2. Conclusions from conceptualisation

Using the findings from the theoretical background, criminal fugitive route-choice behaviour was conceptualised. Different limitations and difficulties in this conceptualisation were found.

Firstly, it was found that while many different suspect and crime characteristics might affect suspect behaviour, no specific behavioural profiles could be used to conceptualise route-choice behaviour. Therefore it was chosen to conceptualise the behaviour by creating dynamic strategy profiles based on behavioural route-choice factors.

From the list of behavioural route-choice factors to include in these strategy profiles, it was found that there are two types of behavioural factors: road characteristic preference and avoidance. The road characteristics seen to be avoided are cameras, obstacles, one-way roads and high traffic. The preferred road characteristics are a high number of lanes, residential roads, a high maximum speed and short roads.

To use the profiles of behavioural route-choice factors, the concept of a route decision needs to be defined. Here it was found that there is a distinction in decisions based on long or short-term goals, which require either low or full network familiarity. These are both found to be improbable in practice. An alternative conceptualisation of combining short and long term goals or using medium-term ones was considered. However, it was found that these require many assumptions and that there is high uncertainty in these assumptions. Because of this, these conceptualisations were not further considered. Because of the unlikelihood of low familiarity with a network for different types of suspects, it was chosen to include long-term goals with full familiarity. This leads to conceptualising a route choice as a whole route between an origin and destination location.

When considering the rationality of the decisions made for the route choices, it was found that there is too much uncertainty and ambiguity in the conceptualisations of inertia and dual process theory to use them for a concrete route-choice conceptualisation. It was chosen to instead use the assumptions of rationality in decision-making to determine how these apply to the conceptualised behaviour. This resulted in the assumptions of a bounded number of possible routes based on the road network used, a probability of outcomes based on assumed knowledge by the fugitive at the start of a route without information updating and an assumption that routes with higher utility are more likely to be used. Finally, the emotional state of a fugitive is included in the conceptualisation through the possibility of changing route-choice strategies.

11.2. Answers to subquestion 2

In the second phase of this study, the following question was answered:

Sub-question 2: *What effect do behavioural route-choice factors have on the routes resulting from criminal fugitive route-choice decision-making?*

From the findings of this study, it can be concluded that although a quantitative method can show which behavioural route choice factors influence the resulting routes through defined route metrics, that the results cannot show the qualitative influence on the actual routes. Next to this, it was found that these different approaches of either quantitative and qualitative research affect the need for demarcating assumptions which can lead to limiting the possibility of representing certain behaviour in the conceptualised behaviour.

When evaluating the results of the case studies and sensitivity analysis, it was found that the influence of behavioural route-choice factors on routes depends on different external environmental factors. Firstly, the choice in origin and destination location of the routes can affect the road characteristics of the environment through which a route goes through and therefore influence how the routes change depending on the route-choice factors. This also shows the reliance on the base case assumptions on behaviour used to compare routes. Secondly, the complete set of road characteristics of the road network used in the formalisation of the model affect the influence of the behavioural factors. Thus reducing the ability to generalise the findings to other road networks.

For the road network of Rotterdam specifically, it was found that the avoidance of high traffic, obstacles and one way roads and the preference of high number of lanes, residential roads and roads with high speed influence the routes resulting from the modelled route-choice behaviour. The avoidance of cameras was not influential on the resulting routes.

Lastly, it was found that there were no behavioural profiles leading to routes with specific characteristics and that in practical application, a broad set of strategies should be included when finding important locations in a road network to use for positioning police units. To do this, a method of using heat maps to find these locations was proposed. This method, combined with the route cost model described in this study, was found to have high applicability, but more research needs to be done on the usability of this method.

11.3. Answers to research question

In this section, the research question is answered, as defined as follows:

What effect do behavioural factors from criminal route-choice behaviour have on escape routes?

From the results of this study, it can be concluded that criminal fugitive route-choice behaviour is complex and that different possible conceptualisations exist. These conceptualisations can be used for different purposes of studying general route-choice behaviour or specific behavioural factors. This affected many of the choices in the conceptualisation of the behaviour and the ability to measure the influence of behavioural factors on the resulting routes. Limitations were found on the measurement techniques used in the quantitative method to measure differences in routes which reduced the ability to interpret the resulting influence of behavioural factors on the routes. This showed that to find the influence of behavioural factors on the routes, a combination of qualitative and quantitative methods is required.

Overall, it was found that for general criminal fugitive route choice behaviour, the routes are affected by a set of route choice, decision making and environmental factors. The route choice factors can be described as preferences and avoidances of the following road characteristics: road type, number of lanes, maximum speed and presence of obstacles or cameras. The decision-making factors consist of the assumption of using long and short-term goals, the level of familiarity with the network, the assumed rationality used in decision making and the emotional state of a fugitive. The environmental factors consist of the origin and destination locations of the routes and road characteristic densities of road networks. The multitude of these relevant factors shows the complexity of criminal fugitive route-choice behaviour and that many factors should be included when determining police positioning locations through modelling escape routes.

11.4. Scientific contribution

As described in Chapter 1, this study aimed to address the knowledge gap of which behavioural factors describe criminal fugitive route choice behaviour and how they influence the resulting routes. The findings of this study add to the literature of different fields.

Firstly, this study adds to the literature on the modelling of human behaviour by showing the complexity of attempting to conceptualise rationality in human decision-making. It shows that simplifications need to be made and that there are still many uncertainties on these simplifications.

Secondly, this study adds to the literature on modelling route-choice behaviour and the different concepts within this behaviour that needs to be specified. It also shows the complexity of choices in network familiarity and goal length on the resulting representation of modelled behaviour and the interpretability of results. Next to this, this study showcases the difficulty of comparing the data types of routes and, therefore, the difficulty in both quantitative and qualitative research of quantifying the influence of behavioural factors on routes. This shows that both qualitative and quantitative research on routes needs to be combined to determine the influence of the multitude of various route-choice factors on the routes.

Lastly, this study adds to the research field of criminal fugitive route-choice behaviour by creating a theoretical background that can be used as an overview of the relevant topics within the modelling of the behaviour. Additionally, it adds to the previous research of Kempenaar (2022) by creating a list of behavioural route-choice factors influencing general criminal fugitive route-choice behaviour and adding a quantitative method to determine the influence of these factors on the escape routes.

11.5. Societal contribution

This study aims to help determine if making likelihood estimations of escape routes is possible and how these could help create positioning suggestions for police units. The results of this study add to this by showing that there are no behavioural profiles that lead to routes with specific characteristics. Therefore it is concluded that individual strategies cannot be used to identify the likely escape routes and that a broad set of strategies should be considered when determining locations with a high likelihood of being included within the escape routes. To do this, a method of heat mapping was proposed, which finds important roads within a road network based on the frequency of their occurrence in the routes of the different strategies. This contributes to the possible methods that could be used in decision support systems, as described in the context, within the control room to reduce the reliability of police positioning choices on the intuition and experience of centralists. Lastly, the model developed in this study can be used as a basis to further study the behaviour that experts see as relevant. This shows that the model and methods described in this study can serve the situational context of fugitive escape in different ways.

11.6. Recommendations for future research

Different recommendations for future research were identified from the discussion and conclusion of the results found in this study. The following list summarises the recommended topics and knowledge gaps that need further research:

- **The possible clustering of routes based on origin and destination locations:** from the sensitivity analysis results, it was found that some routes are affected similarly by the route-choice factors. Research on the clustering of these routes could be performed to determine if patterns within these routes exist.
- **Qualitative influence of described route choices :** from the results of this study, it was found that the quantitative method sensitivity analysis could not fully describe how the identified route-choice factors influence the routes. To gain further understanding of this, more research needs to be done on methods to compare routes qualitatively, and so these can be used to determine the influence of route-choice factors on escape routes.
- **Influence of long or short-term goals and the familiarity of the road network:** in the conceptualisation phase of this study, it was identified that there are different ways to conceptualise the goal length and familiarity level of a fugitive. It was seen how this affects the possible representation of different behaviour. More exploration of the effect on the behaviour and the resulting routes is needed to further understand the different conceptualisation of these behavioural factors.

- **Validation of resulting routes:** as stated in the discussion, validation of general behaviour is difficult because the context highly influences the experiences and knowledge of experts. Therefore, to validate the results of the route cost model developed in this study, more research needs to be done on methods of validation of escape routes.
- **Practical use of heatmaps in decision support systems:** in the discussion, the method of heatmaps was proposed to use in finding important locations to use for positioning police units. Further research on the applications of this method within a practical decision support system is needed to understand whether this is possible.
- **Criminal fugitive route-choice behaviour for different transportation types:** in the discussion, it was stated that when applying the found results of this study to other transportation types than cars, the applicability of assumptions needs to be considered. This includes the applicability of the identified route-choice factors and other contextual factors influencing route-choice behaviour. More research thus needs to be done to understand criminal fugitive route-choice behaviour using different transportation types.
- **Criminal fugitive route-choice behaviour in different road networks:** from the results, it was found that the influence of route-choice factors is related to the distribution of road characteristics in a road network. More research needs to be done on how this difference in road network can influence the routes and whether the assumptions used in this study can directly be applied to different networks.

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A

Search queries for literature review

The following search queries were used for the theoretical background and were generated through the search engine Scopus.

Table A.1: Search queries for literature review

Topic	Search query	Number of papers found
Dual process theory	dual process theory AND crime	8
Modelling route choices	route AND modelling OR simulation AND behaviour AND crime	42
	crime AND route OR path AND choice AND behaviour	30
Camera avoidance	crime AND camera AND avoidance	9
Obstacle avoidance	route AND obstacle AND avoidance AND choice	17
Familiarity effect	route AND choice AND familiarity AND behavioural	28
Risky behaviour	route AND choice AND risky AND behavioural	15
Road characteristics for speed violations	speed AND violations AND car AND road AND characteristics	26
Intertia effect	route AND choice AND inertia AND behavioural	20
Behavioural route seeking factors	human AND behaviour AND simulation OR model AND movement OR motion OR route-choice OR route-seeking	26

B

Interviews

Due to the confidentiality of information from the interviews performed in this study, these interviews are not publicly available.

C List of behavioural route-seeking factors

Table C.1: List of behavioural route-seeking factors from literature review

Factor	Sources	Relevance
Learning / Experience	Ye et al. (2018)	Not relevant, because escape situation can be seen as a separate situation and is not part of a set of reoccurring event
Intertia effect	Bode et al. (2015), Bode and Codling (2013), Li and Guo (2021), Meneguzzer (2023), Moussaïd et al. (2011), and Reynolds (1987)	Relevant
Proximity of exit	Almeida et al. (2013), Barbierato et al. (2020), Haghani and Sarvi (2016), Li et al. (2019), and Lovreglio et al. (2016)	Not relevant, because in escape routes there is no limited set of exits or demarcated network of exits
Lower desire for personal comfort	Almeida et al. (2013) and Cao et al. (2018)	Not relevant, because this is mainly the case for pedestrian behaviour
Convenience of exit / reduced difficulty	Almeida et al. (2013)	Not relevant, because convenience is not relevant in fugitive escape routes
Familiarity / unadventurous factor	Helbing et al. (2002a), Li et al. (2019), and Li and Guo (2021)	Relevant
Lower level of orientation	Reynolds (1987)	Not relevant, because in scope of physical human movement and not route seeking
Asocial behaviour	Reynolds (1987)	Relevant
Nerviousness / stress / mood	Bode et al. (2015), Carpio et al. (2022), Reynolds (1987), and Van Gelder (2013)	Relevant
Behavioural mimicking	Carpio et al. (2022), Haghani and Sarvi (2016), Lovreglio et al. (2016), and Zhu and Shi (2016)	Not relevant, because social order is relevant during criminal situations
Bounded rationality based on information overload	Carpio et al. (2022) and Li and Guo (2021)	Relevant
Obstacle avoidance	Li et al. (2019) and Moussaïd et al. (2011)	Relevant
Collision avoidance / distance keeping	Moussaïd et al. (2011)	Not relevant, because in scope of escape behaviour but not route choices
Crowd density and crowding	Haghani and Sarvi (2016) and Li et al. (2019)	Not relevant, because route seeking on an individual level not in a crowd
Route directness	Li et al. (2019)	Relevant
Inter-individual differences	Kinateder et al. (2014)	Relevant

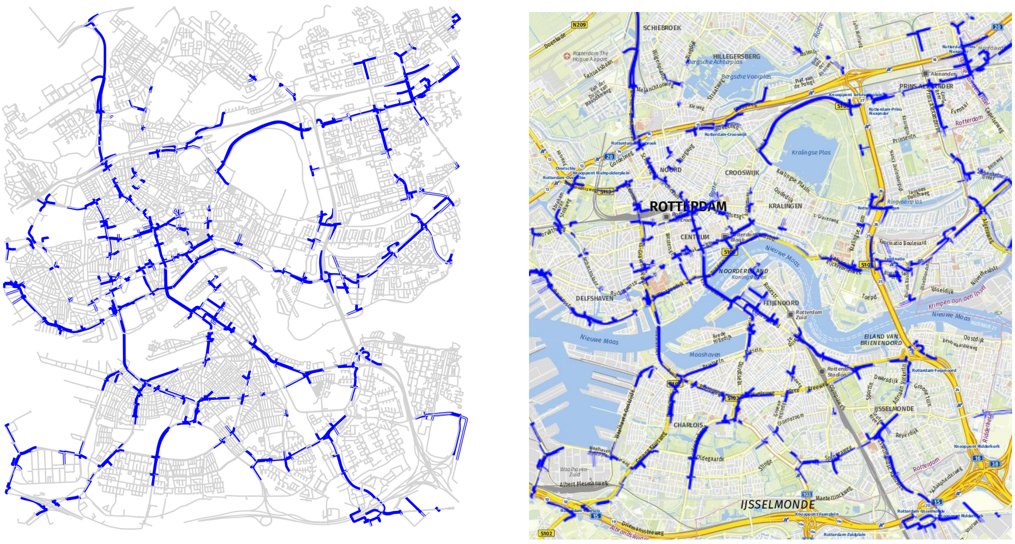
D

Network characteristics

In this appendix, the characteristics of the road network are visualised. This can give insight into the layout of the network and the extent to which specific characteristics are present in the network. This is divided into the obstacles found in the network and the characteristics of the roads. The locations of the obstacles are visualised through the edges, which are marked as adjacent to a node on which the obstacle is present.

D.1. Obstacle graphs

D.1.1. Traffic lights



(a) Locations of traffic lights (blue)

(b) Locations of traffic lights (blue) on Rotterdam map

Figure D.1: Visualisation of traffic lights in Rotterdam network

D.1.2. Bridges

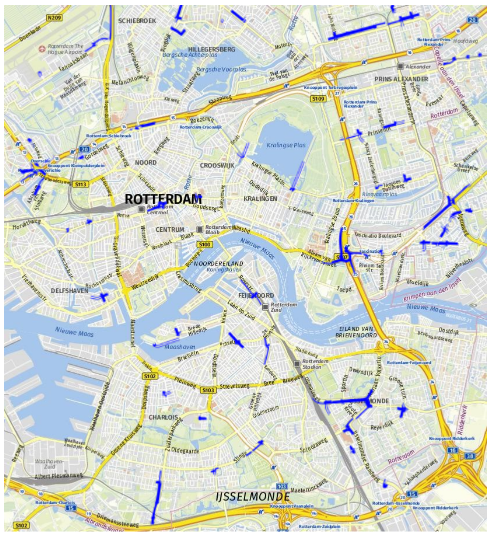
(a) Locations of bridges (blue)

(b) Locations of bridges (blue) on Rotterdam map

Figure D.2: Visualisation of bridges in Rotterdam network

D.1.3. Roundabouts

(a) Locations of roundabouts (blue)

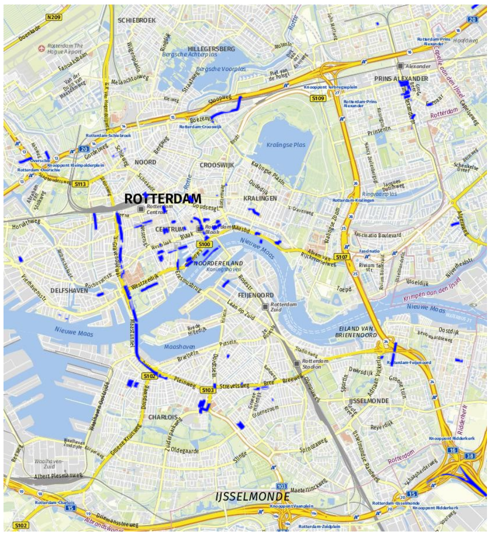


(b) Locations of roundabouts (blue) on Rotterdam map

Figure D.3: Visualisation of roundabouts in Rotterdam network

D.1.4. Tunnels

(a) Locations of tunnels (blue)



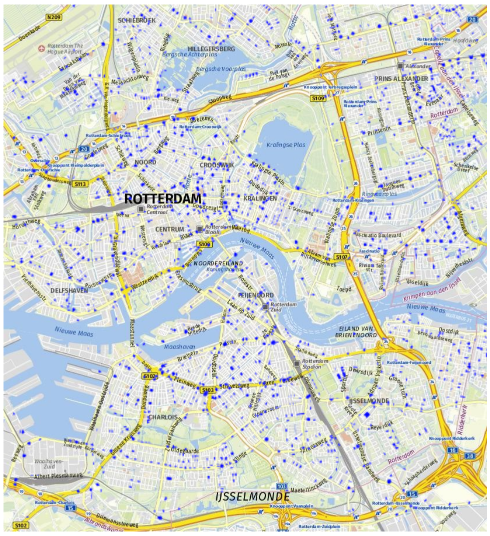
(b) Locations of tunnels (blue) on Rotterdam map

Figure D.4: Visualisation of tunnels in Rotterdam network

D.2. Road characteristics graphs

D.2.1. Short path

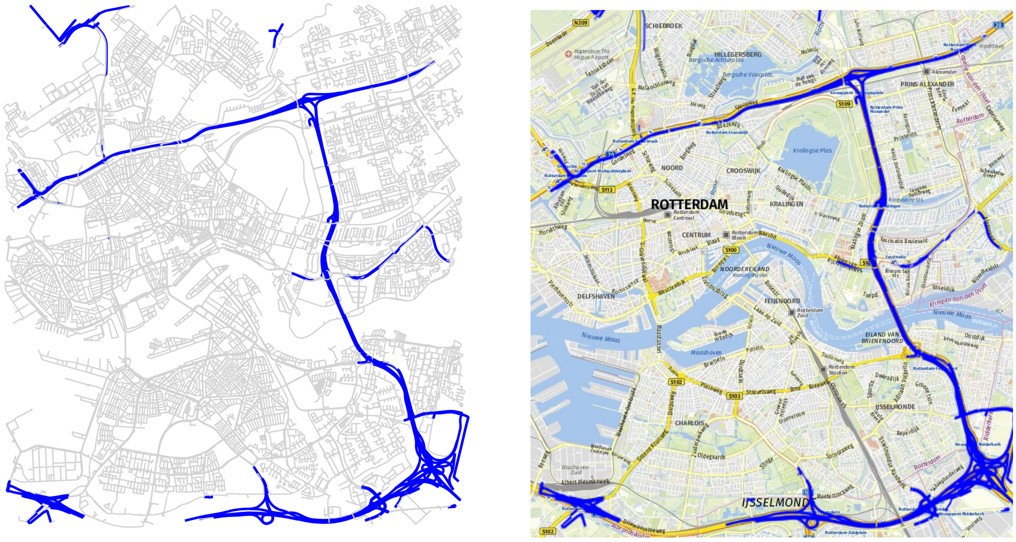
(a) Locations of short roads (blue)



