Optimising fugitive interception

A comparative study into the added value of including more realistic traffic conditions in fugitive interception models

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A comparative study into the added value of including more realistic traffic conditions in fugitive interception models

by

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Preface

In front of you lies the thesis I worked on for the past six months. The opportunity to dive into the world of the decision-making of both criminals and the police is something that still makes my heart leap when I think about it. From a young age, I have been interested in everything that has to do with the police. It makes me, and the little girl in me, very proud to know that with a lot of enthusiasm, I was able to go in this direction.

Not only did I learn about the behaviour of fugitives and the police, but I also challenged myself by saying yes to programming in Python with the little experience I had. This project was an adventure that I could not have done without my amazing graduation committee. Alexander Verbraeck, I am grateful for your enthusiasm and ideas, your trust in me and your words of encouragement. Natalie van der Wal, thank you for sharing your interesting knowledge about all things evacuation, for the fruitful discussions about trying to understand how a criminal would think, and for your flexibility. Irene van Droffelaar, thank you for taking the time each week to look at the code together, and for the very quick email replies. Thank you for restoring my positivity when I lost it somewhere along the way, and for your patience in all your explanations. To all three of you, I have been nothing but happy with your involvement in my project.

I also want to thank my amazing parents, sisters, and friends. Your unwavering support and belief in me kept me going through stressful times. And besides, the time spent with you was a welcome distraction. It has been fun to share my excitement on this project with you.

Lastly, I want to thank the people that were willing to be interviewed. With your experiences, I was able to create a foundation for my model.

All of that being said, I hope you enjoy reading it as much as I enjoyed writing it!

Veerle Zuurdeeg
Delft, August 2024

Summary

In the Netherlands, less than half of violent crimes result in a conviction. One of the most effective methods for ensuring convictions is through red-handed arrests. One way of increasing the number of red-handed arrests arrests is to develop a decision-support system that can determine the optimal police unit distribution over specified positioning locations. Current research in this field often assumes an empty city in these models, ignoring the impact of traffic on escape and interception attempts. This assumption translates into using the maximum road speed for both fugitives and police, overlooking real-world traffic conditions.

To enhance the realism of these models, it is crucial to understand how traffic affects fugitive behaviour and police interception strategies. This thesis explores how traffic conditions, such as congestion and delays caused by traffic lights, impact both escape and interception processes. It examines how these conditions influence the responses of suspects and police and evaluates their effects on police positioning and interception probabilities. The insights gained from this research aim to improve the accuracy of interception strategies and increase the number of red-handed arrests, thereby reducing the number of violent crimes that go unpunished.

The research question addressed was: *What is the added value of taking more realistic traffic into account in the optimal positioning of police units for fugitive interception?* A combination of literature review and interviews was used to develop the discrete event simulation model. Simulation modeling allows for testing complex scenarios in a controlled environment, avoiding the costs and risks associated with real-world experiments. Additionally, criminals are unlikely to behave realistically if they are aware that their actions are being monitored for police learning purposes, which would lead to biased results.

The literature review identified that traffic consists of static, semi-static, and dynamic components, such as traffic lights, open bridges, and congestion. It also highlighted factors influencing criminal behaviour and route choice under high stress. To understand route choice behaviour under high stress, research focused on route choice decision-making processes in stressful situations. This knowledge was supplemented by interviews with parcel delivery drivers, who often operate under high stress. These interviews revealed that stressed individuals often deviate from their planned routes when faced with long delays, which was also found in literature. Additionally, for the road behaviour of police during interception attempts was found that there is a strict code of conduct for driving a priority vehicle, which includes specifications on the speed and the exact position on the road. Integrating these insights, a simulation model was developed to analyse the impact of traffic on interception strategies.

The simulation results revealed a relationship between the inclusion of congestion and delays at regulated intersections and the probability of interception. The probability of interception slightly increased when both fugitive escape routes and police behaviour were based on more realistic traffic conditions. Specifically, when fugitives encountered delays in their way to reach the highway, the likelihood of a successful interception improved. This is because police units generally travel faster than suspects due to their priority status, and traffic delays further increase this speed advantage, making interception more feasible.

Additionally, police positions were optimised in scenarios with and without traffic delays. It was evaluated whether these positions would effectively intercept escape routes generated using the alternative traffic profile. The evaluation showed that positions optimised with realistic traffic conditions were more robust than those optimised without traffic delays. However, this effect was only observed for a crime scene location in the city center, and not for the port docks area, where the robustness of all models was found to be similar. This is likely due to the high interception rate at this location, which made it difficult to assess the impact of traffic.

In conclusion, models that do not account for traffic conditions are less effective at intercepting escape

routes based on realistic traffic scenarios than vice versa. Traffic conditions significantly impact escape routes, making it crucial to include them in model optimisation to maximise interception probability. To mitigate the negative effects of omitting traffic, deploying additional police units is recommended.

The research concludes that the effectiveness of the optimised police positions diminishes when the routes in the evaluation model are generated based on different traffic conditions than those used in the optimisation model. If there is a discrepancy between the traffic conditions in the optimisation and evaluation models, the performance of the optimised positions is negatively affected. However, incorporating traffic into the simulation model generally mitigates this negative impact, regardless of the traffic profile used in the evaluation model. Therefore, it can be concluded that including traffic in the optimisation model is a secure decision in order to increase effectiveness of the optimised positions found.

This correlation was not observed with the mental mode of the suspect during an escape, which was another uncertainty accounted for in the model. The results suggest that incorporating accurate traffic conditions into the optimisation model is more crucial than accounting for the suspect's mental state. It is important to note that traffic impacts more than just congestion and traffic lights: it fundamentally affects the timing of an interception. This impact is twofold: on one hand, accurate traffic estimates may provide the police with more time before the suspect escapes, while on the other hand, incorrect traffic estimates could reduce the time available. Both scenarios could result in fewer interceptions, either the positions might be optimised better with a longer time frame, or the suspect might escape before the police reach their position if the suspect moves through the network faster than anticipated. In contrast, understanding the suspect's mental state focuses on predicting their likely escape routes. To summarise, traffic affects the timing of an interception, whereas the suspect's mental state influences the potential location of an interception.

Future research should explore the impact of more realistic traffic conditions, including dynamic congestion and varying green times for straight and turning directions. This will help determine the optimal level of realism in traffic modeling while managing computational demands. Additionally, investigating more differentiated fugitive and police behaviours could further enhance model accuracy.

Based on the findings, it is recommended that the police integrate realistic traffic conditions to the extent that does not compromise real-time decision support. Prioritising the inclusion of traffic lights over congestion may be beneficial, as traffic light delays more significantly affect interception outcomes. Furthermore, experimenting with different escape speeds can help ensure that optimised positions remain effective even if escape timing varies.