(b) Locations of short roads (blue) on Rotterdam map

Figure D.5: Visualisation of short roads (< 30 meter) in Rotterdam network

D.2.2. High speed



(a) Locations of high speed roads (blue) (b) Locations of high speed roads (blue) on Rotterdam map

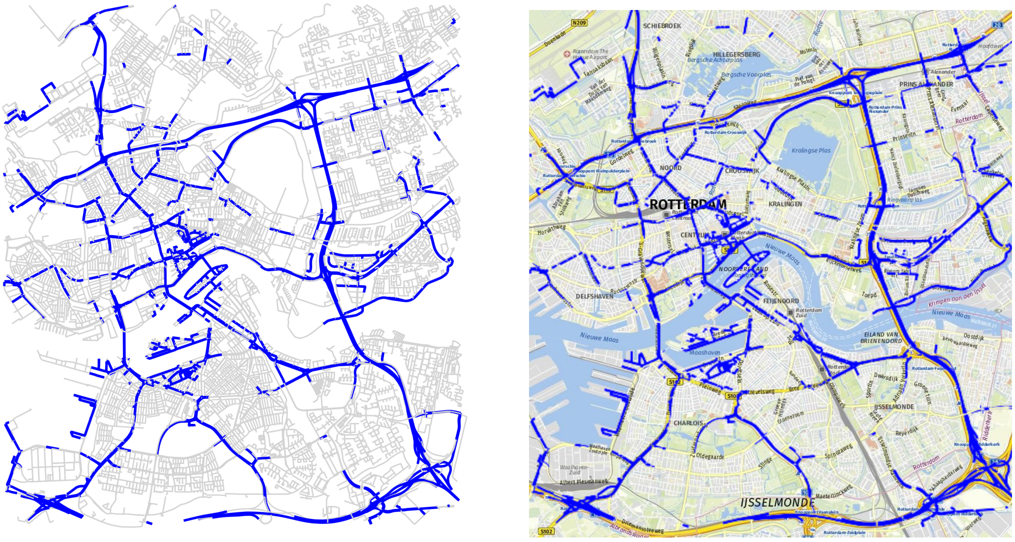
Figure D.6: Visualisation of high speed roads (> 50 km/h) in Rotterdam network

D.2.3. One way roads

(a) Locations of one-way roads (blue) (b) Locations of one-way roads (blue) on Rotterdam map

Figure D.7: Visualisation of one-way roads (> 50 km/h) in Rotterdam network

D.2.4. Wide roads

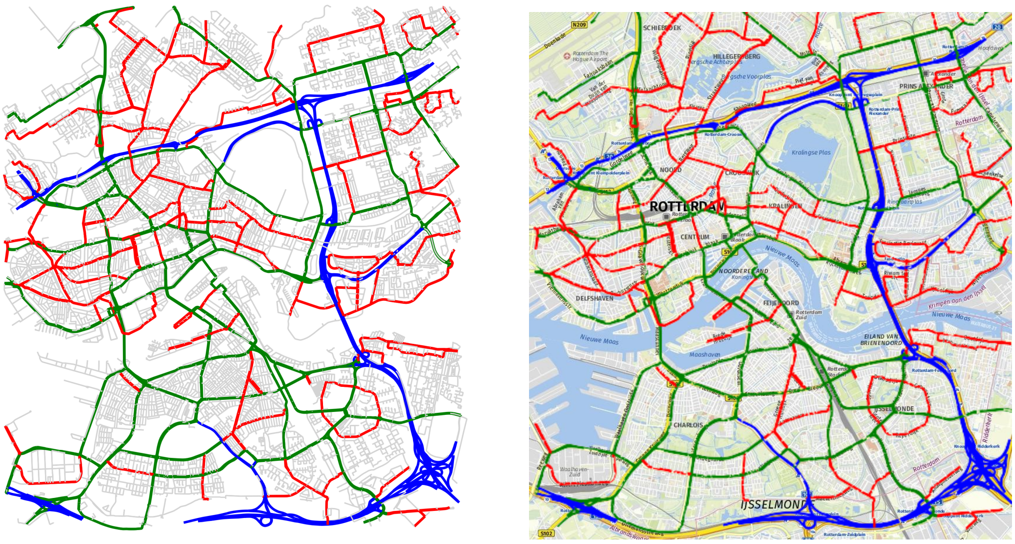


(a) Locations of wide roads (blue)

(b) Locations of wide roads (blue) on Rotterdam map

Figure D.8: Visualisation of wide roads (> 1 lane) in Rotterdam network

D.2.5. Roads categories



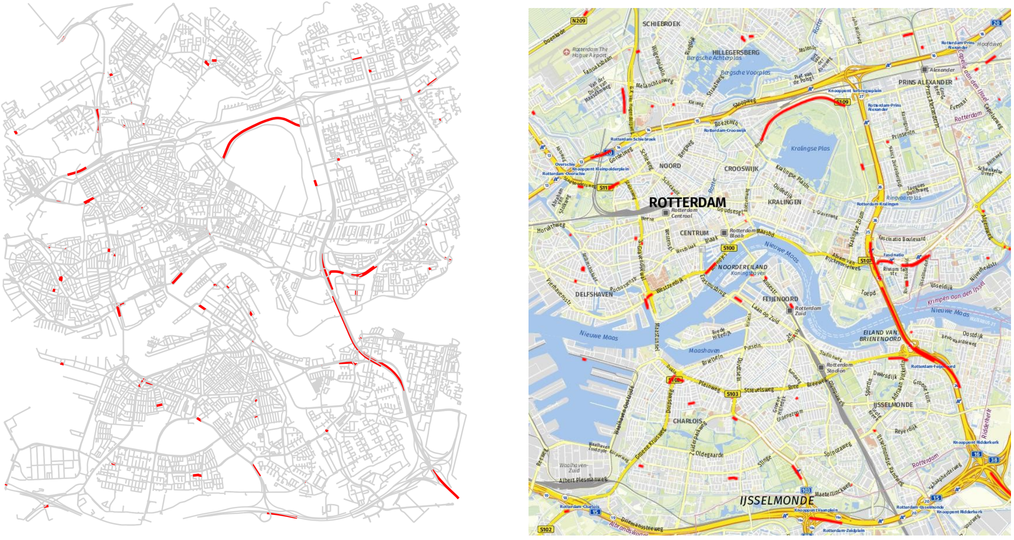
(a) Locations of roads in road categories

(b) Locations of roads in road categories on Rotterdam map

Figure D.9: Visualisation of roads in road categories in the Rotterdam network.

Blue roads are in the categories *motorway*, *motorway_link* or *trunk*. Green roads are in the categories *primary*, *primary_link* or *secondary*. Red roads are in the category *tertiary*.

D.2.6. Cameras



(a) Locations of cameras (red)

(b) Locations of cameras (red) on Rotterdam map

Figure D.10: Visualisation of cameras in Rotterdam network

E

Formalization traffic

For the edge characteristic $traffic$, different formalisations are possible. This appendix describes the different approaches considered and an explanation of the choice of formalisation.

E.1. Traffic measuring methods

Measuring traffic could be done by calculating the driving speed of roads where congestion would cause lower driving speeds. There are two difficulties with this approach. Firstly, the data for driving speed is only available for a part of the road network, which mostly includes main roads. This makes it difficult to generalise this over the whole network. Secondly, driving speed can be influenced by different environmental factors such as time of day, number of lanes, maximum speed or construction. Because of this, the driving speed can become correlated with the other environmental factors in the model. Because of this correlation, the actual influence of traffic can become difficult to determine.

Another option is to rely on assumptions of traffic. The actual traffic is with this not measured but only estimated based on assumptions. This can also be seen as more valid since a fugitive suspect might not be aware of the current traffic situation but can only make an estimate based on experience. This estimation can still be adapted based on the time of day or other environmental factors. For the scope of this project, the traffic estimation is assumed to be constant.

E.2. Traffic formalisation

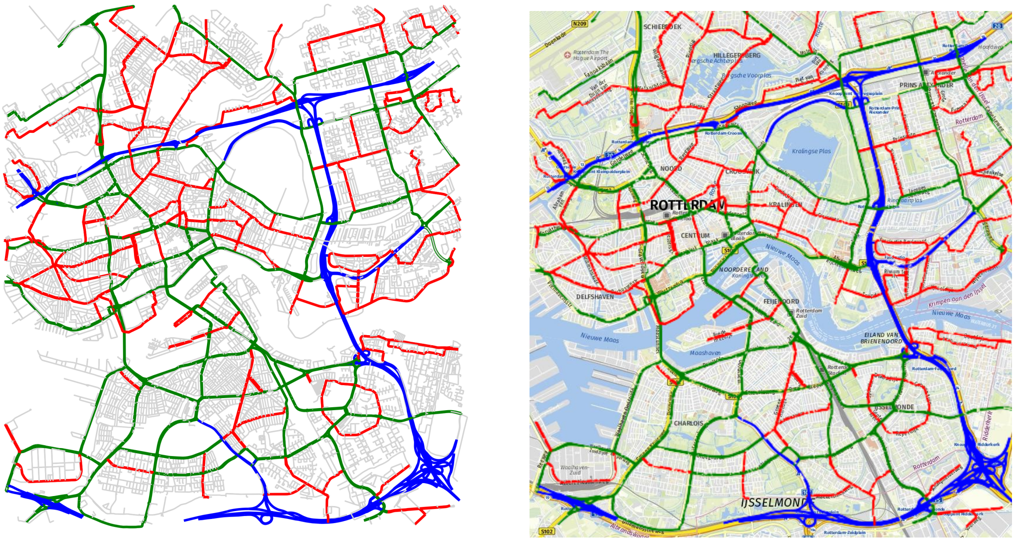
The assumed traffic of a road can be estimated on the characteristics and locations of the roads. The characteristic that influences traffic most is whether a road is of a certain type. Roads can be categorised based on their intended use, capacity, and legal classification. In the Netherlands, there is a division between roads based on whether they are a motorway (road type A) or a highway (road type N). A higher congestion road can be found on the A roads (CBS, n.d.), and we thus assume that, generally, there is a higher level of traffic on these roads.

Openstreetmaps also categorised roads based on their intended use (Wiki Openstreetmaps [OSM], n.d.). The highest categories in this categorisation are motorway and trunk. These are the major highways and the most important road in a network. A lower level is the primary and secondary roads which link large and medium-sized towns. Tertiary roads link smaller towns and villages. An addition to these roads are the links that these roads have, which are the part of the road such as sliproads or ramps that lead to or from the actual road. The road categories are assumed to have different expected traffic densities where importance of a road in a network implies higher traffic density. Because of this, it is chosen to define the traffic into these different categories and to include different traffic influences in the categories.

The difference in the placement of these road categories can be seen in Figure E.1. The number of roads per type can be found in Table E.1

Table E.1: Definition of road type categories

Road type category	OSMNX road types	Total length	Number of edges	Most common maximum speed
Category 1	Motorway, motorway_link, trunk	144 257 m	257	100, 80
Category 2	Primary, primary_link, secondary	263 682 m	2296	50, 80
Category 3	Tertiary	244 750 m	2842	50, 30



(a) Locations of roads in road categories

(b) Locations of roads in road categories on Rotterdam map

Figure E.1: Visualisation of roads in road categories in the Rotterdam network.

Blue roads are in the categories *motorway*, *motorway_link* or *trunk*. Green roads are in the categories *primary*, *primary_link* or *secondary*. Red roads are in the category *tertiary*.

F

Vulnerability analysis

F.1. Method

In this Appendix, the method and results from the vulnerability analysis are presented. For this analysis, each uncertainty in the model is tested to show the vulnerability of the results based on a difference in input values. This ensures that the model represents a change in these input values appropriately and explores the extent of this result change. To do this, sampling is run for each uncertainty variable to determine for which values the results differ in a . This is done in an iterative way, where the scale of the uncertainty values is initially extreme. For factors that have a value above 1 (and thus an avoidance), the maximum value starts at 1000. This value is divided into 10 uniform parts, including 1, to determine at which interval there is no longer a difference in results. This interval is then taken as the new maximum value and again divided into 10 equal parts. This process is iteratively performed until there is no difference between the results from the maximum and the results from the value one below the maximum value. For factors with a value below 1 (and thus a preference), the same process is executed but in the opposite direction. The same set of start and end points is used for each iteration, and the remaining input variables are set to the same values as in the base case, which is described in subsection F.2.1.

F.2. Vulnerability analysis results

F.2.1. Base case

To compare the resulting routes based on input values, a base case is used. In this base case, the influence of all behavioural factors is removed, and only the rational model is used. The values of the behavioural factor multiplication factors MF_i is set to 1, $One\_way\_possible$ is set to False. The number of paths is set to 5. The base case will be used to compare the scenarios with the routes where the uncertainty values are adjusted. The route network and the outcome values can be found in Table F.1 and Figure F.1.

Table F.1: Outcome values of base case

	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
base case	1.0	0.0	2.696	0.458	5.051	9.922

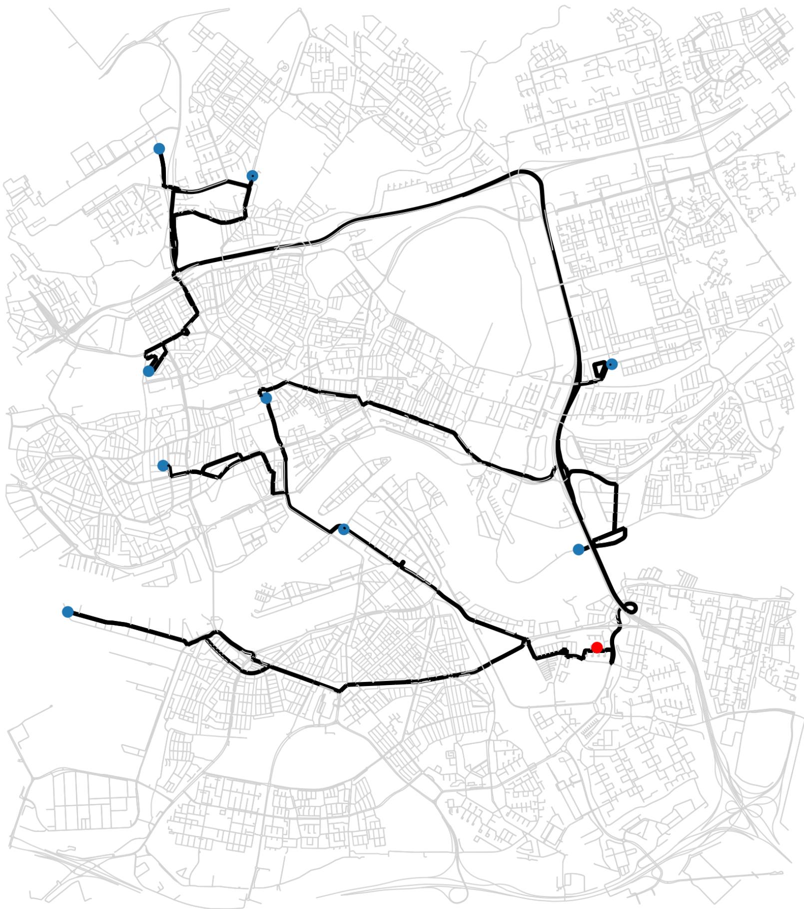


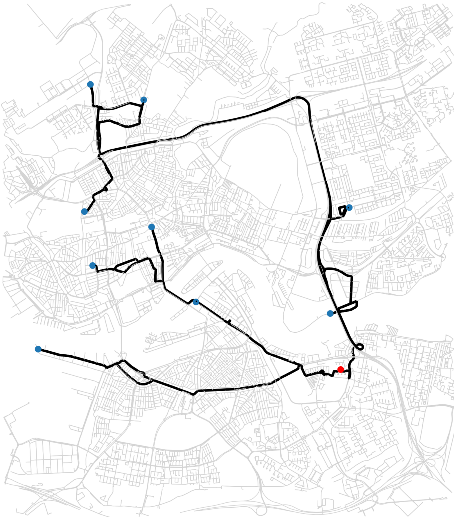
Figure F.1: Base case routes

F.2.2. Result vulnerability analysis: $MF_{camera\ avoidance}$

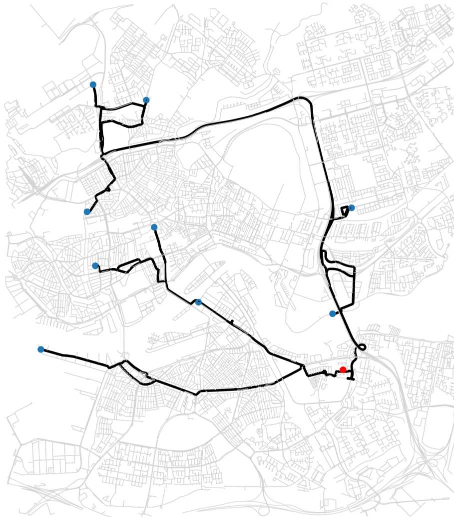
For the input value $MF_{camera\ avoidance}$ the output is seen to variate mainly among the lower values between 1 and 4, as seen in Table F.2. This value difference is also seen in the visualisation of routes, as seen in Figure F.2. Here it is seen that only a limited set of routes is diverted from the original paths in the base case at both low and high values.