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1 Introduction

One of the goals of the Dutch authorities is to ensure a safe and secure society for their citizens (Ministerie van Justitie en Veiligheid, 2023b). The comprehensive approach against organised crime is based on four pillars: prevent, disrupt, punish and protect (Ministerie van Justitie en Veiligheid, 2023a). The percentage of all criminal cases that are solved lies around 25% (CBS, 2023). Crimes of violence have a somewhat higher resolution rate of 45% (CBS, 2023). However, these numbers imply that more than half of violent perpetrators go unpunished. The most successful method to come to a conviction proves to be a red-handed arrest: in 85% of closed cases, the criminal was arrested during or shortly after the crime (Politieacademie, 2007). In these cases, clear evidence is often present, increasing the conviction rate (Politieacademie, 2013). Besides the contribution of red-handedness to increase the possibility of criminals being caught, other benefits are also present. An arrest in the act is a more efficient use of police capacity and resources compared to a criminal investigation (Politieacademie, 2007) (Politieacademie, 2013). Additionally, the important interaction between police and citizens in direct detection cases can contribute to strengthening citizens' trust in the Police (Politieacademie, 2013), which is crucial to police (Politie, 2022). Because of these advantages, increasing the red-handed arrests has been an important area of improvement for Police for several years (Rijksoverheid, 2022) (Politieacademie, 2013). Examples that are mentioned to contribute to this goal include strengthening the public-private collaboration, and wider involving citizens for example through neighborhood prevention teams (Rijksoverheid, 2022). However, another way to increase the number of red-handed arrests, is to improve the decision support system, which is currently under development. This method uses police positioning software that determines the optimal police unit distribution. However, the optimal positions for police units are currently determined based on fugitive escape routes that are generated in a model that uses many abstractions. While this is needed in order to decrease the run time of the real-time support system, it is important to understand whether the abstractions are sensible. The support system that is currently under development uses an 'empty' city, where only the locations of roads and obstacles are included, but where there is no interaction between actors and static or dynamic traffic situations . Therefore, the focus of this thesis lies on finding out the effects of different traffic situations, such as congestion or long traffic light cycles, on the route choice of fleeing suspects. It goes a step further by also looking at how those situations affect police behaviour, and at the implications of this information on the interception points. Therefore, the knowledge from this thesis can aid in the improvement of catching criminals in the act, and consequently with increasing the resolution rate.

1.1. Societal problem

Arresting criminals is vital for a functioning society. Without punishment for undesirable behaviour, the costs relative to the gains in the trade-off for criminals would shrink significantly. An increase in arrest rates would therefore discourage criminals to offend (Becker, 1968), and has a large positive impact on diminishing the negative effects from a crime (Wan, Moffatt, Jones, & Weatherburn, 2012). A higher arrest rate and quicker arrests are both beneficial to Dutch Police and society. This thesis tries to find a way to optimise the strategy of finding an offender after a crime by identifying the effects of traffic conditions on the route choices of fugitives. Forecasting suspects fleeing behaviour could help the police with the decision making process involved in catching a suspect.

However, the need for real-time forecasting makes this problem very complex. While fleeing the scene, suspects have a choice at each intersection of roads, and the number of choices only add to the complexity of forecasting. Simulating is a good tool for predicting outcomes, as there is not a lot of data available on fugitive escape routes. For those reasons will this thesis use a discrete-event model.

All of this being said, the goal is to identify robust positions for police units to maximise the probability of intercepting a fleeing fugitive. This thesis will examine the effect of including traffic in the optimisation models to understand if there is added value in doing so. The insights gained from this research will assist policymakers in making informed decisions about the important considerations for police vehicle allocation and suspect interception strategies. By providing tools that predict fugitive escape routes, an effective policy response can be formulated, ensuring that criminals are apprehended more frequently, ultimately making the Netherlands a safer country.

1.2. State of the art

Over the last years, the Dutch Police has been engaged in a digital transition. This is a direct effect from the digitisation of society (Politie, 2023b). In order to keep working effectively, it is important to innovate on this topic. Even though the use of Artificial Intelligence (AI) in police work is still in its infancy, the Dutch Police has the goal to be a global leader on this topic (Landman, 2024). Those applications will mainly be used to support, and not replace, police dispatchers. One of the applications of AI in police work is focused on supporting the decision-making of the control room operators, as they are of high importance in the success rate of an emergency operation. Control room staff will increasingly be supported by smart systems that provide them with information they can use to steer operations (Landman, 2023). The Politielab AI is responsible for the development of this application. More specifically, they are developing an Intelligent Geographical Control Room Assistant (Intelligente Geografische Meldkamer Assistant or IGMA) to help control room operators find suspects on the run. AI is used to calculate the most likely escape routes from the scene of a crime, based on historical data /citelandman2024. These insights can be used to manage police units on the street, in order to intercept fleeing suspects in a more targeted effort. This is in line with the aim to increase the number of red-handed arrests, as mentioned in the annual review of the Dutch Police (Politie, 2023b).

Another example of an AI-application that focuses on helping to increase the interception probability of suspects is QUIN. QUIN stands for QUestion and INvestigate, and is developed by the research organisation TNO (van der Vecht, van Wermeskerken, & Smit, 2018). It is based on the premise that everything that can be done has already happened before, so that each escape attempt is classified as predictable. Using quantitative analysis on historical data, detection of the fugitive can happen more easily (van der Vecht et al., 2018). The main goal of this application is to predict plausible target locations of the escape attempt, where the suspect will go.

Both of these AI-applications try to determine where best to locate the available detection resources so that the interception probability increases. They are both based on historical data, where after they try to find a pattern in the data in order to make predictions for a new crime. The biggest difference between the two is their point of focus. Where IGMA focuses on predicting the most likely escape routes, QUIN tries to predict the target location of a criminal escape. This thesis will focus more on the generation of plausible escape routes.

On this topic, three previous studies have been conducted. Kempenaar (2022) studied criminal fugitive escape routes based on the dual-process theory by van Gelder (2013). This theory conceptualises the thinking of criminals in two mental modes: hot and cool. Because criminal behaviour in escape situations is much more complex and hard to capture in only two modes, Tutuarima (2023) broadened this conceptualisation by finding more factors to include in the modelling of route choice behaviour in order to estimate the likelihood of escape routes. These factors include avoidance of cameras, obstacles, one-way roads and high traffic and preference for a high number of lanes, residential roads, a high maximum speed and short roads. Moreover, a distinction in route choice behaviour was found between short-term and long-term goals (Tutuarima, 2023). Lastly, van Droffelaar, Kwakkel, Mense, and Verbraeck (2024a) studied the effects of those different conceptualisations on the police interception strategy. Here, the hot and cool modes are implemented, in combination with concepts like camera an obstacle avoidance, and preference for a high number of lanes and maximum speed. However, personal attributes such as risk aversion and familiarity with the area, contextual factors such as time and location of the crime, and interaction with other traffic is not taken into account.

1.3. Knowledge gap and scientific relevance

Both Kempenaar (2022) and Tutuarima (2023) state that criminals avoid roads with high traffic density, and that it is an important consideration in the route choice decision-making process. However, this conclusion is based on seemingly strict assumptions such as the traffic density being the same throughout the day, or only taking into account non-rush hours in the simulation.

Figure 1.1 provides insight into the fluctuations of traffic intensity in an urban area at different times and days. This clearly shows that the density, and with that the speed, is not the same during the whole day. This is evidence that it is important to take the changing intensity over time into account in a simulation model. At the same time, the two previous theses created enough of a basis to draw conclusions about the quiet moments in traffic, for example a Sunday afternoon or Monday night when the traffic lights are outside operating hours. Therefore, a knowledge gap identified is how the situation of rush hour with congestion affects the choices made by criminals trying to flee from police after an offense.

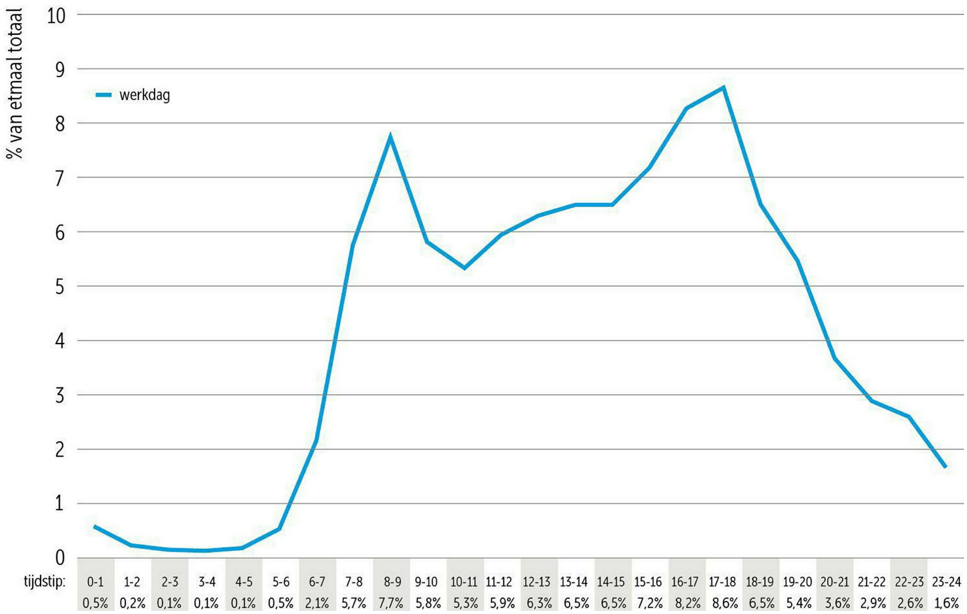

Figure 1.1: Intensity change of car traffic during an average working day within the urban area

Moreover, (van Droffelaar et al., 2024a) does not take into account interaction with other traffic when evaluating different police interception strategies. In this research, both suspects and police units move through the city road network with the maximum speed that applies to a road. At intersections, where two or more roads cross each other, the delaying effects of traffic crossing are not considered. This delaying effect is most prevalent where traffic lights are located, as traffic is accumulated here. A second knowledge gap in the research on interception strategies and the ideal positioning of police units is the effect of the delays at intersections present in real life traffic. Studying this in combination with congestion during rush hour could create understanding about the effects of traffic on the optimal police interception strategies.

Hence, the goal of this thesis is to find out whether including traffic in the simulation model would impact the optimal police interception strategy. By combining knowledge from the criminal decision-making field and the traffic engineering field it is tried to reduce the solution range of fugitive interception points, and to relax assumptions currently used in the simulations on this topic (van Droffelaar et al., 2024a).

1.4. Research questions

In order to fill in the described knowledge gap, the following research question can be drawn up:

What is the added value of taking more realistic traffic into account in the optimal positioning of police units for fugitive interception?

To be able to answer the overarching research question, four sub questions are drawn-up, each focusing on a different aspect of the research question. In the sub questions, the focus lies on the modelled reality, where it is impossible to include all realistic aspects of the world. Later, a translation is made to what this means for the real world, so that the research question can be answered. The first sub question is as follows:

1. How can realistic traffic conditions for fugitive interceptions be described?

This first sub question tries to find a way to describe the behaviour of traffic in a realistic way. Therefore, information on both traffic management and traffic flow theory is needed. On the basis of those two research fields, a realistic understanding of the traffic in a city is created. Specifically, congestion and traffic obstacles such as traffic lights and roundabouts and their effect on the traffic flow are studied. With this knowledge, a model can be built that incorporates these factors.

2. How do the different actors in an fugitive escape attempt react to traffic conditions?

Secondly, when the traffic conditions are included in the model, it is important to know how actors react to them. In an interception, two actors are involved: the suspect and the police. Each actor behaves a certain way during an interception, dependent on the situation on the road. Therefore, the behaviour for both the suspect and the police under the different road circumstances need to be studied.

3. What is the effect of including realistic traffic on the calculated interception probability of fugitive suspects?

With the third sub question, knowledge on the effect of traffic on the interception probability is built. With this, a comparison can be made between the interception probabilities of the simulation model with and without realistic traffic included.

4. What is the effect of including more realistic traffic on the optimal police positions in order to maximise the interception probability?

Here, an optimisation is done on the positions of police units, so that the highest possible interception percentage is found. Comparing these positions with the positions optimised in a city with no traffic gives an idea of how much the optimal positions differ between the two situations. This will help in defining the overall effect of including traffic on the interception strategy of police.

The sub questions focus on the modelled reality, with the overarching research question providing an answer for the real world. Therefore, combining the answers on the four sub questions, the level of importance of including realistic traffic in the control room support system can be found.

The hypothesis is that, when restrictions are added to the free traffic flow currently used in models, the probabilities of fugitive interception will increase. This follows from the prior described expectations in possibilities for police and criminals: when a criminal drives in a dense area with a low speed, the police has more time to intercept them. Combining this with the fact that police do not have to follow traffic rules leads to the hypothesis of a higher interception probability when traffic is included in the simulation model.

Given that delays lead to increased time before a suspect reaches the highway, the police have more time to intercept them before they escaped. Therefore, when traffic is included, it is expected that the optimal police positions will be farther from the crime scene.

1.5. Scope

In order for this study to be feasible within the set time frame, a few choices were made about the scope of the project. First of all, a spatial boundary is put in place. Therefore, this thesis will focus on the city of Rotterdam only, as this a typical European city in terms of population (Wikipedia, 2024). This creates the possibility to extend the results to other similar European cities. This city is also interesting to use as it has all types of roads, from highways to small city roads, and because it is accessible for cars. Besides, Rotterdam is the city used in previous studies by Kempenaar (2022) and Tutuarima (2023), on which this study is based.

Secondly, only car-based escapes will be taken into account. Including different modes of fleeing would lead to a too big project, as the modes are quite distinctive. For example, when a criminal flees on foot, they can hide in buildings or bushes, while a person with a car can impossibly hide the car somewhere.

Moreover, it is impossible to take into account all possible crimes. Therefore, this thesis focuses on crimes that take place regularly in the city of Rotterdam, and crimes that require a low level of collaboration between different police departments. Concretely this means that the focus will be on crimes such as explosions and burglaries.

Even though the decision-making process is continuous, the choice is made not to use real-time simulation for this project. This is decided because of time constraints for this project. Therefore, the assumption is made that the time it takes to run the simulation is zero.