Table F.2: Model output from uncertainty analysis on $MF_{camera\ avoidance}$

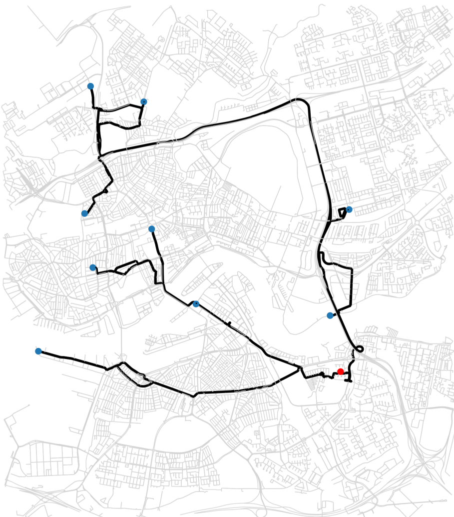
MF_{CA}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	2.696	0.458	5.051	9.922
2	1.028	0.003	2.816	0.400	5.161	9.950
3	1.079	0.009	2.819	0.420	5.323	10.484
4	1.123	0.039	2.803	0.421	5.451	10.939
5	1.123	0.039	2.803	0.421	5.451	10.939
6	1.123	0.039	2.803	0.421	5.451	10.939
7	1.123	0.039	2.803	0.421	5.451	10.939
8	1.123	0.039	2.803	0.421	5.451	10.939
9	1.123	0.039	2.803	0.421	5.451	10.939
10	1.123	0.039	2.803	0.421	5.451	10.939
20	1.123	0.039	2.803	0.421	5.451	10.939
30	1.123	0.039	2.803	0.421	5.451	10.939
40	1.123	0.039	2.803	0.421	5.451	10.939
50	1.123	0.039	2.803	0.421	5.451	10.939
60	1.123	0.039	2.803	0.421	5.451	10.939
70	1.123	0.039	2.803	0.421	5.451	10.939
80	1.123	0.039	2.803	0.421	5.451	10.939
90	1.123	0.039	2.803	0.421	5.451	10.939
100	1.123	0.039	2.803	0.421	5.451	10.939
200	1.123	0.039	2.803	0.421	5.451	10.939
300	1.123	0.039	2.803	0.421	5.451	10.939
400	1.123	0.039	2.803	0.421	5.451	10.939
500	1.123	0.039	2.803	0.421	5.451	10.939
600	1.123	0.039	2.803	0.421	5.451	10.939
700	1.123	0.039	2.803	0.421	5.451	10.939
800	1.123	0.039	2.803	0.421	5.451	10.939
900	1.123	0.039	2.803	0.421	5.451	10.939
1000	1.123	0.039	2.803	0.421	5.451	10.939



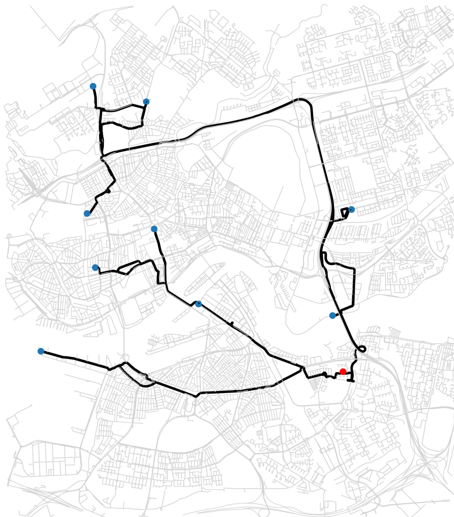
(a) Route visualisation of model run with $MF_{Camera\ avoidance} = 2$



(b) Route visualisation of model run with $MF_{Camera\ avoidance} = 4$



(c) Route visualisation of model run with $MF_{Camera\ avoidance} = 4$



(d) Route visualisation of model run with $MF_{Camera\ avoidance} = 1000$

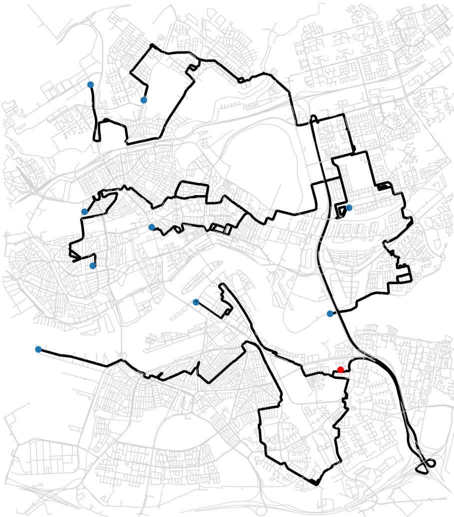
Figure F.2: Route visualisation for different values of $MF_{Camera\ avoidance}$

F.2.3. Result vulnerability analysis: $MF_{obstacle\ avoidance}$

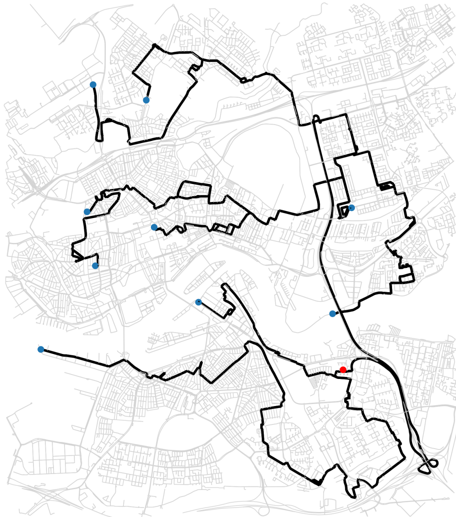
For the values of input variable $MF_{obstacle\ avoidance}$, it can be seen in Table F.3 that the outputs differ until values around 320. It can be seen in Figure F.3 that there are large changes between the routes with obstacle avoidance and the base case. The changes between the values of obstacle avoidance are small.

Table F.3: Model output from uncertainty analysis on $MF_{obstacle\ avoidance}$

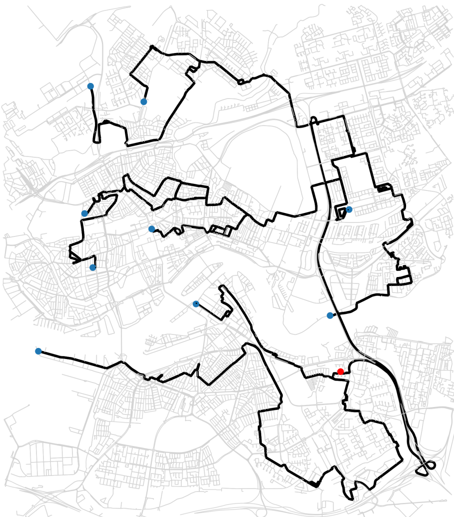
MF_{OA}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	2.696	0.458	5.051	9.922
100	2.986	0.766	2.627	1.206	5.348	9.834
200	3.044	0.696	2.624	1.215	5.531	8.474
300	3.066	0.712	2.591	1.199	5.462	8.552
310	3.071	0.713	2.595	1.200	5.452	8.512
320	3.077	0.716	2.610	1.205	5.467	8.394
321	3.077	0.716	2.610	1.205	5.467	8.394
322	3.077	0.716	2.610	1.205	5.467	8.394
323	3.077	0.716	2.610	1.205	5.467	8.394
324	3.077	0.716	2.610	1.205	5.467	8.394
325	3.077	0.716	2.610	1.205	5.467	8.394
326	3.077	0.716	2.610	1.205	5.467	8.394
327	3.077	0.716	2.610	1.205	5.467	8.394
328	3.084	0.724	2.623	1.212	5.479	8.327
329	3.084	0.724	2.623	1.212	5.479	8.327
330	3.084	0.724	2.623	1.212	5.479	8.327
340	3.084	0.724	2.623	1.212	5.479	8.327
350	3.084	0.724	2.623	1.212	5.479	8.327
360	3.084	0.724	2.623	1.212	5.479	8.327
370	3.084	0.724	2.623	1.212	5.479	8.327
380	3.084	0.724	2.623	1.212	5.479	8.327
390	3.084	0.724	2.623	1.212	5.479	8.327
400	3.084	0.724	2.623	1.212	5.479	8.327
500	3.084	0.724	2.623	1.212	5.479	8.327
600	3.084	0.724	2.623	1.212	5.479	8.327
700	3.084	0.724	2.623	1.212	5.479	8.327
800	3.084	0.724	2.623	1.212	5.479	8.327
900	3.084	0.724	2.623	1.212	5.479	8.327
1000	3.084	0.724	2.623	1.212	5.479	8.327



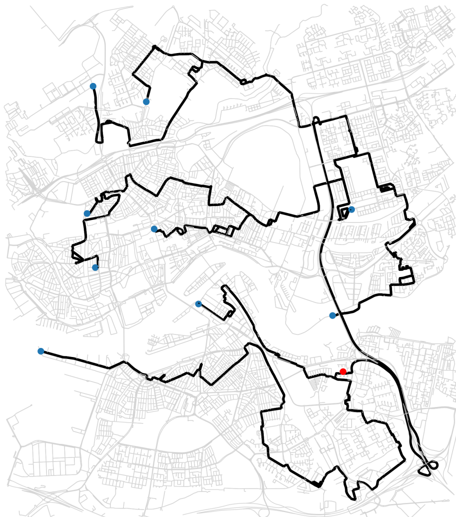
(a) Route visualisation of model run with $MF_{obstacle\,avoidance} = 100$



(b) Route visualisation of model run with $MF_{obstacle\,avoidance} = 200$



(c) Route visualisation of model run with $MF_{obstacle\,avoidance} = 300$



(d) Route visualisation of model run with $MF_{obstacle\,avoidance} = 400$

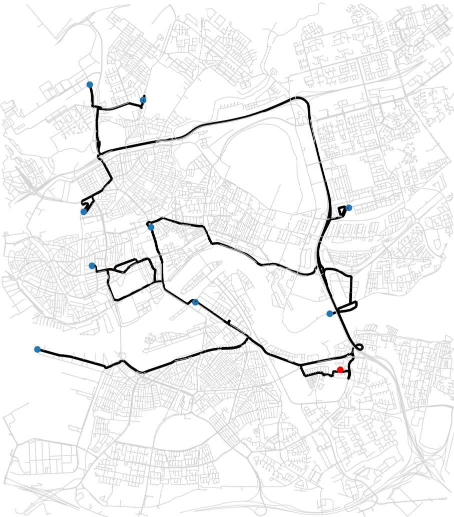
Figure F.3: Route visualisation for different values of $MF_{obstacle\,avoidance}$

F.2.4. Result vulnerability analysis: $MF_{lane\ preference}$

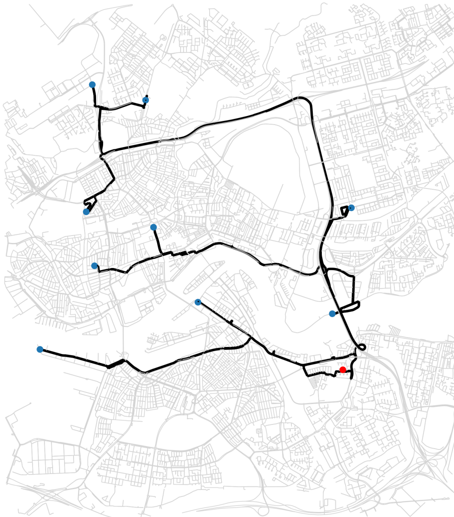
For the input variable $MF_{lane\ preference}$ the output is seen to differ at all ranges, as seen in Table F.4. In Figure F.4 can be seen that the routes differ among the different values but that the difference between these routes is dependent on the input value. Not all routes are seen to be influenced.

Table F.4: Model output from uncertainty analysis on $MF_{lane\ preference}$

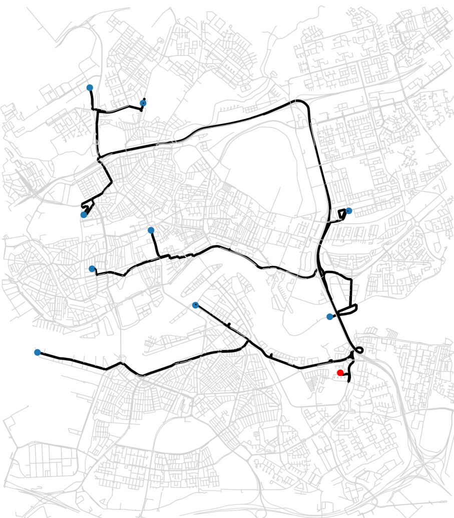
MF_{LP}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
0.1	1.112	0.056	3.289	0.777	5.341	9.827
0.2	1.010	0.006	3.515	0.898	5.120	9.434
0.3	0.968	0.003	3.543	0.807	5.645	8.746
0.4	0.968	0.003	3.543	0.807	5.645	8.746
0.5	0.964	0.003	3.537	0.802	5.625	8.803
0.6	0.960	0.003	3.451	0.913	5.594	9.020
0.7	0.958	0.003	3.093	0.958	5.575	9.194
0.8	0.963	0.002	2.813	0.400	5.544	9.071
0.9	0.968	0.002	2.814	0.345	5.572	9.010
1	1.000	0.000	2.696	0.458	5.051	9.922



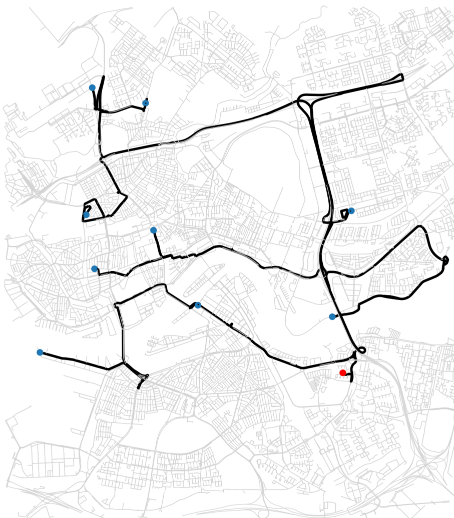
(a) Route visualisation of model run with $MF_{lane\,preference} = 0.8$



(b) Route visualisation of model run with $MF_{lane\,preference} = 0.6$



(c) Route visualisation of model run with $MF_{lane\,preference} = 0.3$



(d) Route visualisation of model run with $MF_{lane\,preference} = 0.1$

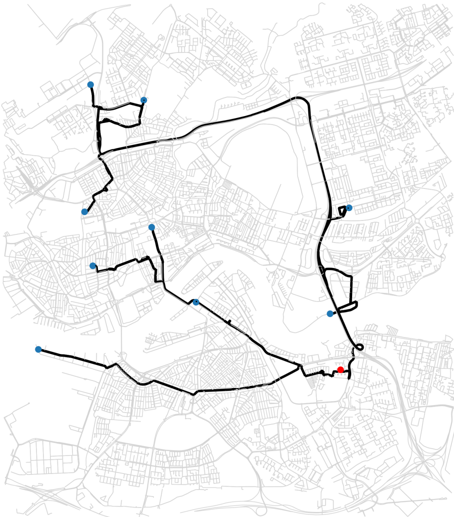
Figure F.4: Route visualisation for different values of $MF_{lane\,preference}$

F.2.5. Result vulnerability analysis: $MF_{residential\ preference}$

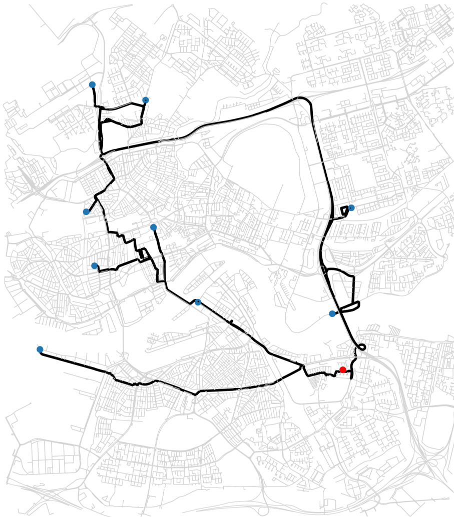
For the $MF_{residential\ preference}$ input value, it is seen that the output differs at each value of the input. This difference in output routes can be seen in Figure F.5 through the difference in routes and the use of residential roads.

Table F.5: Model output from uncertainty analysis on $MF_{residential\ preference}$

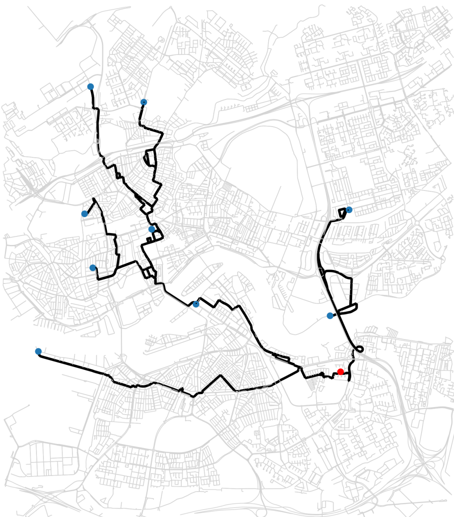
MF_{RP}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
0.1	1.982	0.962	3.910	2.233	5.417	5.720
0.2	1.917	1.025	3.681	2.012	5.141	7.368
0.3	1.861	1.006	3.560	2.041	5.101	7.505
0.4	1.513	0.449	2.891	0.986	4.778	7.782
0.5	1.256	0.092	2.835	0.498	5.221	7.166
0.6	1.039	0.003	2.696	0.373	4.995	9.253
0.7	1.018	0.002	2.719	0.366	5.047	9.556
0.8	1.015	0.002	2.724	0.363	5.083	9.527
0.9	1.011	0.002	2.723	0.364	5.111	9.596
1	1.000	0.000	2.696	0.458	5.051	9.922



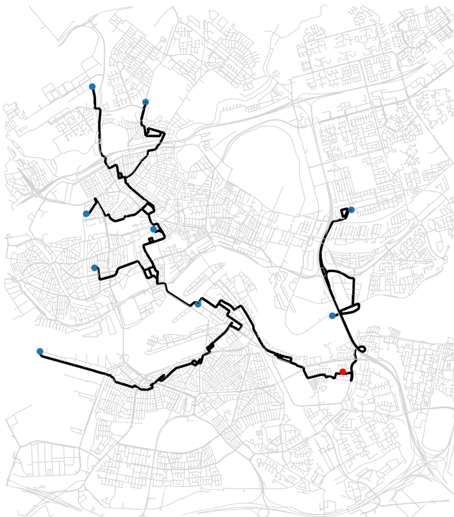
(a) Route visualisation of model run with $MF_{residential\,preference} = 0.8$



(b) Route visualisation of model run with $MF_{residential\,preference} = 0.6$



(c) Route visualisation of model run with $MF_{residential\,preference} = 0.3$



(d) Route visualisation of model run with $MF_{lane\,preference} = 0.1$

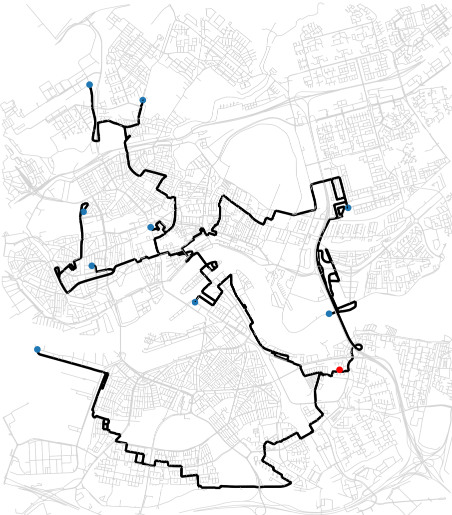
Figure F.5: Route visualisation for different values of $MF_{residential\,preference}$

F.2.6. Result vulnerability analysis: $MF_{one\ way\ avoidance}$

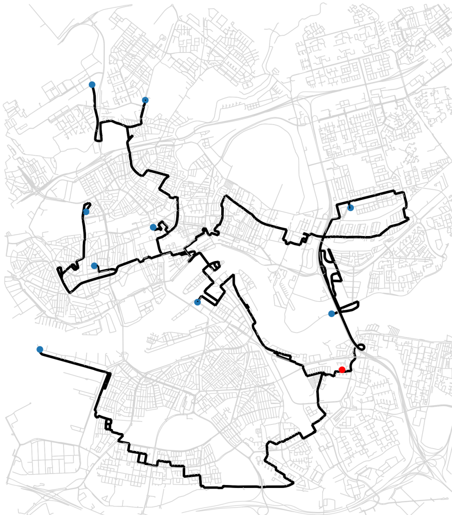
For the input variable $MF_{one\ way\ avoidance}$, it was seen that the output differs in intervals, namely that for a certain input range, the same route output is found as seen in Table F.6. The values were seen to change up until the value of 590. The paths are variated throughout the variable space as seen in Figure F.6.

Table F.6: Model output from uncertainty analysis on $MF_{one\ way\ avoidance}$

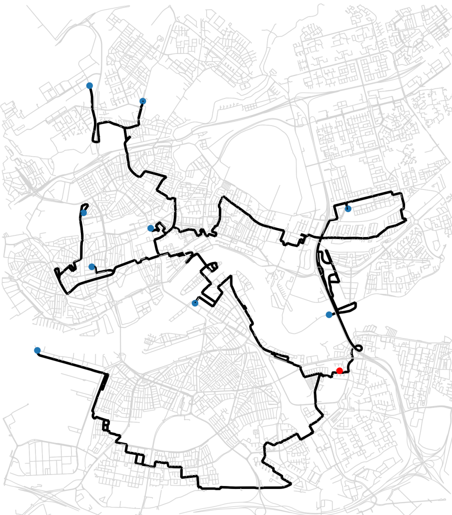
MF_{OW}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	2.696	0.458	5.051	9.922
100	2.832	1.900	3.479	2.428	5.851	4.823
200	3.257	3.766	3.660	2.726	5.349	7.606
300	3.257	3.766	3.660	2.726	5.349	7.606
400	3.369	4.746	3.739	2.805	4.779	8.909
500	3.572	7.011	3.882	2.902	4.925	8.856
510	3.572	7.011	3.882	2.902	4.925	8.856
520	3.572	7.011	3.882	2.902	4.925	8.856
530	3.572	7.011	3.882	2.902	4.925	8.856
540	3.572	7.011	3.882	2.902	4.925	8.856
550	3.572	7.011	3.882	2.902	4.925	8.856
560	3.572	7.011	3.882	2.902	4.925	8.856
570	3.572	7.011	3.882	2.902	4.925	8.856
580	3.572	7.011	3.882	2.902	4.925	8.856
590	3.572	7.011	3.882	2.902	4.925	8.856
591	3.572	7.011	3.882	2.902	4.925	8.856
592	3.572	7.011	3.882	2.902	4.925	8.856
593	3.572	7.011	3.882	2.902	4.925	8.856
594	3.689	6.593	4.036	3.004	5.032	9.141
595	3.689	6.593	4.036	3.004	5.032	9.141
596	3.689	6.593	4.036	3.004	5.032	9.141
597	3.689	6.593	4.036	3.004	5.032	9.141
598	3.689	6.593	4.036	3.004	5.032	9.141
599	3.689	6.593	4.036	3.004	5.032	9.141
600	3.689	6.593	4.036	3.004	5.032	9.141
700	3.689	6.593	4.036	3.004	5.032	9.141
800	3.689	6.593	4.036	3.004	5.032	9.141
900	3.689	6.593	4.036	3.004	5.032	9.141
1000	3.689	6.593	4.036	3.004	5.032	9.141



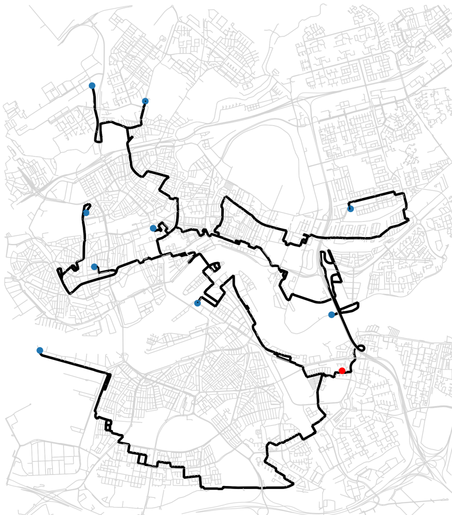
(a) Route visualisation of model run with $MF_{one\,way\,preference} = 100$



(b) Route visualisation of model run with $MF_{one\,way\,preference} = 200$



(c) Route visualisation of model run with $MF_{one\,way\,preference} = 400$



(d) Route visualisation of model run with $MF_{one\,way\,preference} = 600$

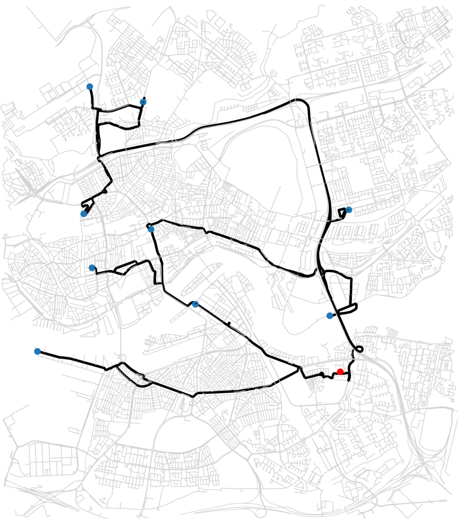
Figure F.6: Route visualisation for different values of $MF_{one\,way\,preference}$

F.2.7. Result vulnerability analysis: $MF_{high\ speed\ preference}$

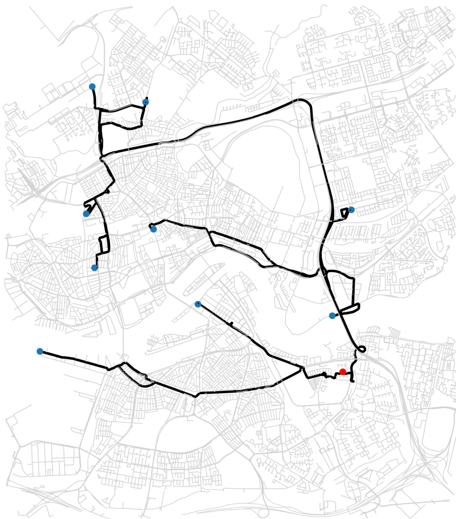
For the input variable $MF_{high\ speed\ preference}$ it is seen in Table F.7 that for almost all values, the output differs. This difference can be seen in the route visualisation in Figure F.7. Here it can be seen that some routes are changed but some routes remain the same as the base case.

Table F.7: Model output from uncertainty analysis on $MF_{high\ speed\ preference}$

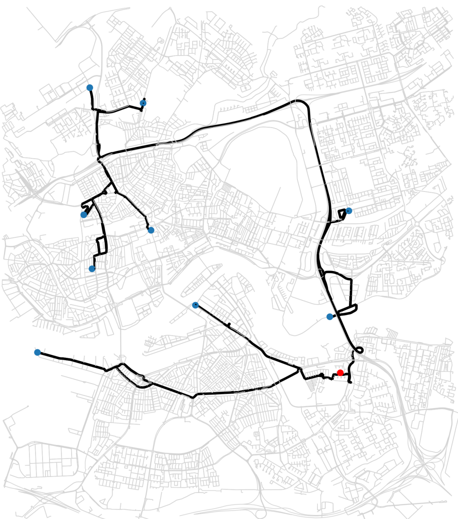
MF_{HS}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
0.1	1.114	0.010	3.183	0.926	5.642	9.270
0.2	1.006	0.009	3.349	1.431	5.411	10.341
0.3	0.971	0.002	3.375	1.350	4.934	10.715
0.4	0.971	0.002	3.375	1.350	4.934	10.715
0.5	0.983	0.002	3.332	1.339	4.995	10.513
0.6	1.003	0.006	3.017	1.313	5.115	9.778
0.7	1.017	0.004	2.655	0.778	5.227	9.096
0.8	1.017	0.003	2.645	0.693	5.215	9.224
0.9	1.004	0.000	2.664	0.535	5.077	9.766
1	1.000	0.000	2.696	0.458	5.051	9.922



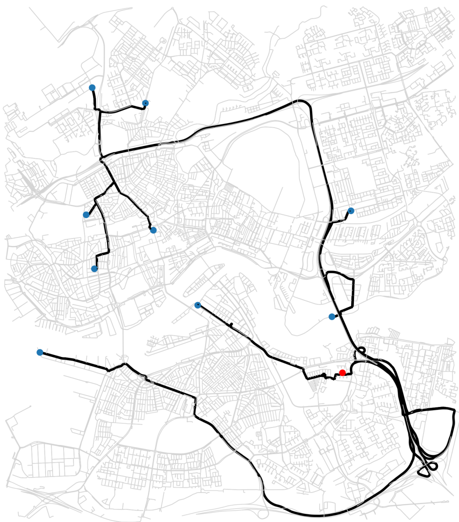
(a) Route visualisation of model run with $MF_{high\,speed\,preference} = 0.8$



(b) Route visualisation of model run with $MF_{high\,speed\,preference} = 0.6$



(c) Route visualisation of model run with $MF_{high\,speed\,preference} = 0.3$



(d) Route visualisation of model run with $MF_{high\,speed\,preference} = 0.1$

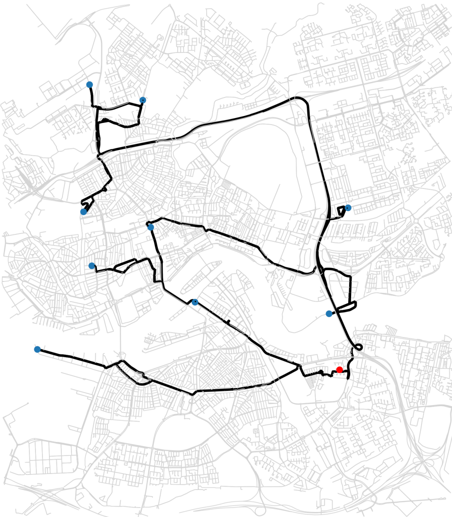
Figure F.7: Route visualisation for different decreasing values of $MF_{high\,speed\,preference}$

F.2.8. Result vulnerability analysis: $MF_{short\ road\ preference}$

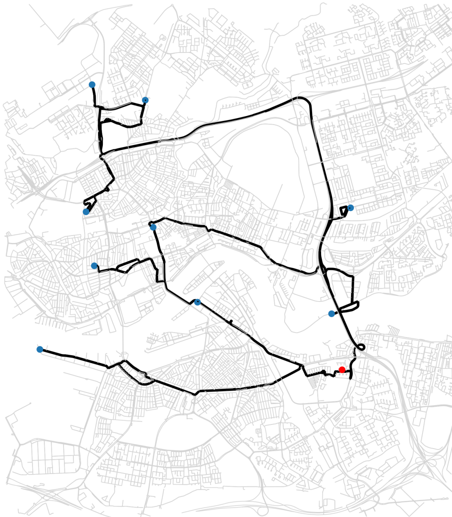
In Table F.8, it can be seen that the output values differ slightly for each input variation. This change cannot clearly be seen from the visualisation, as seen in Figure F.8 where the difference in chosen routes is not visible.

Table F.8: Model output from uncertainty analysis on $MF_{short\ road\ preference}$

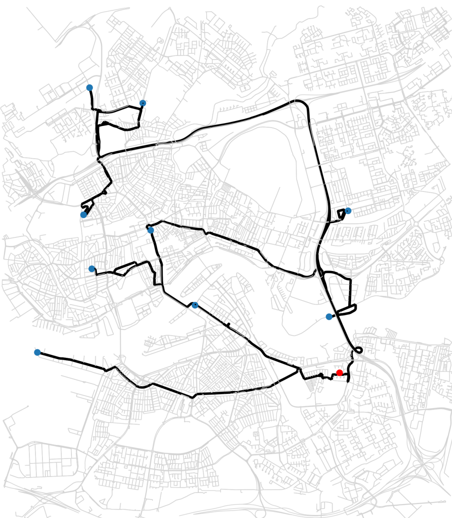
MF_{SR}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
0.1	1.044	0.005	2.599	0.582	5.231	8.956
0.2	1.025	0.002	2.639	0.525	5.140	9.251
0.3	1.026	0.001	2.637	0.528	5.143	9.232
0.4	1.018	0.001	2.665	0.462	5.152	9.358
0.5	1.016	0.001	2.665	0.462	5.135	9.506
0.6	1.016	0.001	2.665	0.462	5.135	9.506
0.7	1.014	0.001	2.666	0.460	5.120	9.638
0.8	1.014	0.001	2.666	0.460	5.120	9.638
0.9	1.014	0.001	2.666	0.460	5.120	9.638
1	1.000	0.000	2.696	0.458	5.051	9.922



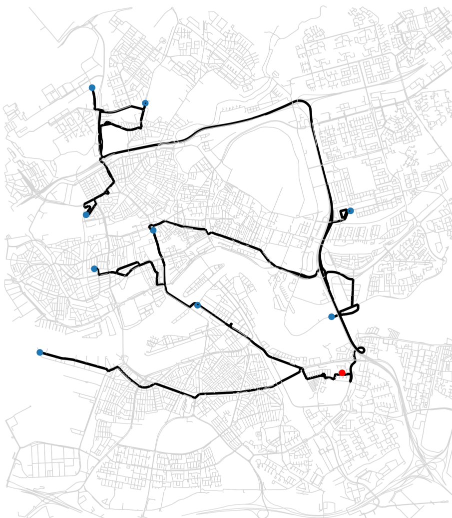
(a) Route visualisation of model run with $MF_{short\,road\,preference} = 0.8$



(b) Route visualisation of model run with $MF_{short\,road\,preference} = 0.6$



(c) Route visualisation of model run with $MF_{short\,road\,preference} = 0.3$



(d) Route visualisation of model run with $MF_{short\,road\,preference} = 0.1$

Figure F.8: Route visualisation for different decreasing values of $MF_{short\,road\,preference}$

F.2.9. Result vulnerability analysis: One way possible

The value range of the $one\ way\ possible$ is limited to True and False and thus only the True case can show the difference in routes. The result of setting the variable to True can be seen in Figure F.9 where it is seen that the routes are different from the basecase.

Table F.9: Model output from uncertainty analysis on One way possible

one way possible	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
False	1.000	0.000	2.696	0.458	5.051	9.922
True	1.0139	0.054	2.539	0.456	5.506	7.709

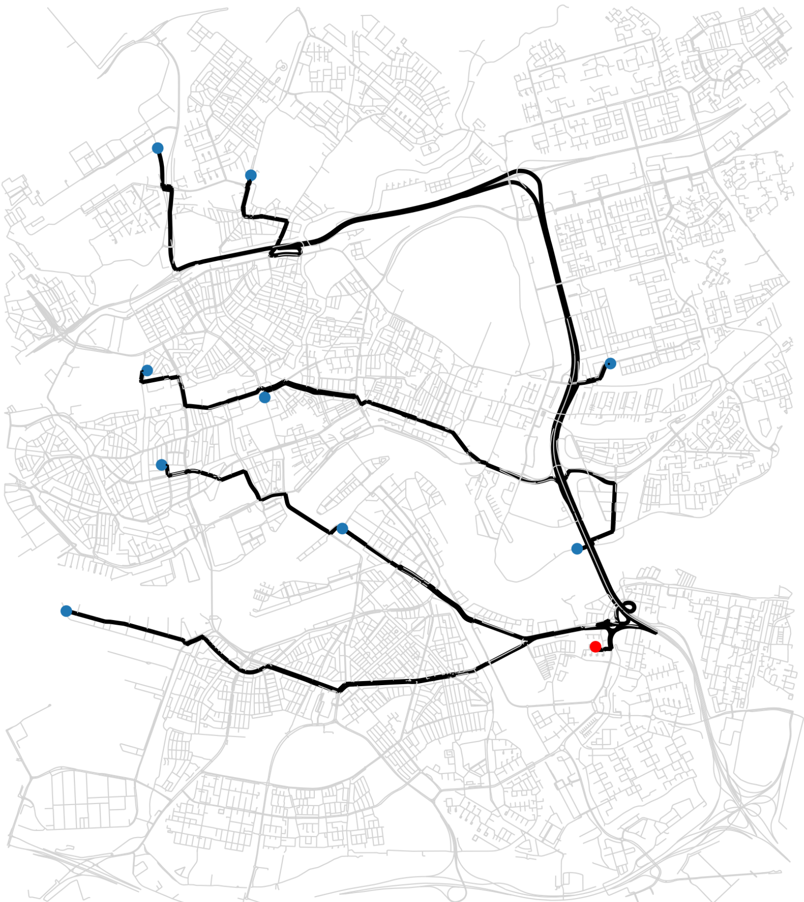


Figure F.9: Route visualisation of $One\_way\_possible = True$

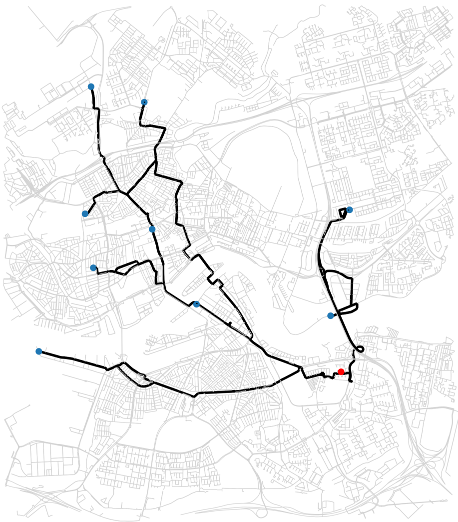
F.2.10. Result vulnerability analysis: Traffic avoidance

For the results of the traffic avoidance input space, there is a division between the TA_i values and the $MF_{traffic\_avoidance}$ behavioural multiplication factor. First, the analysis of the separate TA_i values will be presented. Then, the analysis of the $MF_{traffic_avoidance}$ is shown where all TA_i are assumed to be equal to 1.