Lastly, a time boundary is put in place. Earlier research (Kempenaar, 2022) (Tutuarima, 2023) mostly focused on normal and non-rush hour, which excludes the more dense and less-defined traffic moments. To really focus on those circumstances, the simulation will run for 30 minutes during rush-hour.

1.6. Methods per sub question

The methods, data requirements and tools that are needed to answer each sub question will be explained here. The research uses the mixed-method design, with both qualitative and quantitative methods.

Question 1

This sub question tries to find out which traffic conditions are important to include in the simulation model so that an interception attempt can be modelled more realistically. In order to generate plausible routes, it is not necessary to create a digital twin of the city of Rotterdam with all the exact delays and travel times. Therefore, it is not important to study the exact pattern of congestion in Rotterdam or the regulation of every single traffic light. However, it is important to study the traffic conditions at the right level of detail. Two research areas can be distinguished here: traffic management (traffic lights, roundabouts, cameras, etc.) and traffic flow theory, which creates a knowledge base on the formation of congestion and traffic jams. This sub question will be answered by conducting a literature study into those two subjects.

Question 2

The second sub question leads to a conceptualisation of both fugitive route choice behaviour and police behaviour in different traffic conditions. To reach this goal, two qualitative methods are needed: a literature study and interviews. The literature study will focus on understanding how people react to different traffic conditions. Because of limited research on specifically the criminal fugitive route choice, the route choice behaviour under normal circumstances are also taken into account. The difference between people and fugitives is the time pressure under which the route choice has to be made. Therefore, route choice decision-making under stress is also studied in literature. Moreover, this is where interviews might come in useful. The optimal group to interview would be people that have experience in fleeing from police, but this is not feasible. Therefore, it would be useful to find a group of people that might feel the same time pressure while driving through a city. Parcel deliverers could be classified as a group of people driving under immense time pressure as they get paid per package delivered. The goal of interviewing those people is to understand the route choice and behaviour of people under pressure. This can be used in the conceptualisation of fugitive route choice behaviour. The second group of actors studied for behaviour in various traffic situations is the police. This knowledge will be gained using a literature study. It is expected that it will be challenging to find concrete information. Therefore, the used databases are not only limited to Scopus, but police videos on YouTube and public documents will also be studied for a more complete insight.

Question 3
Sub question 3 tries to find the effect of traffic on the interception probability of suspects. To study this effect, a simulation model is used. The lack of data on fugitive escapes makes the simulation approach useful to gain insights into the effects of traffic conditions. Besides, it is impossible to conduct those experiments in real life: the moment a criminal knows it is an experiment, their behaviour will change. Moreover, looking into many possible futures can only be done using simulation modelling (Shojaei & Shao, 2017). Changing the way traffic is included, while keeping all other variables unchanged, makes it possible to study only the effect of traffic on the interception probability. The answer to this research question provides insight into how big the difference is between the two situations, which will help in determining the importance of including traffic into fugitive escape simulations.

Question 4
Sub question 4 can also be answered by examining the outcomes of the simulation model for fugitive interception. This involves comparing optimal police positions between scenarios that include traffic and those that do not. Previous research has highlighted the difficulty of identifying suitable metrics for such comparisons (Tutuarima, 2023), and the available metrics often proved challenging to interpret. Consequently, this study relies on interception success as the primary criterion to evaluate the effectiveness of the optimised positions.

1.7. Research flow diagram
Figure 1.2 translates the methods from each of the sub questions into a flow diagram that provides insight into how the different research steps are connected. Besides, it shows that sub questions 1 and 2 are not really interconnected. This implies that those two questions can be researched simultaneously. Sub question 3 combines the knowledge found from the earlier steps, so that finally a conclusion and discussion can be written.

1.8. Thesis outline
The structure of this report is as follows. Chapter 2 describes the theoretical background on traffic, fugitive behaviour, and police behaviour based on a literature study and interviews. In chapter 3, the model is described using concepts and formalisation tables and figures. Chapter 4 presents the experimental design of the experiments. The results of those experiments are detailed in chapter 5. Chapter 6 contains a discussion of the outcomes. Finally, chapter 7 presents the conclusions, including the implications of these conclusions and subsequent recommendations.

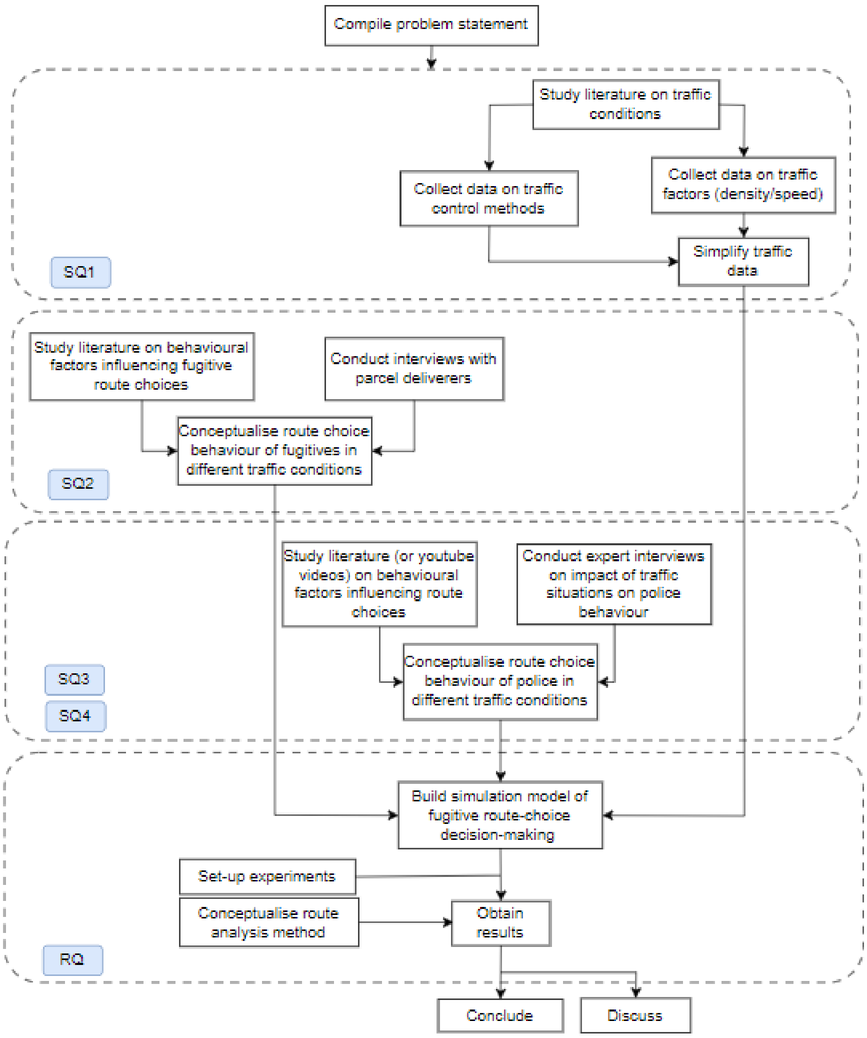

Figure 1.2: Research flow diagram

2

Theoretical background

In this chapter, a theoretical background will be created. To do this, a combination of a literature review and expert interviews will be carried out. The information obtained will be useful for the conceptualisation and building of the simulation model, and will help to answer the sub and research questions. The theoretical background will focus on three aspects, in line with the three sub questions: traffic engineering, offenders escape behaviour, and police behaviour.

Articles for the literature study are gathered using the search engine Scopus. Each subject is researched using a different set of search terms, which will be specified in the associated parts. Next to the search terms, inclusion and exclusion criteria are specified: the article has to be available in either English or Dutch, and in order not to limit the search too much, papers of all years are included. Literature will be selected based on relevance in the order of title, abstract and finally its full text (Snyder, 2019). Moreover, the backwards snowballing method will be used to find more in-dept information on specific topics. Lastly, reports from the TU Delft repository are also included in the literature search. The search terms used, and the relevant articles discovered can be found in Appendix A.

Besides, interviews with parcel deliverers at various companies are conducted. The goal from these interviews is to understand how the feeling of stress plays a role in decisions made in traffic. The main point of interest is to find out what behaviour different traffic circumstances trigger in people with high stress. The knowledge gained from these interviews will be used to shape the theoretical background.

2.1. Traffic

The environment of car-based traffic consists of different aspects, which can be categorised into static, semi-static and dynamic components (Tutuarima, 2023). Static components include fixtures such as traffic lights and roundabouts. Semi-static components comprise occurrences like accidents, open bridges, constructions and events. Traffic itself can be seen as a dynamic component in the environment.

2.1.1. Traffic flow theory

Traffic flow models can be modelled on three different levels: macroscopic, mesoscopic or microscopic models (Guerrieri & Mauro, 2021). This research focuses on the macroscopic level, which is based on relationships between the variables flow (q), space mean speed (v) and density (k). These relationships are known as the fundamental flow relationship, which states that the flow is equal to the density multiplied by the space mean speed (Guerrieri & Mauro, 2021). Free flow conditions are present when every road user maintains their desired speed, which happens when a road section is travelled by few vehicles fairly distant from each other, so when both vehicle density and flow is low (Guerrieri & Mauro, 2021). When the traffic demand and with that the flow and density increase, the headways between vehicles decrease. Drivers react to the reduction in space by lowering their speed. From a certain density it becomes difficult or even risky to overtake other drivers to obtain the desired speed. This leads to platoon formation, where the average flow speed is influenced by the slowest vehicles on the road (Guerrieri & Mauro, 2021). A shock wave can be created when a slow vehicle is present on the road, which causes other road users to initially reduce their gap distance, but eventually brake. This braking becomes more severe for each following vehicle, creating an accordion effect (Guerrieri & Mauro, 2021). These two phenomena provide the theory behind congestion formation. During rush hour, the traffic demand increases significantly. The flow theory explains how this leads to a reduction in the average speed of vehicles.

The degree of saturation on a road segment is how much of the capacity is used. When 80% of road capacity is in use, the traffic starts to become congested (Guerrieri & Mauro, 2021). The degree of saturation gets to 1 when the demand exceeds the capacity. In this case, vehicles move up in the queue under stop and go conditions.

The most important variable of a road is the capacity, which is the maximum flow during a given period of time. Capacity is among others dependent on the gap acceptance and road speed (Guerrieri & Mauro, 2021).

All of this taken into account, the situation during rush hour can be explained. Each road has a maximum capacity at which traffic can flow in an optimal state. However, between 16:00 and 18:00, the capacity is utilised to such an extent that the degree of saturation exceeds the 80% limit. This is the point at which congestion starts to form. The increase in traffic flow is a consequence of the high number of vehicles on the road, which in turn leads to a reduction in the available road space per vehicle. Consequently, mean speed is reduced. As the traffic flow and density on a road increase, the average speed tends to decrease. With this, the forming of congestion and traffic jams is explained.

2.1.2. Traffic management

Traffic management is the deliberate manipulation of traffic flows to optimise the traffic flow (CROW, 2022b). It is used both for average daily situations and for situations of major disruption (CROW, 2022b). As traffic management measures can be very different across different countries, the theoretical background will focus on The Netherlands.

CROW (2022b) published a handbook for traffic management, which encompasses everything from background information to concrete management measures. Mainly this source will be used to create an overview about traffic management for cars in The Netherlands. In traffic management, a distinction is made between rush hour, off-peak hours and weekends. Moreover, there are a few special temporary situations that need attention in traffic management, which are roadworks, events and incidents (CROW, 2022b). Eight categories of traffic management measures are mentioned, which are the following:

- Inform
- Warn
- Organisational measures
- Traffic control instruments
- Network control concepts
- Measures for optimising motorway traffic
- Other measures for influencing routes
- Measures for utilisation and extension of infrastructure

Measures that fall under the 'inform' category focus on providing essential information to road users, without any form of pressure. Dynamic Message Signs (DMS), known as DRIPs in Dutch, offer real-time updates on traffic conditions such as jam length and travel times. Additionally, static signs offer guidance under normal circumstances, while dynamic signs adapt to events that change the route, for example a bypass as a result of roadworks. Radio broadcasts and in-car systems also deliver traffic information, helping drivers make informed decisions for smoother journeys (CROW, 2022b).

In the 'warn' category, Motorway Traffic Management (MTM) employs various measures to alert drivers to potential hazards on motorways. Matrix signage plays a crucial role in this regard, providing warnings for traffic jams, prompting speed adjustments to ensure safety. Additionally, drivers on both motorways and regional roads are alerted to upcoming open bridges, allowing them to adjust their speed and approach accordingly. Weather-related warnings are also conveyed through these signs (CROW, 2022b).

Under 'organizational measures', protocols are established that are used to manage traffic during events and incidents. In such instances, designated teams are mobilised to coordinate responses, ensuring efficient handling of traffic disruptions and mitigating potential safety risks (CROW, 2022b).

'Traffic control instruments' encompass various tools utilised to manage and regulate traffic flow. This includes traffic lights, intelligent traffic lights, ramp metering systems (in Dutch: toeritdoseerinstallaties) at highway entrances, and lane control systems. These instruments play a vital role in optimizing traffic flow, enhancing safety, and minimizing congestion on road networks (CROW, 2022b).

'Network control concepts' encompass strategies and technologies aimed at improving travel times and overall efficiency within a transportation network. This can be achieved either by using traffic lights or ramp metering systems (CROW, 2022b).

'Measures for optimizing motorway traffic' is specifically aimed at motorways. Strategies include dynamic traffic signaling such as adjusted speed limits or a red cross and variable message signs to alert drivers of congestion or incidents. Another strategy used in optimizing motorway traffic, is putting down screens after a serious accident to prevent watch queues in the opposite direction (CROW, 2022b).

'Other measures for influencing routes' include the provision of parallel lanes, bypasses at junctions and roundabouts. Junction bypasses provide alternative routes for drivers to avoid congested areas, improving overall route efficiency and reducing journey times. Roundabouts help regulate the flow of traffic at intersections, promoting continuous movement and minimising delays for drivers choosing specific routes (CROW, 2022b).