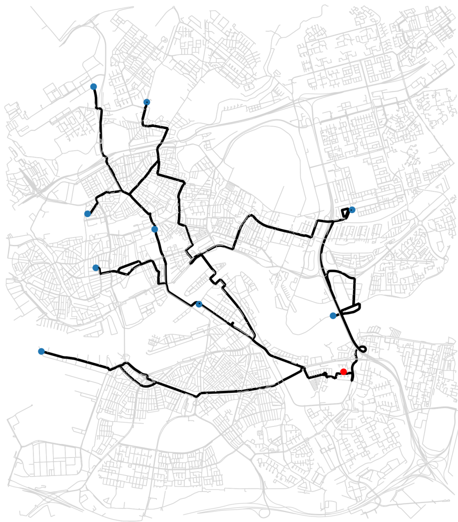
Result vulnerability analysis: TA_1
For the TA_1 input variable, the difference in output is mainly seen in the values between 1 and 5, as seen in Table F.10. This is visualised in Figure F.10 where it can be seen that the routes vary from the base case but that only select routes differ when the value of TA_1 becomes higher.

Table F.10: Model output from uncertainty analysis on TA_1

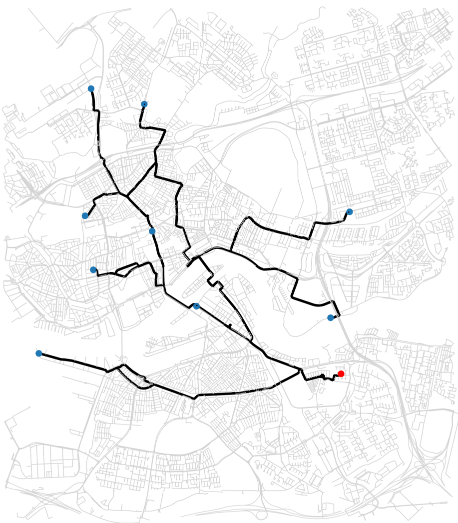
TA_1	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	2.696	0.458	5.051	9.922
2	1.456	0.550	3.284	1.967	4.644	9.062
3	1.456	0.550	3.284	1.967	4.644	9.062
4	1.602	0.578	3.359	2.227	4.919	8.709
5	2.031	1.292	4.166	1.934	5.738	9.623
6	2.031	1.292	4.166	1.934	5.738	9.623
7	2.031	1.292	4.166	1.934	5.738	9.623
8	2.031	1.292	4.166	1.934	5.738	9.623
9	2.031	1.292	4.166	1.934	5.738	9.623
10	2.031	1.292	4.166	1.934	5.738	9.623
20	2.031	1.292	4.166	1.934	5.738	9.623
30	2.031	1.292	4.166	1.934	5.738	9.623
40	2.031	1.292	4.166	1.934	5.738	9.623
50	2.031	1.292	4.166	1.934	5.738	9.623
60	2.031	1.292	4.166	1.934	5.738	9.623
70	2.031	1.292	4.166	1.934	5.738	9.623
80	2.031	1.292	4.166	1.934	5.738	9.623
90	2.031	1.292	4.166	1.934	5.738	9.623
100	2.031	1.292	4.166	1.934	5.738	9.623
200	2.031	1.292	4.166	1.934	5.738	9.623
300	2.031	1.292	4.166	1.934	5.738	9.623
400	2.031	1.292	4.166	1.934	5.738	9.623
500	2.031	1.292	4.166	1.934	5.738	9.623
600	2.031	1.292	4.166	1.934	5.738	9.623
700	2.031	1.292	4.166	1.934	5.738	9.623
800	2.031	1.292	4.166	1.934	5.738	9.623
900	2.031	1.292	4.166	1.934	5.738	9.623
1000	2.031	1.292	4.166	1.934	5.738	9.623



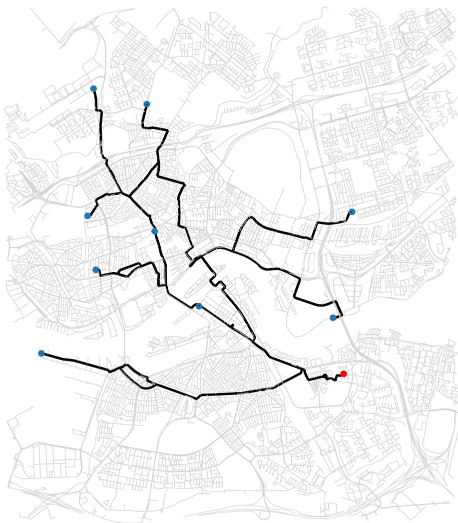
(a) Route visualisation of model run with $TA_1 = 2$



(b) Route visualisation of model run with $TA_1 = 4$



(c) Route visualisation of model run with $TA_1 = 5$



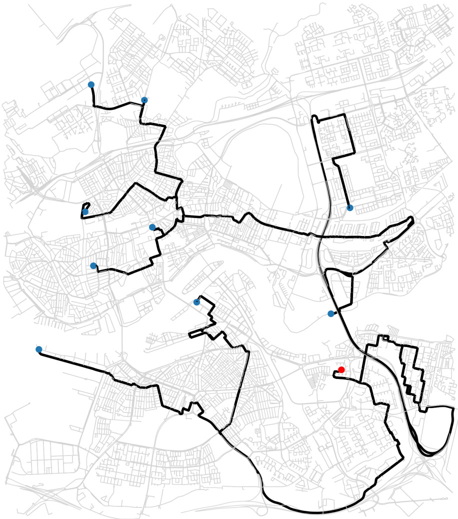
(d) Route visualisation of model run with $TA_1 = 10$

Figure F.10: Route visualisation for different values of TA_1

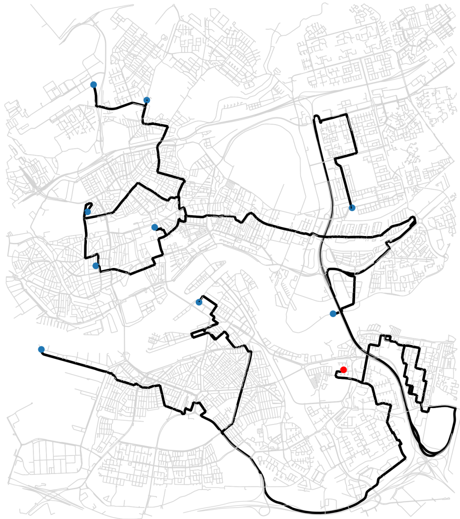
Result vulnerability analysis: TA_2
For the input variable TA_2 it can be seen in Table F.11 that there is a difference in output until around the value of 160. In the visualisation in Figure F.11 it can be seen that some routes differ from the base case at low levels of TA_2 and that the routes differ more when the value becomes larger.

Table F.11: Model output from uncertainty analysis on TA_2

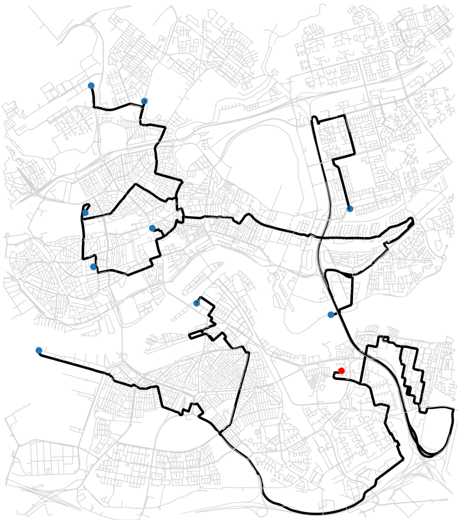
TA_2	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	2.696	0.458	5.051	9.922
100	3.994	2.321	4.149	1.682	6.386	5.742
110	3.994	2.321	4.149	1.682	6.386	5.742
120	3.994	2.321	4.149	1.682	6.386	5.742
130	3.994	2.321	4.149	1.682	6.386	5.742
140	3.994	2.321	4.149	1.682	6.386	5.742
141	3.994	2.321	4.149	1.682	6.386	5.742
142	3.994	2.321	4.149	1.682	6.386	5.742
143	3.994	2.321	4.149	1.682	6.386	5.742
144	3.994	2.321	4.149	1.682	6.386	5.742
145	3.994	2.321	4.149	1.682	6.386	5.742
146	3.999	2.312	4.144	1.677	6.400	5.630
147	4.004	2.303	4.142	1.674	6.414	5.520
148	4.014	2.288	4.151	1.679	6.440	5.321
149	4.014	2.288	4.151	1.679	6.440	5.321
150	4.020	2.279	4.162	1.687	6.456	5.213
160	4.020	2.279	4.162	1.687	6.456	5.213
170	4.020	2.279	4.162	1.687	6.456	5.213
180	4.020	2.279	4.162	1.687	6.456	5.213
190	4.020	2.279	4.162	1.687	6.456	5.213
200	4.020	2.279	4.162	1.687	6.456	5.213
300	4.020	2.279	4.162	1.687	6.456	5.213
400	4.020	2.279	4.162	1.687	6.456	5.213
500	4.020	2.279	4.162	1.687	6.456	5.213
600	4.020	2.279	4.162	1.687	6.456	5.213
700	4.020	2.279	4.162	1.687	6.456	5.213
800	4.020	2.279	4.162	1.687	6.456	5.213
900	4.020	2.279	4.162	1.687	6.456	5.213
1000	4.020	2.279	4.162	1.687	6.456	5.213



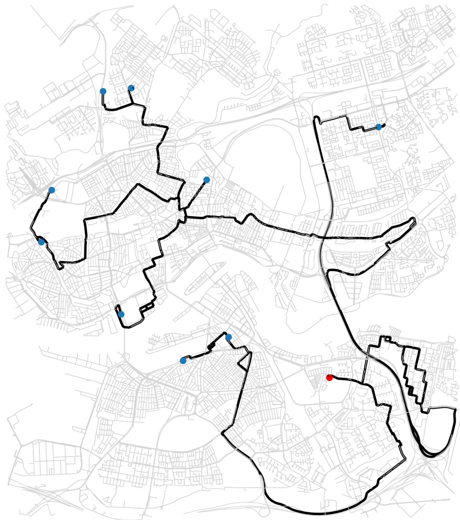
(a) Route visualisation of model run with $TA_2 = 100$



(b) Route visualisation of model run with $TA_2 = 147$



(c) Route visualisation of model run with $TA_2 = 148$



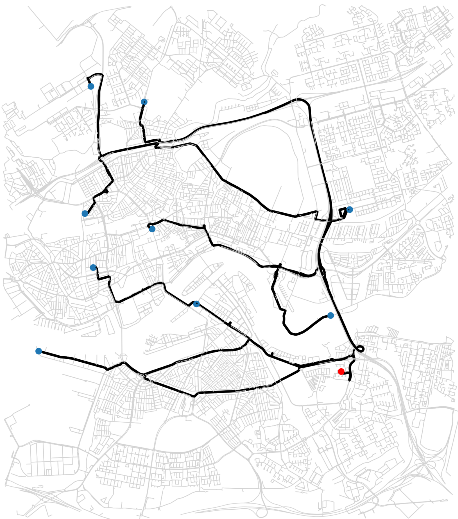
(d) Route visualisation of model run with $TA_2 = 200$

Figure F.11: Route visualisation for different values of TA_2

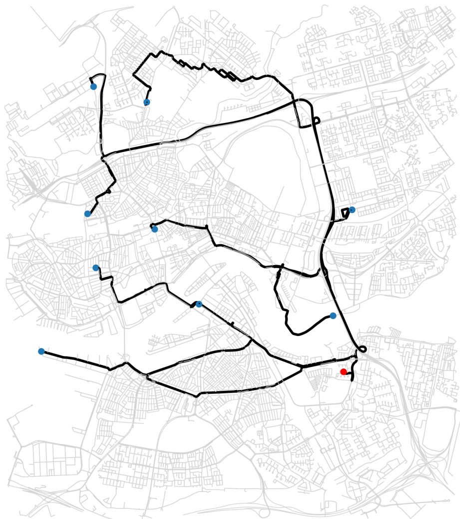
Result vulnerability analysis: TA_3
For the input variable TA_3, it can be seen in Table F.12 that the output varies until TA_3 reaches values around 60. In the visualisation in Figure F.12 it can be seen that throughout the different values, some routes change, and some routes remain the same.

Table F.12: Model output from uncertainty analysis on TA_3

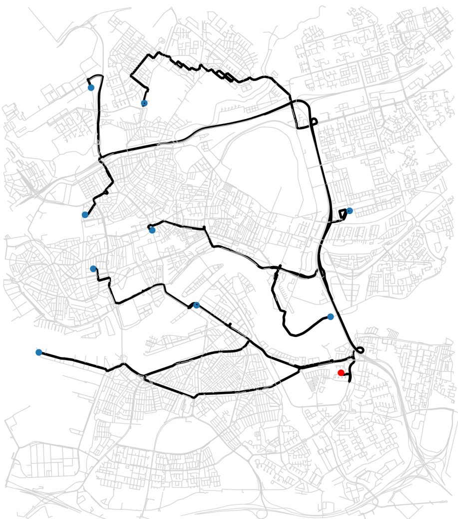
TA_3	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	2.696	0.458	5.051	9.922
10	1.179	0.145	2.952	0.697	5.499	9.857
20	1.247	0.285	2.927	0.732	4.523	11.197
30	1.249	0.283	2.923	0.730	4.530	11.232
31	1.249	0.283	2.923	0.730	4.530	11.232
32	1.249	0.283	2.923	0.730	4.530	11.232
33	1.251	0.282	2.917	0.722	4.538	11.276
34	1.251	0.282	2.917	0.722	4.538	11.276
35	1.255	0.280	2.909	0.710	4.549	11.348
36	1.255	0.280	2.909	0.710	4.549	11.348
37	1.255	0.280	2.909	0.710	4.549	11.348
38	1.255	0.280	2.909	0.710	4.549	11.348
39	1.255	0.280	2.909	0.710	4.549	11.348
40	1.256	0.280	2.902	0.690	4.552	11.376
50	1.256	0.280	2.902	0.690	4.552	11.376
60	1.256	0.280	2.902	0.690	4.552	11.376
70	1.256	0.280	2.902	0.690	4.552	11.376
80	1.256	0.280	2.902	0.690	4.552	11.376
90	1.256	0.280	2.902	0.690	4.552	11.376
100	1.256	0.280	2.902	0.690	4.552	11.376
200	1.256	0.280	2.902	0.690	4.552	11.376
300	1.256	0.280	2.902	0.690	4.552	11.376
400	1.256	0.280	2.902	0.690	4.552	11.376
500	1.256	0.280	2.902	0.690	4.552	11.376
600	1.256	0.280	2.902	0.690	4.552	11.376
700	1.256	0.280	2.902	0.690	4.552	11.376
800	1.256	0.280	2.902	0.690	4.552	11.376
900	1.256	0.280	2.902	0.690	4.552	11.376
1000	1.256	0.280	2.902	0.690	4.552	11.376



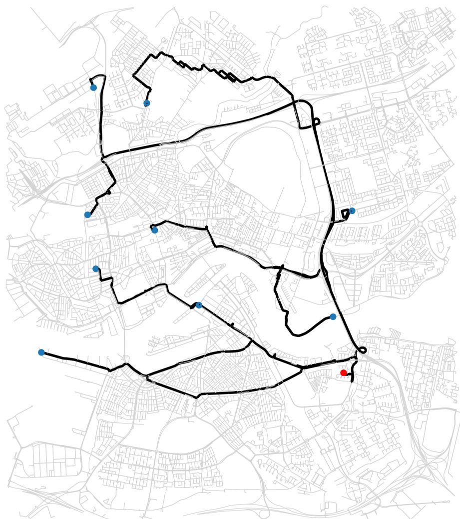
(a) Route visualisation of model run with $TA_3 = 10$



(b) Route visualisation of model run with $TA_3 = 20$



(c) Route visualisation of model run with $TA_3 = 30$



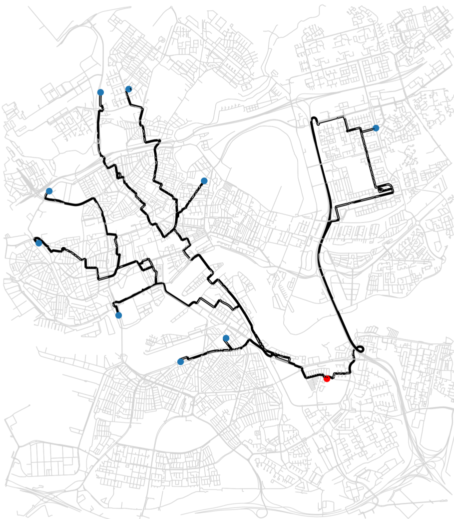
(d) Route visualisation of model run with $TA_3 = 40$

Figure F.12: Route visualisation for different values of TA_3

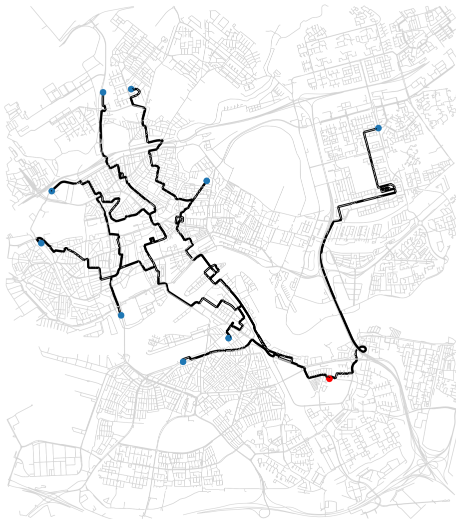
Result vulnerability analysis: $MF_{traffic\ avoidance}$
For the input value $MF_{traffic\_avoidance}$, it can be seen in Table F.13 that output values differ until values around 300. From the output visualisation in Figure F.13 it can be seen that the route network for these different values differs greatly among the different values and when compared to the base case.