The last category 'measures for utilisation of infrastructure' encompasses measures such as traffic signs, rush-hour lanes and continuous lineage on a road. These are all aimed at controlling the use of roads (CROW, 2022b).

The most complicated aspects of the above list are the precise operation of ramp metering, traffic lights and roundabouts. Since highways are the spatial boundary in this study, it is only necessary to take a closer look at traffic lights and roundabouts, which will be done in sections 2.1.2 and 2.1.2.

Traffic lights

To program traffic lights, traffic control installations are used. Four ways of programming traffic lights at an intersection can be distinguished (CROW, 2022a):

- **Rigid:** this is characterised by a fixed sequence with fixed green, red and cycle times, regardless of traffic volume.
- **Vehicle-dependent:** characteristics: mostly a fixed sequence, but this can be deviated from if there is no traffic supply, for priorities or based on waiting times. Green and red times and thus cycle time depend on traffic supply. Information on traffic supply comes from detection (e.g. a cyclist pressing the button).
- **Semi-rigid:** this type is based on a fixed cycle time, but is flexible within it. A semi-rigid regulation is a rigid regulation in which changes are made by means of vehicle-dependent interventions. These modifications are temporary; they always apply for one cycle only. Since the interventions are vehicle-dependent, the relevant signal groups must be equipped with detectors. This kind of regulation is often used to create green waves.
- **Traffic-dependent:** a feature of traffic-dependent control is that the overall traffic process is measured. Based on the in flowing and out flowing traffic at detectors, the control is systematically optimised. At greater distances, optimisation can also be done from intersection to intersection.

In The Netherlands, about 85% of all regulated intersections have vehicle-dependent control (CROW, 2022a). However, the quality differences between vehicle-dependent and rigid regulations for an intersection of the same structure become smaller as the intersection load increases. With increasing intersection load, the green times of a vehicle-dependent control are increasingly bounded by the maximum green times, so the lengths of the green times show less and less fluctuation. As a result, vehicle-dependent control increasingly manifests itself as a rigid control (CROW, 2022a). As the scope of this thesis is limited to rush hour, the control strategy used at intersections can be classified as rigid control.

A traffic light in a rigid-functioning control system has five important attributes (Dijker & Knoppers, 2006). These are the position of the traffic light, the lane it corresponds to, and the green, yellow and cycle times (Dijker & Knoppers, 2006). Yellow light aims to indicate that red light is approaching. Reaction time and safe stopping distance must be taken into account when calculating the length of this light. The length of a yellow light depends on the direction of traffic, as this influences the speed and therefore reaction time. A subdivision is made between straight ahead and turning directions (CROW, 2022a). According to the Manual for Traffic Signal Control 2022 by CROW, a safe yellow time for turning traffic is always 3 seconds, regardless of the maximum road speed (CROW, 2022a). Traffic that continues in the same direction, the safe yellow time is dependent of the maximum speed on the road (CROW, 2022a). At 80 km/h, 5 seconds of yellow is considered as safe, which decreases by half a second for every 10 km/h lower maximum speed, to a yellow time of 3,5 seconds at 50 km/h (CROW, 2022a). The maximum cycle length at an intersection is 90 seconds in the presence and 120 seconds in the absence of slow-moving traffic like pedestrians or cyclists (CROW, 2014). These maximum times are put into place to counteract individuals running the red light as a result of a long waiting time. The exact cycle length is dependent on how complicated intersection is, and the amount of phases needed to serve all directions.

In a cycle, all directions are covered exactly once. However, these directions do not turn green one by one, but certain combinations of directions turn green at the same time, reducing the cycle time. However, there is one condition for combining different directions, and that is that they can not be conflicting. To determine the number of phases in a cycle, first a conflict matrix is compiled. There are hardly any regulations or guidelines for designing the conflict matrix for a regulated intersection. However, it is obvious that perpendicularly crossing directions should not have green at the same time and are therefore conflicting directions (CROW, 2022a). Directions of which all or part of the traffic flows merge are usually also considered conflicting directions. If part of the traffic turns from a direction that is not controlled by an arrow light, this turning traffic will often cross other directions (CROW, 2022a). The conflict between two directions is then called a partial conflict. In these cases, the traffic engineer decides whether directions with a partial conflict are considered as conflicting directions. From the compiled matrix, the combination of directions, also called signalling groups, can be chosen. The goal is to combine as much directions without conflicts as possible.

As seen, conflicting directions do not get green at the same time in a traffic control system. For safety reasons, there is a transition period between successive green phases of conflicting directions, which is used to handle moving traffic and to clear the intersection before the next cars get on the intersection (CROW, 2022a). This is generally referred to as clearing time. The length of the clearing time depends on the attainable speed of the traffic on the previous signalling group.

In addition to regulating each intersection separately, it is also possible to regulate network of intersections together. When using network control, the cycles of several intersections are coordinated to optimise the traffic flow of one or more traffic types in the network or to prevent traffic at one intersection from obstructing traffic at another intersection (CROW, 2022a). The best-known phenomenon of this is the green wave, in which a vehicle platoon arrives at a downstream intersection immediately after the start of the green phase. This allows the platoon to proceed unimpeded and the vehicles will experience little or no loss time (CROW, 2022a). The implementation of a green wave is sometimes required to ensure road safety. This is the case for intersections in a range of 150 meter of each other, as motorists driving away from the first intersection do not expect to be confronted with another red traffic light at a very short distance (CROW, 2022a). In addition, the lane space between two closely spaced intersections is often insufficient to allow a lot of traffic to line up, resulting in a blockage of the upstream intersection. Besides the requirement of a green wave between two intersections in close range, the choice for implementing green waves is a policy decision made by the road authority. In the city of Rotterdam this is the Municipality of Rotterdam (Rijkswaterstaat, n.d.).

Another decision made by the road authority is whether or not to give priority to public transport. Important quality characteristics of public transport are travel time, punctuality and regularity, which can be achieved more efficiently when a bus or tram is given priority in crossing an intersection (CROW, 2022a). In order to give priority to public transport, the traffic control system can either prolong green time, speed up a cycle, or reserve two realisations per cycle (CROW, 2014).

Roundabouts

The basic and most used type of roundabouts have one lane only. In addition, roundabouts with two or three lanes exist, the so-called multi-lane roundabouts. a roundabout is used to achieve simplification of conflict handling in places where there is not enough traffic to install traffic lights. A basic roundabout can be classified as a M/M/1-queue system (Fortuijn, 2011). This implies that the system has only a single server, uses the FIFO service discipline and that the waiting line is of infinite size (Lehoczky, 1996). Another aspect of the M/M/1 system is that the arrival rate and the service rate are not state-dependent, so the number of cars arriving at a roundabout is independent of the length of the queue.