Table F.13: Model output values from uncertainty analysis on $MF_{traffic\ avoidance}$

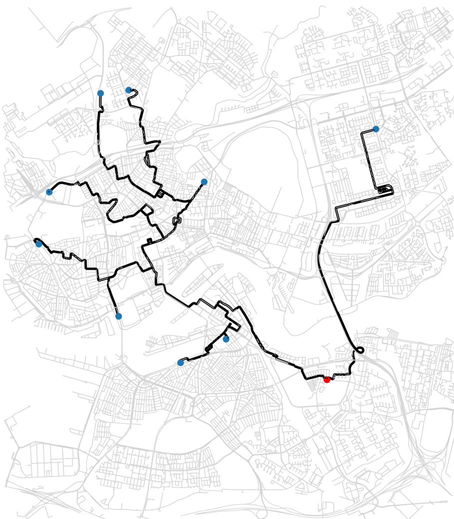
MF_{TA}	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	2.696	0.458	5.051	9.922
100	2.826	1.752	4.066	3.004	6.205	4.216
200	3.125	3.413	4.427	3.017	6.099	5.845
210	3.125	3.413	4.427	3.017	6.099	5.845
220	3.125	3.413	4.427	3.017	6.099	5.845
230	3.125	3.413	4.427	3.017	6.099	5.845
240	3.125	3.413	4.427	3.017	6.099	5.845
250	3.125	3.413	4.427	3.017	6.099	5.845
260	3.125	3.413	4.427	3.017	6.099	5.845
270	3.125	3.413	4.427	3.017	6.099	5.845
280	3.125	3.413	4.427	3.017	6.099	5.845
281	3.125	3.413	4.427	3.017	6.099	5.845
282	3.125	3.413	4.427	3.017	6.099	5.845
283	3.125	3.413	4.427	3.017	6.099	5.845
284	3.125	3.413	4.427	3.017	6.099	5.845
285	3.125	3.413	4.427	3.017	6.099	5.845
286	3.151	3.356	4.434	2.970	6.130	6.018
287	3.151	3.356	4.434	2.970	6.130	6.018
288	3.151	3.356	4.434	2.970	6.130	6.018
289	3.151	3.356	4.434	2.970	6.130	6.018
290	3.151	3.356	4.434	2.970	6.130	6.018
300	3.151	3.356	4.434	2.970	6.130	6.018
400	3.151	3.356	4.434	2.970	6.130	6.018
500	3.151	3.356	4.434	2.970	6.130	6.018
600	3.151	3.356	4.434	2.970	6.130	6.018
700	3.151	3.356	4.434	2.970	6.130	6.018
800	3.151	3.356	4.434	2.970	6.130	6.018
900	3.151	3.356	4.434	2.970	6.130	6.018
1000	3.151	3.356	4.434	2.970	6.130	6.018



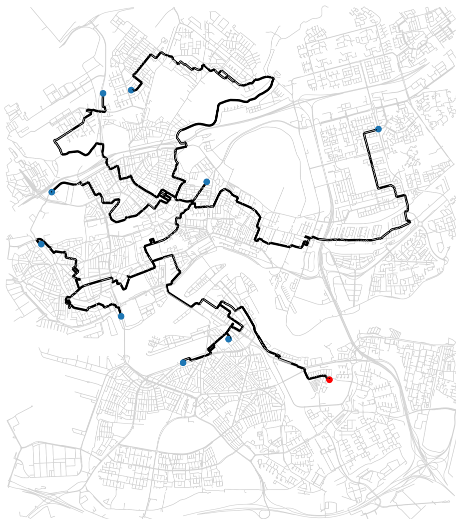
(a) Route visualisation of model run with $MF_{traffic\,avoidance} = 3$



(b) Route visualisation of model run with $MF_{traffic\,avoidance} = 5$



(c) Route visualisation of model run with $MF_{traffic\,avoidance} = 10$



(d) Route visualisation of model run with $MF_{traffic\,avoidance} = 200$

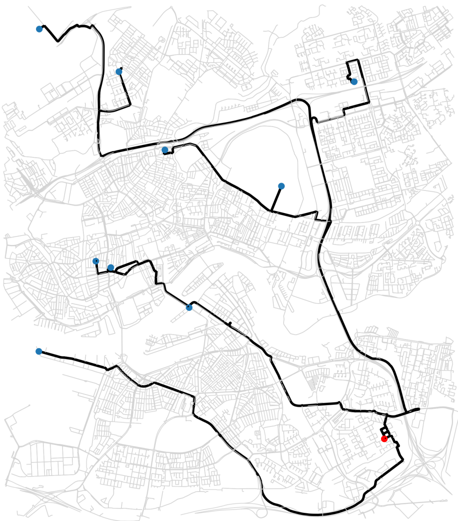
Figure F.13: Route visualisation for different values of $MF_{traffic\,avoidance}$

G
Reproducibility and variability analysis

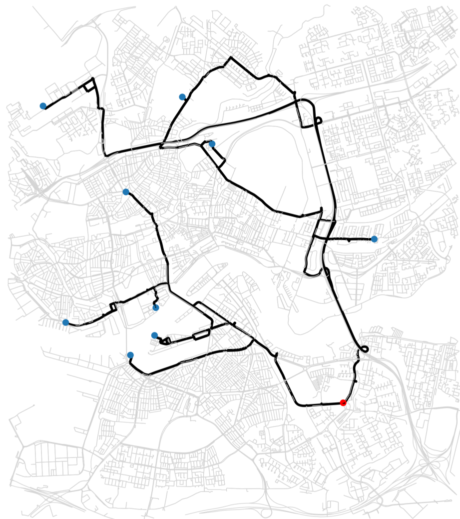
For the reproducibility analysis, the model is run for the same input variables and OD location set to determine that the outcomes are deterministic and reproducible. Next, it is tested that the outcomes differ among different OD location sets used. This is evaluated by running the model 5 times for 5 different OD location sets. The results in Table G.1 show that for each OD location set, the different iterations produce the same result and that the result differs among the OD location sets. All other variables are kept as defined in the base case. The difference in OD location sets is visualised in Figure G.1

Table G.1: Outcome values from reproducibility and variability for OD location sets

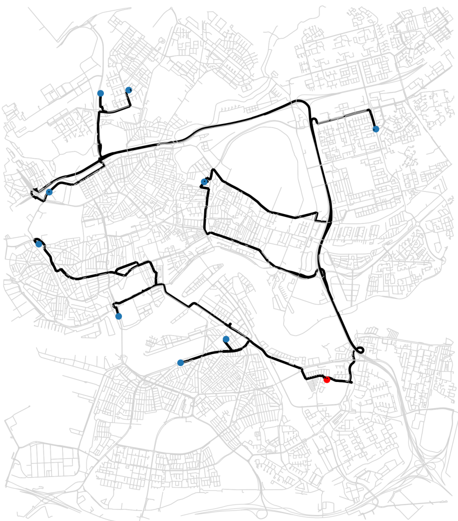
OD location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	0.000	3.126	0.716	6.043	10.246
1	1.000	0.000	3.126	0.716	6.043	10.246
1	1.000	0.000	3.126	0.716	6.043	10.246
1	1.000	0.000	3.126	0.716	6.043	10.246
1	1.000	0.000	3.126	0.716	6.043	10.246
2	1.000	0.000	2.336	0.290	6.227	12.542
2	1.000	0.000	2.336	0.290	6.227	12.542
2	1.000	0.000	2.336	0.290	6.227	12.542
2	1.000	0.000	2.336	0.290	6.227	12.542
2	1.000	0.000	2.336	0.290	6.227	12.542
3	1.000	0.000	2.893	0.497	4.363	12.260
3	1.000	0.000	2.893	0.497	4.363	12.260
3	1.000	0.000	2.893	0.497	4.363	12.260
3	1.000	0.000	2.893	0.497	4.363	12.260
3	1.000	0.000	2.893	0.497	4.363	12.260
4	1.000	0.000	2.305	0.947	5.512	8.388
4	1.000	0.000	2.305	0.947	5.512	8.388
4	1.000	0.000	2.305	0.947	5.512	8.388
4	1.000	0.000	2.305	0.947	5.512	8.388
4	1.000	0.000	2.305	0.947	5.512	8.388
5	1.000	0.000	1.783	0.206	5.094	8.616
5	1.000	0.000	1.783	0.206	5.094	8.616
5	1.000	0.000	1.783	0.206	5.094	8.616
5	1.000	0.000	1.783	0.206	5.094	8.616
5	1.000	0.000	1.783	0.206	5.094	8.616



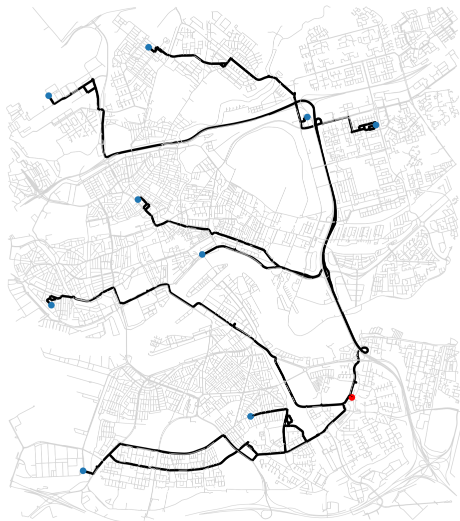
(a) Route visualisation of model run for OD location set 1



(b) Route visualisation of model run for OD location set 2



(c) Route visualisation of model run for OD location set 3



(d) Route visualisation of model run for OD location set 4

Figure G.1: Route visualisation for different OD location sets

H Supporting results

H.1. Scatter plots of outcomes experiments

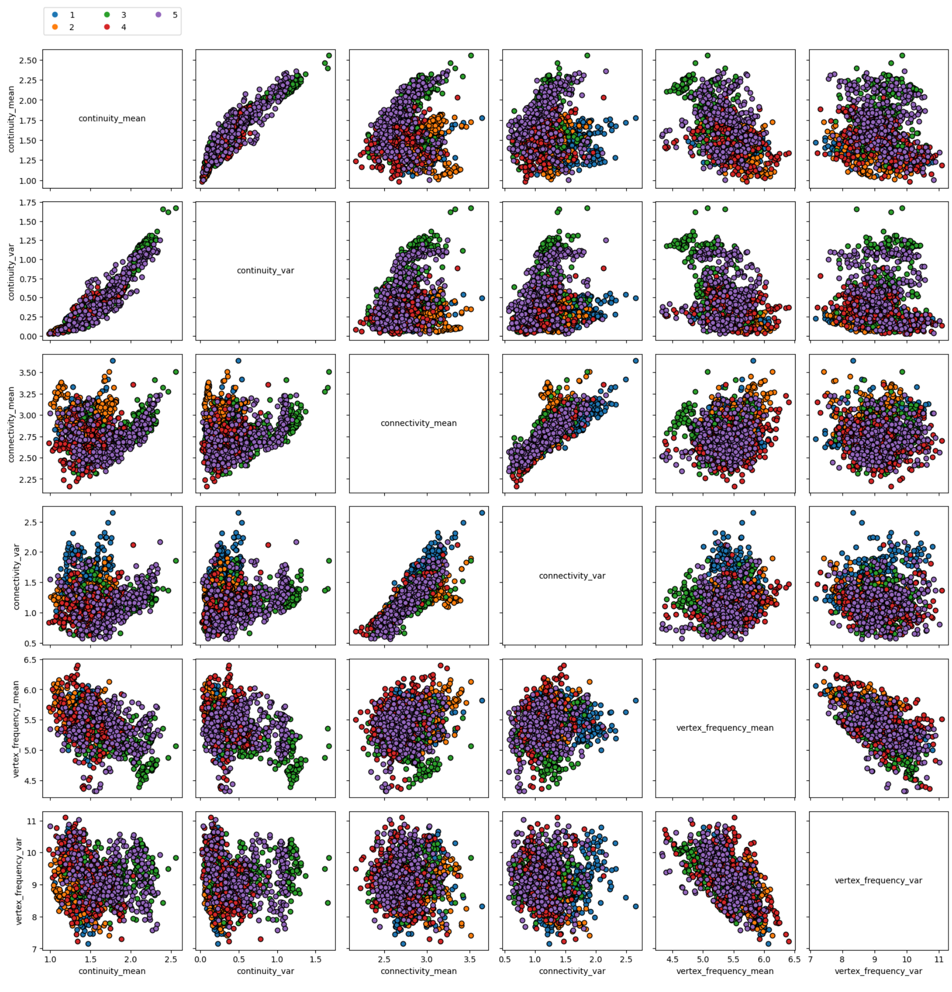


Figure H.1: Scatter plots of outcomes of experiment 1

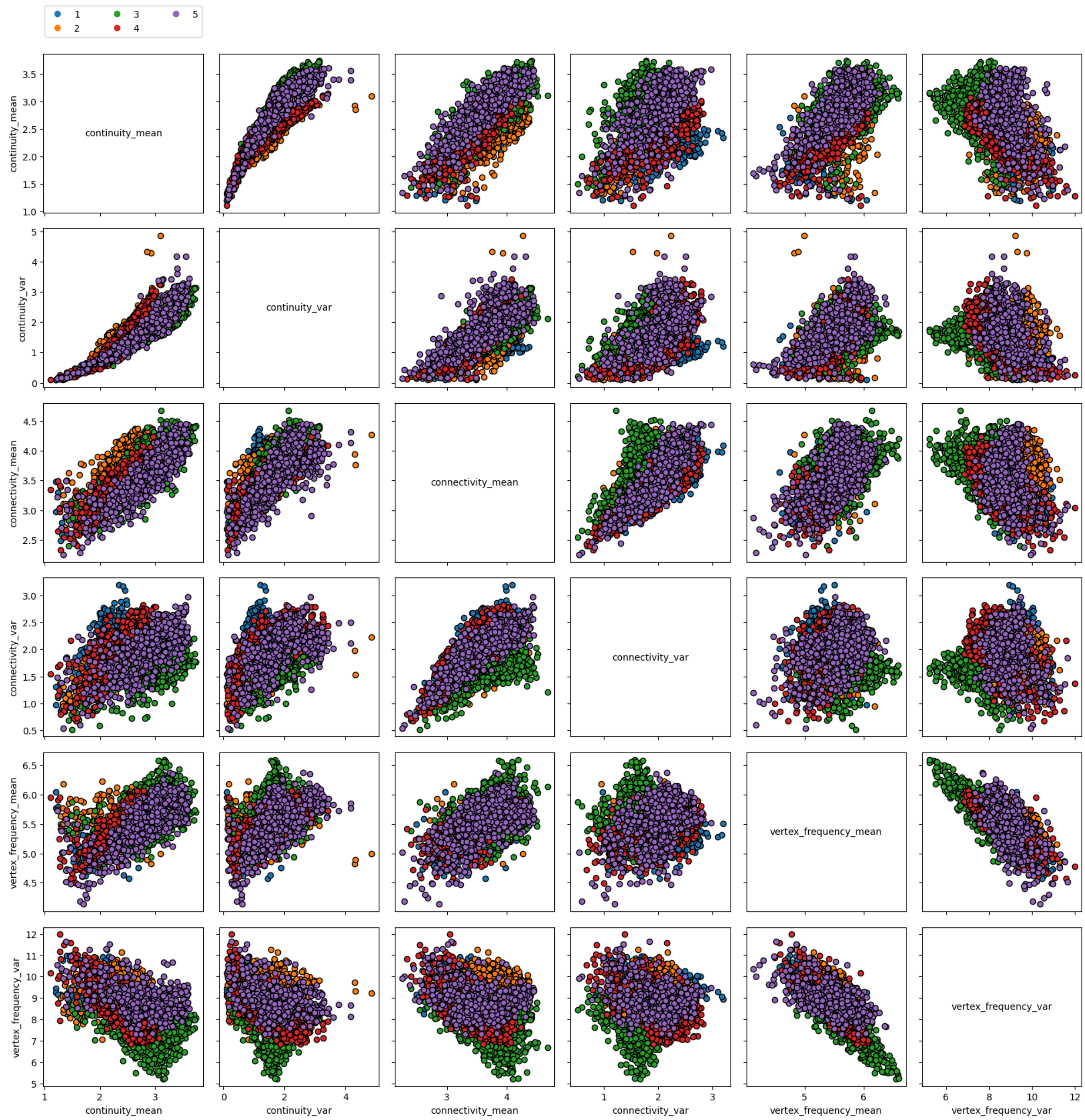


Figure H.2: Scatter plots of outcomes of experiment 3

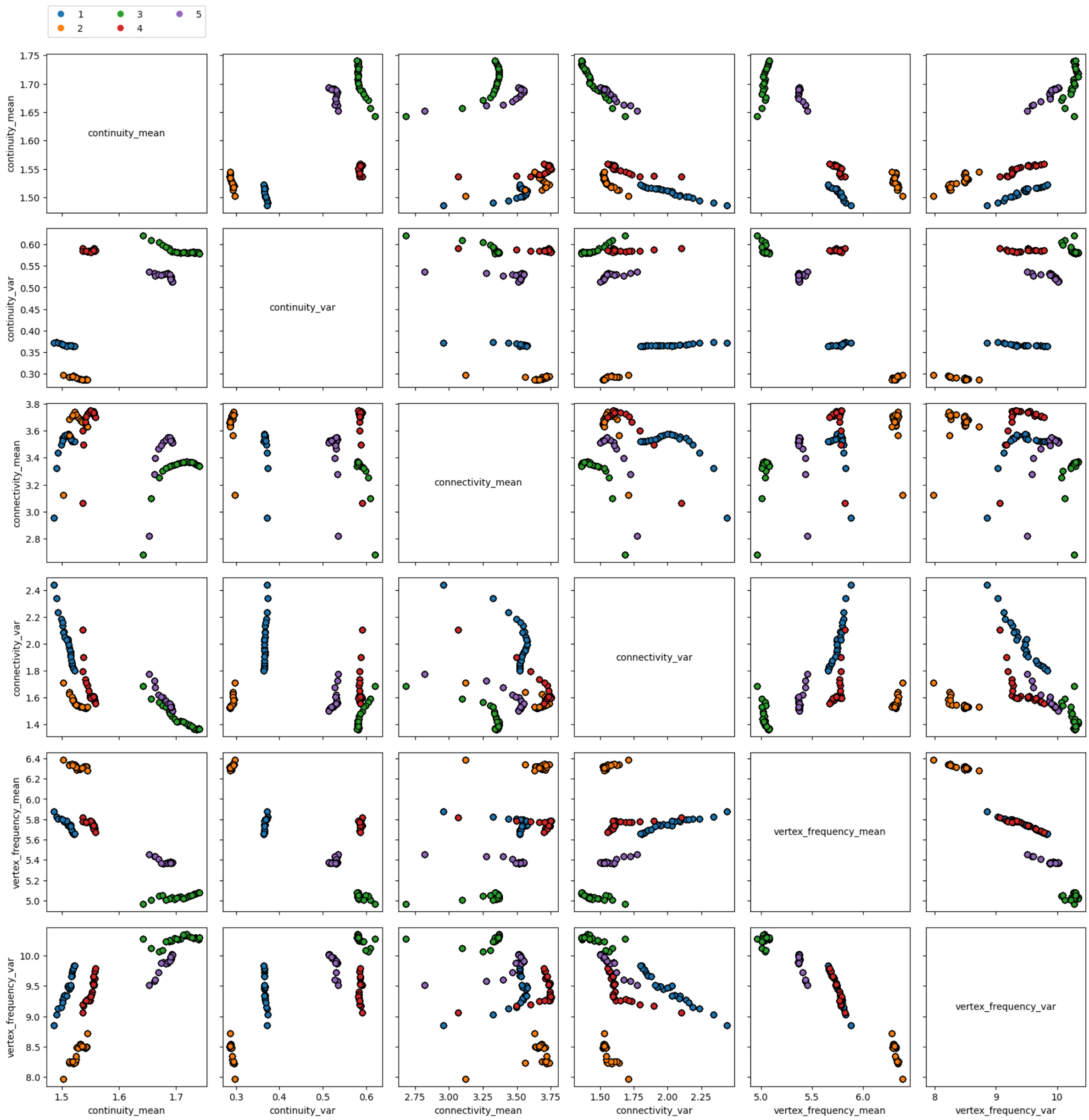


Figure H.3: Scatter plots of outcomes of experiment 4

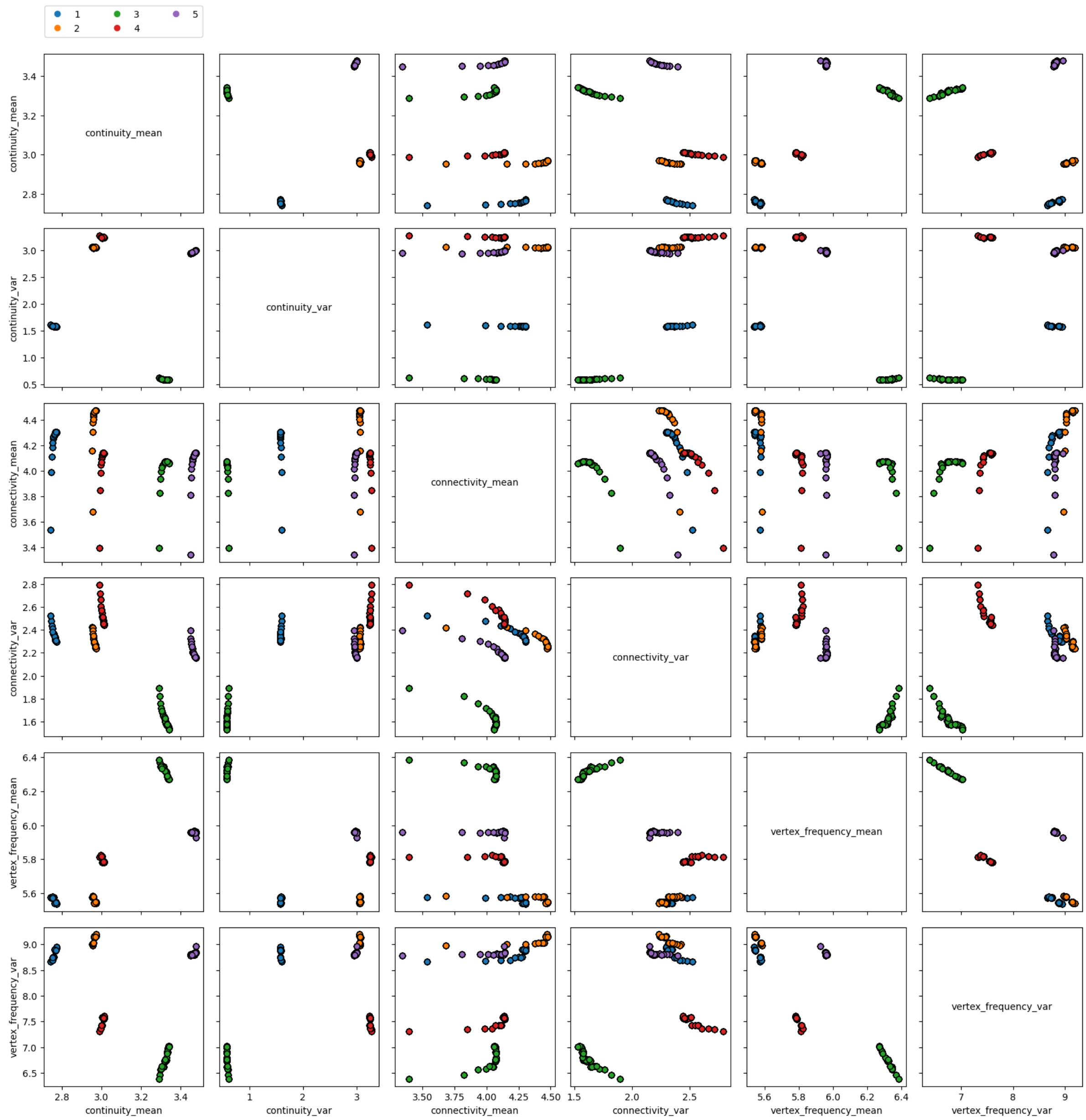


Figure H.4: Scatter plots of outcomes of experiment 5

H.2. Correlation matrices experiment 1

Table H.1: Correlation between TA_i and outcome values for experimental design run 1 for location set 1

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
TA_1	tau	0.407	0.603	0.384	0.516	-0.319	0.216
	p-value	7.356-26	1.093e-54	3.540e-23	1.386e-40	1.752e-16	2.349e-08
TA_2	tau	0.559	0.343	0.127	-0.055	-0.182	-0.122
	p-value	2.598e-47	8.784e-19	1.084e-03	0.157	2.550e-06	1.625e-03
TA_3	tau	0.029	-0.012	0.011	-0.118	-0.0365	0.031
	p-value	0.456	0.764	0.769	2.359e-03	0.346	0.421

Table H.2: Correlation between TA_i and outcome values for experimental design run 1 for location set 2

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
TA_1	tau	0.247	0.213	0.399	0.258	0.028	0.106
	p-value	1.692e-10	3.627e-08	7.410e-25	2.474e-11	0.468	0.006
TA_2	tau	0.720	0.707	-0.128	0.132	-0.377	-0.061
	p-value	3.904e-77	1.910e-74	9.394e-04	6.818e-04	2.333e-22	0.116
TA_3	tau	0.086	0.099	0.213	0.148	-0.056	0.179
	p-value	2.692e-02	1.098e-02	3.975e-08	1.270e-04	0.149	0.000

Table H.3: Correlation between TA_i and outcome values for experimental design run 1 for location set 3

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
TA_1	tau	0.477	0.564	0.345	0.317	-0.326	0.261
	p-value	6.483e-35	3.181e-48	5.022e-19	2.523e-16	3.413e-17	1.457e-11
TA_2	tau	0.501	0.359	0.173	0.060	-0.265	0.050
	p-value	2.937e-38	1.744e-20	7.896e-06	1.194e-01	7.688e-12	1.986e-01
TA_3	tau	0.059	0.052	0.271	0.155	-0.106	0.103
	p-value	0.130	0.183	2.607e-12	6.481e-05	6.033e-03	8.067e-03

Table H.5: Correlation between TA_i and outcome values for experimental design run 1 for location set 5

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
TA_1	tau	0.539	0.653	0.368	0.300	0.061	-0.072
	p-value	4.867e-44	7.796e-64	1.957e-21	9.824e-15	0.117	0.0629
TA_2	tau	0.446	0.263	0.016	0.054	-0.344	-0.046
	p-value	9.575e-31	1.148e-11	0.682	0.163	6.375e-19	0.233
TA_3	tau	0.018	-0.016	0.168	0.026	-0.194	0.120
	p-value	0.648	0.673	1.439e-05	0.502	5.300e-07	0.002

Table H.4: Correlation between TA_i and outcome values for experimental design run 1 for location set 4

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
TA_1	tau	0.522	0.667	0.324	0.381	0.0269	-0.422
	p-value	2.051e-41	1.480e-66	5.575e-17	7.645e-23	0.487	1.184e-27
TA_2	tau	0.469	0.288	0.003	0.091	-0.511	0.053
	p-value	1.026e-33	1.036e-13	0.938	1.914e-02	8.898e-40	0.174
TA_3	tau	0.058	0.037	0.322	0.207	-0.183	0.125
	p-value	0.133	0.338	9.809e-17	9.298e-08	2.264e-06	1.195e-03

H.3. Correlation matrices for experiment 3

Table H.6: Correlation between MF_i and outcome values for experimental design run 3 for location set 1

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
$MF_{camera\ avoidance}$	tau	0.010	0.031	-0.007	0.032	-0.024	0.016
	p-value	0.691	0.213	0.796	0.200	0.345	0.524
$MF_{obstacle\ avoidance}$	tau	0.391	0.214	0.295	-0.081	0.220	0.089
	p-value	5.140e-54	2.396e-17	1.387e-31	1.357e-03	2.919e-18	3.980e-04
$MF_{one\ way\ avoidance}$	tau	0.248	0.235	0.203	0.282	-0.047	0.064
	p-value	1.101e-22	1.502e-20	7.885e-16	6.528e-29	6.213e-02	1.160e-02
$MF_{traffic\ avoidance}$	tau	0.267	0.306	0.247	0.150	0.126	-0.077
	p-value	3.770e-26	9.203e-34	1.561e-22	2.647e-09	5.939e-07	2.324e-03
$MF_{lane\ preference}$	tau	0.106	0.112	-0.036	-0.042	0.160	-0.055
	p-value	2.739e-05	8.751e-06	1.506e-01	9.266e-02	2.258e-10	2.870e-02
$MF_{residential\ preference}$	tau	-0.231	-0.285	-0.211	-0.129	-0.103	-0.043
	p-value	5.436e-20	1.322e-29	5.863e-17	3.551e-07	4.231e-05	8.816e-02
$MF_{high\ speed\ preference}$	tau	0.207	0.187	0.276	0.231	0.320	-0.318
	p-value	2.309e-16	1.372e-13	8.132e-28	5.244e-20	1.094e-36	2.302e-36

Table H.7: Correlation between MF_i and outcome values for experimental design run 3 for location set 2

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
$MF_{camera\ avoidance}$	tau	-0.010	-0.003	0.029	-0.005	0.049	-0.017
	p-value	0.697	0.898	0.257	0.851	0.05	0.506
$MF_{obstacle\ avoidance}$	tau	0.280	0.266	0.267	0.296	-0.020	0.128
	p-value	1.301e-28	7.404e-26	4.240e-26	9.111e-32	4.398e-01	3.808e-07
$MF_{one\ way\ avoidance}$	tau	0.235	0.254	0.224	0.351	-0.124	0.052
	p-value	1.199e-20	9.959e-24	7.671e-19	6.453e-44	8.884e-07	3.852e-02
$MF_{traffic\ avoidance}$	tau	0.356	0.310	0.288	0.059	0.172	-0.145
	p-value	5.025e-45	1.081e-34	4.015e-30	2.001e-02	1.070e-11	8.934e-09
$MF_{lane\ preference}$	tau	0.137	0.173	-0.049	0.042	0.130	-0.049
	p-value	5.248e-08	8.373e-12	5.308e-02	9.468e-02	2.541e-07	0.054
$MF_{residential\ preference}$	tau	-0.325	-0.300	-0.265	-0.111	-0.228	0.164
	p-value	8.586e-38	1.710e-32	9.159e-26	1.147e-05	1.777e-19	9.477e-11
$MF_{high\ speed\ preference}$	tau	0.114	0.074	0.208	0.012	0.200	-0.207
	p-value	6.182e-06	3.243e-03	1.612e-16	0.632	2.412e-15	2.135e-16

Table H.8: Correlation between MF_i and outcome values for experimental design run 3 for location set 3

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
$MF_{camera\ avoidance}$	tau	-0.015	-0.017	0.007	0.035	-0.027	0.025
	p-value	0.562	0.506	0.776	0.167	0.286	0.317
$MF_{obstacle\ avoidance}$	tau	0.241	0.104	0.184	-0.101	0.320	-0.264
	p-value	1.320e-21	3.967e-05	3.093e-13	6.644e-05	8.867e-37	1.381e-25
$MF_{one\ way\ avoidance}$	tau	0.219	0.286	0.135	0.116	-0.154	0.221
	p-value	3.731e-18	1.120e-29	8.772e-08	4.616e-06	1.198e-09	2.296e-18
$MF_{traffic\ avoidance}$	tau	0.341	0.361	0.298	0.157	0.109	-0.086
	p-value	1.212e-41	2.149e-46	3.246e-32	5.287e-10	1.642e-05	6.652e-04
$MF_{lane\ preference}$	tau	0.221	0.083	-0.138	-0.103	0.291	-0.144
	p-value	2.397e-18	1.072e-03	4.705e-08	4.387e-05	1.149e-30	1.259e-08
$MF_{residential\ preference}$	tau	-0.317	-0.308	-0.294	-0.087	-0.170	0.071
	p-value	3.627e-36	3.109e-34	2.256e-31	5.821e-04	1.662e-11	5.172e-03
$MF_{high\ speed\ preference}$	tau	0.161	0.171	0.265	0.180	0.158	-0.157
	p-value	2.045e-10	1.263e-11	8.820e-26	1.059e-12	4.187e-10	4.950e-10

Table H.9: Correlation between MF_i and outcome values for experimental design run 3 for location set 4

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
$MF_{camera\ avoidance}$	tau	0.012	0.034	0.012	0.007	0.018	-0.030
	p-value	0.628	0.182	0.642	0.790	0.469	0.238
$MF_{obstacle\ avoidance}$	tau	0.195	0.164	0.234	0.143	0.120	0.015
	p-value	1.151e-14	8.531e-11	1.904e-20	1.484e-08	2.010e-06	5.464e-01
$MF_{one\ way\ avoidance}$	tau	0.259	0.254	0.129	0.287	0.045	-0.109
	p-value	1.324e-24	9.732e-24	3.249e-07	5.713e-30	7.336e-02	1.604e-05
$MF_{traffic\ avoidance}$	tau	0.307	0.261	0.319	0.273	0.241	-0.258
	p-value	6.980e-34	4.656e-25	1.333e-36	3.289e-27	1.303e-21	1.544e-24
$MF_{lane\ preference}$	tau	0.173	0.148	0.070	-0.073	0.341	-0.289
	p-value	7.598e-12	4.979e-09	5.737e-03	4.002e-03	1.558e-41	2.492e-30
$MF_{residential\ preference}$	tau	-0.243	-0.209	-0.296	-0.294	-0.125	0.142
	p-value	7.392e-22	1.200e-16	1.163e-31	2.099e-31	7.834e-07	1.846e-08
$MF_{high\ speed\ preference}$	tau	0.324	0.383	0.319	0.174	0.341	-0.384
	p-value	1.382e-37	6.686e-52	1.830e-36	5.284e-12	1.606e-41	2.847e-52

Table H.10: Correlation between MF_i and outcome values for experimental design run 3 for location set 5

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
$MF_{camera\ avoidance}$	tau	-0.003	0.008	-0.021	-0.050	0.005	0.038
	p-value	0.895	0.741	0.411	0.047	0.830	0.137
$MF_{obstacle\ avoidance}$	tau	0.258	0.236	0.249	0.177	0.223	0.075
	p-value	1.450e-24	1.068e-20	7.161e-23	2.693e-12	9.103e-19	3.114e-03
$MF_{one\ way\ avoidance}$	tau	0.277	0.332	0.135	0.151	0.016	-0.089
	p-value	4.843e-28	1.781e-39	9.730e-08	2.045e-09	5.376e-01	4.059e-04
$MF_{traffic\ avoidance}$	tau	0.304	0.241	0.321	0.272	0.190	-0.066
	p-value	2.248e-33	1.312e-21	6.140e-37	5.124e-27	5.382e-14	8.544e-03
$MF_{lane\ preference}$	tau	0.186	0.171	-0.011	-0.097	0.430	-0.326
	p-value	1.550e-13	1.171e-11	6.735e-01	1.165e-04	6.963e-65	4.336e-38
$MF_{residential\ preference}$	tau	-0.277	-0.180	-0.309	-0.150	-0.171	-0.123
	p-value	4.573e-28	1.099e-12	1.664e-34	2.888e-09	1.318e-11	1.210e-06
$MF_{high\ speed\ preference}$	tau	0.193	0.236	0.294	0.312	0.189	-0.169
	p-value	1.992e-14	7.912e-21	2.626e-31	4.671e-35	6.739e-14	2.122e-11

H.4. Correlation between outcomes for experiment 3

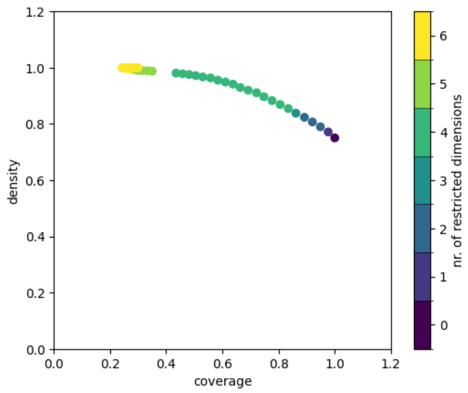
Table H.11: Correlation between outcome values for experimental design run 3

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
continuity	tau	1.000					
mean	p-value	0.000					
continuity	tau	0.676	1.000				
variance	p-value	0.000	0.000				
connectivity	tau	0.461	0.480	1.000			
mean	p-value	0.000	0.000	0.000			
connectivity	tau	0.131	0.181	0.273	1.000		
variance	p-value	3.75E-31	3.43E-58	7.31E-130	0.000		
vertex	tau	0.488	0.403	0.318	-0.027	1.000	
frequency mean	p-value	0.000	2.79E-280	2.21E-175	1.56E-02	0.000	
vertex	tau	-0.358	-0.231	-0.073	0.069	-0.483	1.000
frequency variance	p-value	9.98E-221	1.47E-93	9.69E-11	8.27E-10	0.000	0.000

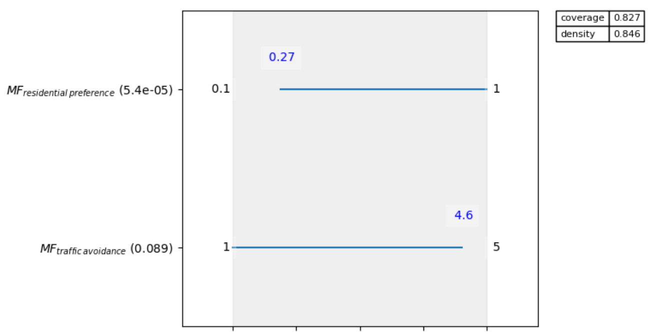
H.5. Results scenario analysis experiment 3

In this appendix, the results of the performed scenario analysis are explained, and the found limitations are described. The scenario analysis was performed on different aggregation levels of the data. Firstly on the separate data sets per location set and secondly on the combined data set. For threshold values for the PRIM method, it was chosen to include either high or low values of the outcome statistics where the threshold was determined to be higher than the 75% or lower than the 25% percentile. This resulted in a set of PRIM boxes for each location set and all combined for each outcome on either a low or a high threshold. When the trade-off plots of the density and coverage of the boxes found were analysed, it became clear that there was no PRIM outcome that yielded boxes with sufficiently high coverage and density (> 0.8).