To calculate the average waiting time at a roundabout, the capacity and intensity on the road are needed. The relationship between these variables is as follows (Fortuijn, 2011):

$$d_e = \frac{3600}{C_e - Q_e} \tag{2.1}$$

where:

d_e = average waiting time [s/pcu]

C_e = driveway lane capacity at the given roundabout load for the driveway [pcu/h]

Q_e = intensity driveway lane [pcu/h]

Sometimes, a limit of 50 seconds of waiting time per passenger car unit is used as a criterion for the functioning of a roundabout (Fortuijn, 2011). This is the amount of waiting time that occurs in a situation where the roundabout reaches is practical capacity, at a saturation level of 80% (Fortuijn, 2013). The higher the saturation becomes, the higher the average waiting time will be. However, the waiting times among the different roads connected to the roundabout will not be distributed evenly, as there will always be a main road that is used more frequently than the others. Even in situations where the waiting time is zero, the roundabout reduces speed, the maximum speed on a roundabout lies around 30 km/h due to the small radius of the curve (Fortuijn, 2013).

2.2. Fugitive escape behaviour

Understanding the escape behaviour of fugitives requires a combination of two fields of research, as there is not much research on the escape route choice of fugitives. These research fields are criminal decision-making and route-choice behaviour in high-stress situations. As Tutuarima (2023) has conducted an extensive literature study into the criminal fugitive route-choice behaviour, this thesis is used as a foundation for the literature study on this topic. This knowledge is enhanced by relevant literature found using the Scopus database.

2.2.1. Criminal decision-making

In collaboration with the Dutch National Police, Tutuarima (2023) found that criminal decision-making is determined by three overarching topics: suspect characteristics, crime characteristics and criminal behaviour. The details of what this entails are presented in figure 2.1.

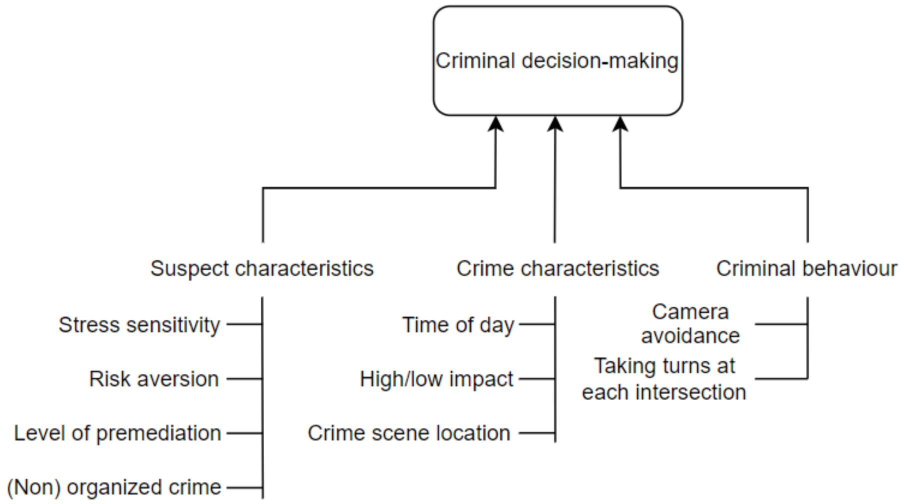

Figure 2.1: The criminal decision-making topics (adapted from Tutuarima (2023))

First of all, an explanation of suspect characteristics is given. There are many different factors that influence whether or not a person is likely to commit a crime, but no consensus exists on what are the most important factors (Tutuarima, 2023). An incomplete list of factors that influence the decision to engage in crimes are low self-control, impulsivity, sensation-seeking tendencies (Burt, Sweeten, & Simons, 2014), fear of apprehension, and perceived risk.

- **Stress sensitivity:** Pickett, Rochie, and Pogarsky (2017) found that stress is an important factor in the criminal decision-making process. The level of stress sensitivity is subjective to a persons criminal experience. People with more experience generally perceive less stress (Tutuarima, 2023). This same logic goes for the level of premeditation (Tutuarima, 2023): the higher the premeditation of a crime, the lower the perceived stress level.
- **Risk aversion:** this also is dependent on the levels of premeditation and experience. If those two factors are low, an offender is more likely to take risks compared to when premeditation and experience are high (Tutuarima, 2023). Moreover, the amount of risk taken is also dependent on the distance to the desired destination: the closer criminals get, the more risk is taken (Tutuarima, 2023).
- **Level of premeditation:** there are three levels of premeditation to be differentiated: high, medium and low (Tutuarima, 2023). Criminals with a high premeditation grade execute a very well-laid out plan, while criminals with low premeditation level are often opportunistic and have a less strategic plan (Zhang et al., 2016). Police see the effects of this very clearly in the way an offender acts: (Tutuarima, 2023) (van Heukelom, 2024).
- **(Non) organised crime:** the level of organisation affects the decision-making a lot. Criminals that organised their offense well execute a well laid-out plan (Zhang et al., 2016), resulting in fewer ad hoc decisions.

Secondly, the impact of crime characteristics on the decision-making process needs to be studied, as those were found to be relevant for the fugitive route-choice behaviour (Tutuarima, 2023).

- **Time of day:** this impacts the amount of traffic in the city and the number of police units available (Tutuarima, 2023). Those two factors influence the decision-making in terms of committing the crime and fleeing afterwards.
- **High/low impact crime:** this measures the impact of a crime on society. High-impact crimes include robbery, assault and residential burglaries (Kempenaar, 2022). These crimes often have a high level of organisation behind them, and evoke more aggression and violence than low-impact crimes (Tutuarima, 2023). However, it is also possible that a crime escalates from low to high impact.

- **Crime scene location:** the crime scene location is dependent on the type of crime. Tutuarima (2023) states that organised high-impact crimes more often take place in cities and busy areas, while low-organised crimes are often located near the suspect's home. Moreover, a known theory is that crime predicts crime (Zhang et al., 2016): spatial correlations can be found in the occurrences of crime (Short et al., 2008).

Lastly, two criminal behavioural factors have been compiled by Tutuarima (2023) in collaboration with the Dutch National Police that impact the criminal decision-making.

- **Camera avoidance:** criminal behaviour as a result of cameras has two sides. On the one hand, criminals try to avoid being caught on camera (Tutuarima, 2023). This is particularly true in high-organised and premeditated crimes, because in those cases camera placement can be studied at both the crime scene and the planned route (Tutuarima, 2023) (van Schijndel, Schreijenberg, Homburg, & Dekkers, 2012). On the other hand, cameras often do not discourage offenders from committing a crime, but their behaviour is adapted: they for example try to be unrecognizable (van Schijndel et al., 2012). The same goes for avoiding cameras during an escape: offenders tend to avoid areas with high visibility to blend in the crowd (van Heukelom, 2024) (Zhao, Li, & Guo, 2020). This information leads to the conclusion that camera avoidance is a relevant behavioural factor, even though it is not always a priority for fugitives (Tutuarima, 2023).
- **Taking turns at each intersection:** this behaviour stems from the goal to be unpredictable for police. Changing the direction often can mainly be seen in fugitives with high stress. When a fugitive wants to conduct this type of behaviour, short roads are preferred to maximise the number of turns (Tutuarima, 2023).