Another option that was explored was to increase the set of data points that were seen as values of interest. This was done for values higher or lower than the 50% percentile and values higher than the 25% percentile or lower than the 75% percentile. The outcomes for the 50% percentile runs did not yield any useful scenarios. The higher than 25% percentile found PRIM boxes with sufficiently enough density and coverage (> 0.8). An example of the PRIM trade-off can be seen in Figure H.5a. The input ranges of the smallest box with a density and coverage of at least 0.8 can be seen in Figure H.5b. The resulting ranges of the limited input values are still a large subset of the total ranges. What can also be seen is that although the given PRIM box has a high density of values of interest, it also still has a high density of values that are not of interest. This is showcased in Figure H.6, which shows both that the resulting box is still a large range within the limited input ranges and that the distribution of values of interest overlaps strongly with the values that are not of interest.



(a) Trade off for PRIM boxes continuity_mean > 2.286036



(b) Smallest box with coverage and density > 0.8

Figure H.5: Results of PRIM analysis for continuity mean <

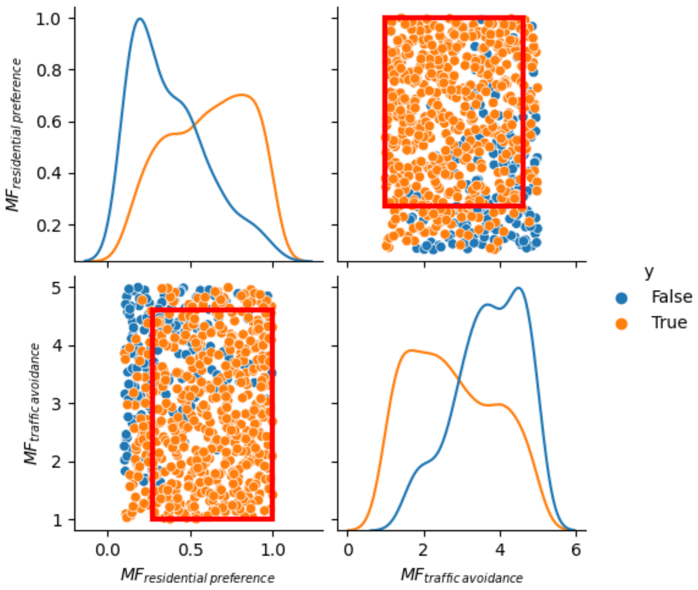
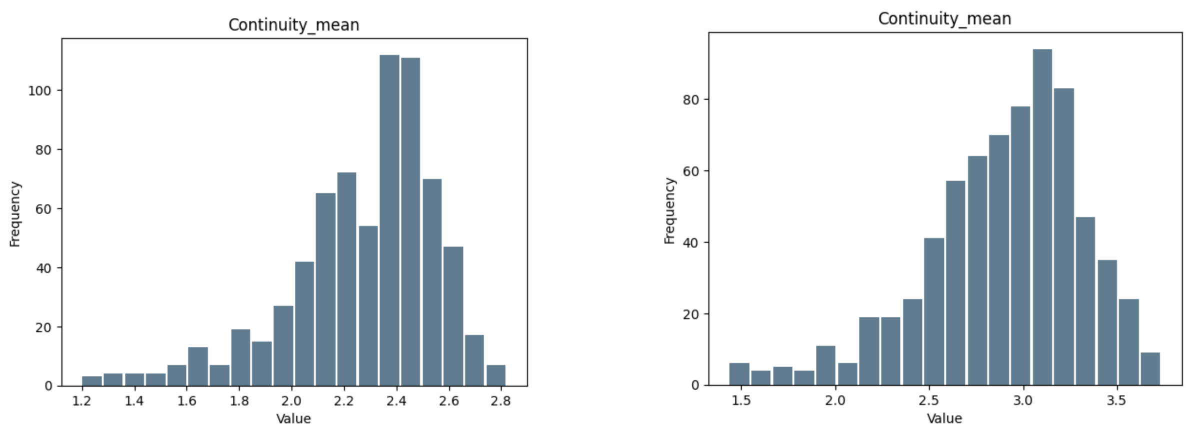


Figure H.6: Distribution of data values of interest for chosen PRIM box

Another limitation of scenario analysis of the combined location set is that the distribution of the separated sets is not equal. This can be seen in Figure H.7 where the peak of the distribution of continuity mean for location set 1 is around 2.4 while the mean for location set 3 is around 3.0. When combining the sets, the threshold value will include different percentages of the separate distributions and, therefore not represent the difference in behaviour within these sets.

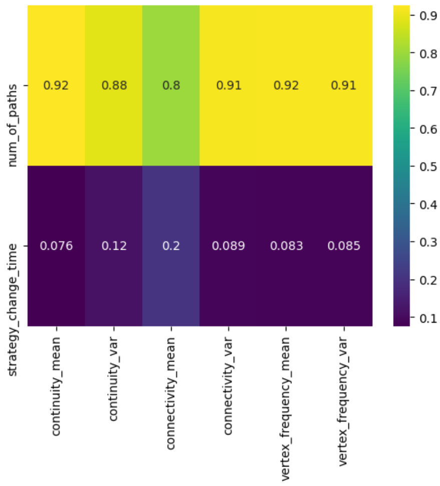


(a) Histogram of continuity mean for location set 1 in experiment 3

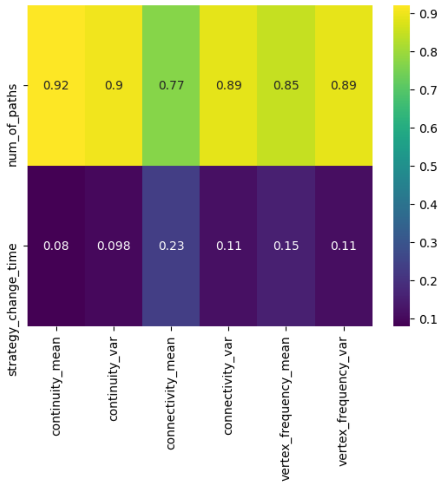
(b) Histogram of continuity mean for location set is 3 in experiment 3

Figure H.7: Histograms of continuity mean for location set 1 and 3 for experiment 3

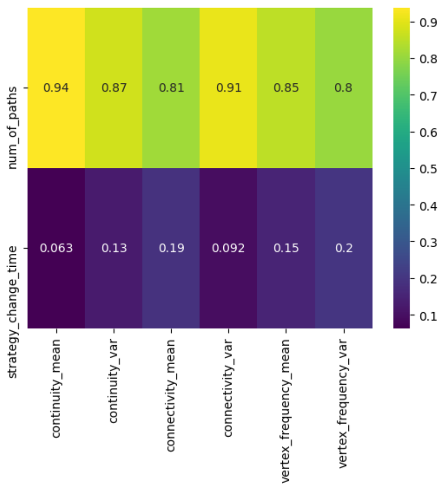
H.6. ETRF importance values for experiment 4



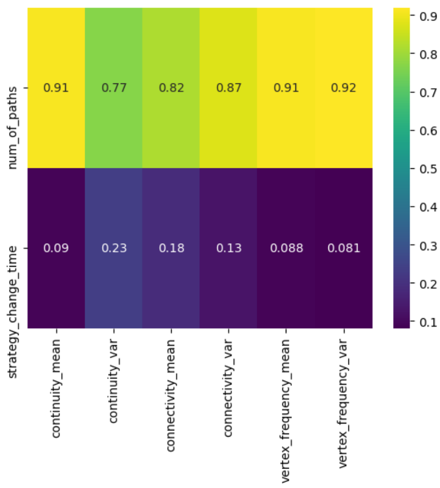
(a) Location set 1



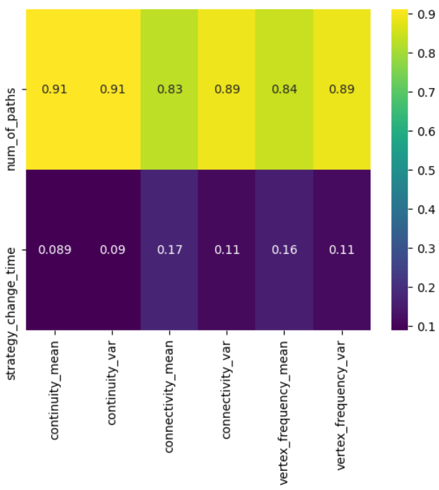
(b) Location set 2



(c) Location set 3



(d) Location set 4



(e) Location set 5

Figure H.8: The ETRF importance value of experiment 4 for separated location sets

H.7. Results sensitivity analysis for experiment 5

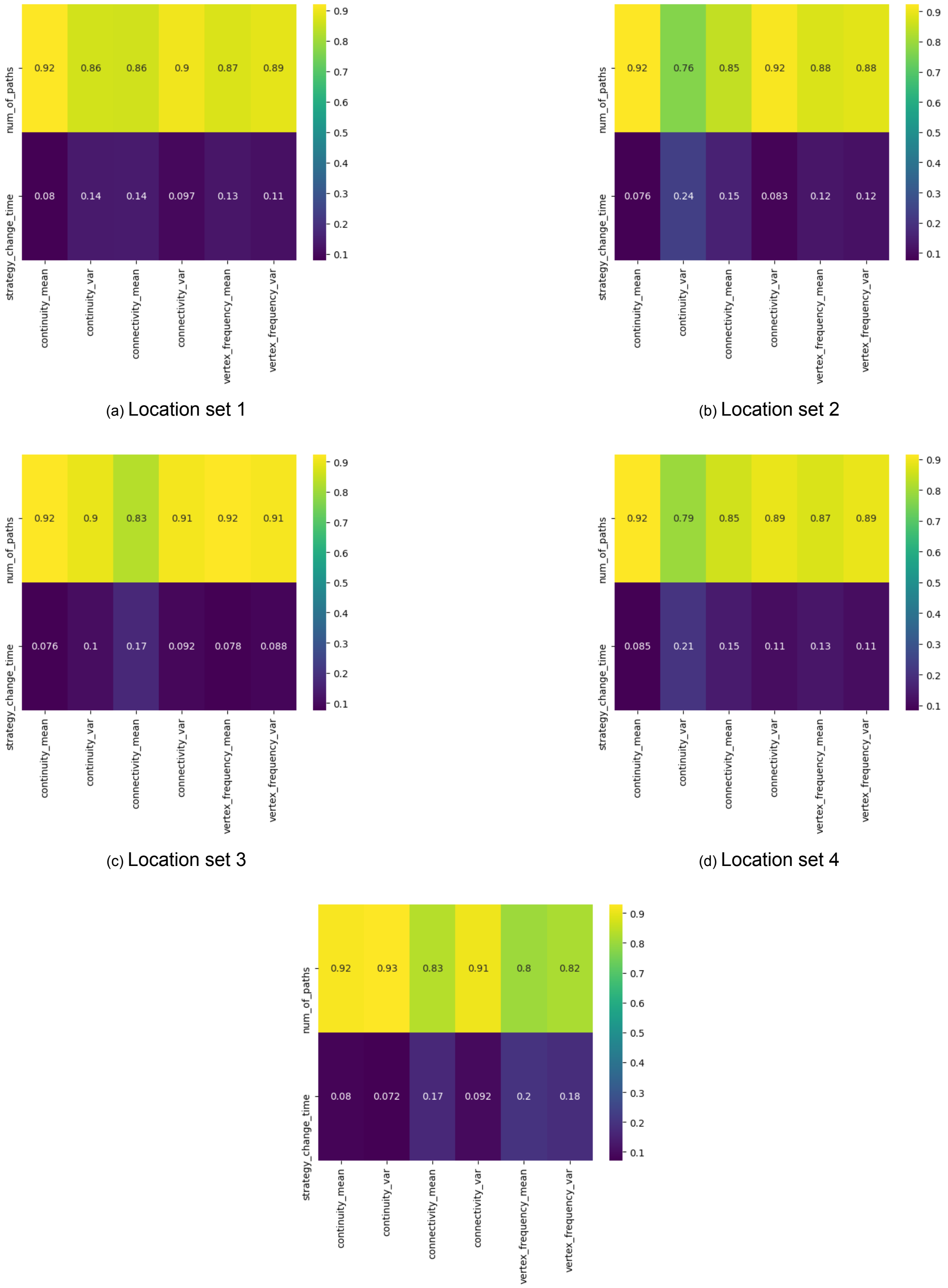
Table H.12: Mean and variance of outcome values of experiment 5

Location set		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	mean	2.76	1.58	4.24	2.35	5.55	8.84
	standard deviation	0.01	0.01	0.16	0.06	0.02	0.09
	coefficient of variation	0.0	0.0	0.04	0.02	0.0	0.01
2	mean	2.96	3.06	4.41	2.29	5.56	9.11
	standard deviation	0.01	0.01	0.16	0.06	0.02	0.06
	coefficient of variation	0.0	0.0	0.04	0.02	0.0	0.01
3	mean	3.32	0.59	4.02	1.63	6.31	6.76
	standard deviation	0.01	0.01	0.14	0.09	0.03	0.17
	coefficient of variation	0.0	0.02	0.03	0.05	0.0	0.03
4	mean	3.0	3.25	4.08	2.52	5.8	7.51
	standard deviation	0.01	0.01	0.15	0.09	0.01	0.09
	coefficient of variation	0.0	0.0	0.04	0.04	0.0	0.01
5	mean	3.47	2.98	4.07	2.2	5.96	8.82
	standard deviation	0.01	0.02	0.17	0.06	0.01	0.04
	coefficient of variation	0.0	0.01	0.04	0.03	0.0	0.0

Table H.13: Correlation between num_of_paths and outcome values for experimental design run 5

Location set	continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
1	1.000	-0.553	0.833	-0.973	-0.500	0.747
2	0.993	-0.240	0.753	-0.980	-0.213	0.687
3	0.993	-0.593	0.393	-0.973	-0.887	0.880
4	0.973	-0.293	0.427	-0.987	-0.373	0.593
5	0.993	0.967	0.847	-0.960	-0.180	0.600

H.8. ETRF importance values for experiment 5



(a) Location set 1

(b) Location set 2

(c) Location set 3

(d) Location set 4

(e) Location set 5

Figure H.9: The ETRF importance value of experiment 5 for separated location sets

H.9. Correlation matrices experiment 4 per location set

Table H.14: Correlation between input and outcome values for experimental design run 4 for location set 1

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	1.000	-0.653	-0.020	-0.987	-0.880	0.913
	p-value	7.545e-92	3.033e-40	0.684	1.819e-89	1.488e-71	6.217e-77
strategy change time	tau	-0.029	-0.031	-0.055	0.026	0.014	-0.010
	p-value	5.529e-01	0.520	0.255	0.586	0.773	0.840

Table H.15: Correlation between input and outcome values for experimental design run 4 for location set 2

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	1.000	-0.793	-0.513	-0.853	-0.367	0.620
	p-value	7.545e-92	1.691e-58	1.732e-25	2.151e-67	9.129e-14	2.053e-36
strategy change time	tau	-0.029	0.020	0.023	0.012	0.086	-0.076
	p-value	0.553	0.678	0.642	0.805	0.08	0.119

Table H.16: Correlation between input and outcome values for experimental design run 4 for location set 3

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	1.000	-0.593	0.36	-0.920	0.720	0.353
	p-value	7.545e-92	1.714e-33	2.528e-13	4.942e-78	1.683e-48	6.874e-13
strategy change time	tau	-0.029	0.061	-0.09	0.013	0.041	-0.113
	p-value	0.553	0.208	0.064	0.784	0.394	0.020

Table H.17: Correlation between input and outcome values for experimental design run 4 for location set 4

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	0.913	0.067	-0.067	-0.793	-0.707	0.860
	p-value	6.217e-77	0.175	0.175	1.691e-58	8.726e-47	2.017e-68
strategy change time	tau	-0.040	-0.112	-0.023	-0.019	0.028	-0.034
	p-value	0.415	0.021	0.629	0.690	0.560	0.480

Table H.18: Correlation between input and outcome values for experimental design run 4 for location set 5

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	0.853	-0.84	-0.053	-0.973	-0.187	0.933
	p-value	2.152-67	2.318e-65	0.278	4.077e-87	1.480e-4	2.956e-80
strategy change time	tau	-0.026	0.03	-0.009	0.032	0.061	-0.031
	p-value	0.590	0.530	0.850	0.515	0.211	0.522

H.10. Correlation matrices experiment 5 per location set

Table H.19: Correlation between input and outcome values for experimental design run 5 for location set 1

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	1.000	-0.553	0.833	-0.973	-0.500	0.747
	p-value	7.545e-92	2.392e-29	2.341e-64	4.077e-87	2.897e-24	5.031e-52
strategy change time	tau	-0.029	-0.023	-0.065	0.026	-0.014	0.024
	p-value	0.553	0.636	0.181	0.590	0.779	0.617

Table H.20: Correlation between input and outcome values for experimental design run 5 for location set 2

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	0.993	-0.240	0.753	-0.980	-0.213	0.687
	p-value	1.182e-90	0.100e-6	6.320e-53	2.749e-88	1.400e-5	2.839e-44
strategy change time	tau	-0.032	-0.026	-0.055	0.028	0.024	-0.003
	p-value	0.515	0.598	0.254	0.560	0.617	0.959

Table H.21: Correlation between input and outcome values for experimental design run 5 for location set 3

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	0.993	-0.593	0.393	-0.973	-0.887	0.880
	p-value	1.182e-90	1.714e-33	1.296e-15	4.077e-87	1.296e-72	1.488e-71
strategy change time	tau	-0.029	0.061	-0.081	0.031	0.022	-0.029
	p-value	0.554	0.208	0.097	0.519	0.648	0.551

Table H.22: Correlation between input and outcome values for experimental design run 5 for location set 4

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	0.973	-0.293	0.427	-0.987	-0.373	0.593
	p-value	4.077e-87	2.486e-09	4.227e-18	1.819e-89	3.238e-14	1.714e-33
strategy change time	tau	-0.031	-0.039	-0.083	0.030	-0.004	0.034
	p-value	0.526	0.422	0.876	0.540	0.937	0.487

Table H.23: Correlation between input and outcome values for experimental design run 5 for location set 5

		continuity mean	continuity variance	connectivity mean	connectivity variance	vertex frequency mean	vertex frequency variance
num of paths	tau	0.993	0.967	0.847	-0.96	-0.180	0.600
	p-value	1.182e-90	5.938e-86	2.254e-66	8.491e-85	2.530e-4	3.276e-34
strategy change time	tau	-0.030	-0.039	-0.025	0.03	-0.023	0.005
	p-value	0.539	0.420	0.612	0.539	0.636	0.917