2.2.2. Route-choice decision-making

In this section, literature on general route-choice decision-making is studied. Therefore, the knowledge from the literature study by Tutuarima (2023) is combined with literature from Scopus (see Appendix A). To create an overview of important route-choice decisions, the areas of evacuation and commuting are also taken into account. However, the focus will be on how this knowledge can be used in criminal escape behaviour.

In traffic, three control levels that characterise tasks in traffic are distinguished, which are the strategic, tactical and operational level (Michon, 1979). The strategic level defines the planning stage of a journey and takes place in advance. Choices such as the goal, route and vehicle type are part of this level (Michon, 1979). Secondly, the tactical level includes the decisions that have to made from moment during driving, such as the choice of lane, driving speed and manoeuvres (Michon, 1979). Lastly, there is the operational level, relating to the actual execution of manoeuvres such as merging and reacting to a traffic light. It incorporates skills of steering and braking (Michon, 1979). In each level, the time pressure increases: in the strategic level there is no time constraint, while the operational level does not give time to think before acting is expected (Michon, 1979). On these different levels, Tutuarima (2023) studied factors that influence route choice behaviour. These can be found in figure 2.2.

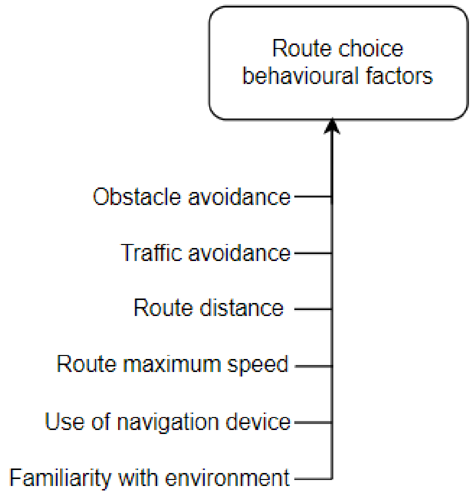

Figure 2.2: The route-choice decision-making topics (adapted from Tutuarima (2023))

- **Obstacle avoidance:** this is a well-described phenomenon in the field of microscopic human crowd-behaviour. Both in small-scale evacuations, such as fire-evacuations in buildings (Bode & Codling, 2013) (Snopková et al., 2023), and large-scale evacuations, such as tsunami-evacuations of whole areas (Takabatake, Fujisawa, Esteban, & Shibayama, 2020), the preference for a spacious escape-route is found (Tutuarima, 2023). This directly translates to an absence of obstacles. Obstacles in traffic include traffic lights, intersections and roundabouts (Tutuarima, 2023). Saxena, Rashidi, Dixit, and Waller (2018) found a dis-utility of between 20 to 40 seconds for traffic lights.
- **Traffic avoidance:** traffic can be seen as a dynamic obstacle. Therefore, the same logic goes to the avoidance of traffic as to the obstacle avoidance (Tutuarima, 2023).
- **Route distance:** when taking into account long-term goals over short-term goals, the route distance is minimised over the travel speed (Tutuarima, 2023).
- **Route maximum speed:** when a driver is driven by short-term goals, they see the maximum speed as more important than the total route distance (Ringhand & Vollrath, 2019).
- **Use of navigation device:** a study by Mackett (2021) presented that people that use Google Maps tend to ignore observable environmental information, such as crowds, and stick to the suggested route from the navigation device. Google Maps uses travel distance in combination with real time traffic information to calculate the fastest route.
- **Familiarity with environment:** the extent to which a suspect is familiar with the surrounding area of the crime determines the ability to find a good escape route (Tutuarima, 2023). Various studies in building evacuations agree on the importance of familiarity in the exit and route-choice. Individuals seem to exhibit a preference to follow what they believe to be a 'sure route' to safety rather than take a chance on following fire exit signs in a direction that they are not familiar with (Johnson, 2005). This is in line with Sime (1983), who states that people are most likely to use the entrance as evacuation-exit, as this is the exit they are familiar with. Moreover, in non-stress situations such as commutes, the behaviour of familiarity is also present (Tutuarima, 2023).

The factors mentioned in the presented list can be divided into three groups: road characteristic preference, road characteristics avoidance (Tutuarima, 2023), and network knowledge. Before the semi-static and dynamic components of traffic can be included into the simulation model, it is necessary to look deeper into the implications of these factors. It is known that people avoid high-traffic and obstacles, but the knowledge on how this is done in fugitive escapes is not known. Therefore, the research area of stress in traffic is is examined in the next paragraph.

2.2.3. Stressed behaviour in traffic

Individuals may experience heightened stress when faced with time pressure, arising from the discrepancy between desired actions and what can realistically be performed in temporal constraints (Cœugnet, Naveteur, Antoine, & Anceaux, 2013). An offender is under huge time pressure to escape before police catches them, and according to Cœugnet et al. (2013), time pressure leads to feelings of stress. Pawar and Velaga (2020) state that time pressure creates stress when a driver has limited time to reach their destination. Therefore, it is safe to assume that criminals fleeing a crime scene are dealing with some level of stress during the escape. In this section, the effects of stress on behaviour in traffic is studied.

Besides time pressure, stress can also be caused by various environmental factors. For instance congestion, which is known to provoke feelings of stress, anger, and aggression among drivers (Hennessy & Wiesenthal, 1999). These emotions can induce risky behaviour on the road, as evidenced by research suggesting that anger and stress contribute to such behaviours (Emo, Matthews, & Funke, 2016) (Cœugnet et al., 2013). Although there is evidence to say that stress is a cause of risky behaviour, Emo et al. (2016) present that this kind of behaviour can be predicted more accurately by people's habitual behaviour patterns than mere emotional state. Age, driving frequency, educational level (Rezapur-Shahkolai, Taheri, Etesamifard, Roshanaei, & Shirahmadi, 2020) and gender (Bode & Codling, 2013) are explanatory variables of risky behaviour found in literature.

Besides people that experience some level of stress, there are individuals that suffer from extreme stress and anxiety in traveling as a result of mental health conditions such as anxiety disorders (Mackett, 2021) (Ratering, van der Heijden, & Martens, 2024). The effects of this extreme stress and anxiety are of interest in this thesis to understand the way these emotions affect the behaviour in traffic. Wayfinding uses a range of skills: recalling information from memory, interpreting information from the environment, and taking decisions based on this (Mackett, 2021). However, anxiety can impair those cognitive functions crucial for effective wayfinding (Mackett, 2021). Ratering et al. (2024) found that the feeling of being locked up and not being able to escape is a trigger that increases the already present anxiety even more. This phenomenon affects the choice of route for people with stress, and leads to an avoidance of the spaces that evoke a sense of confinement, such as heavy traffic conditions, tunnels and bridges (Ratering et al., 2024).

In navigating through traffic, drivers display a remarkable willingness to opt for alternative routes to avoid being stuck at a red light, even when it entails additional travel time and distance (Ringhand & Vollrath, 2017). This preference highlights the importance placed on maintaining free-flowing traffic, underscoring a reluctance to endure the inconvenience of waiting at traffic signals (Ringhand & Vollrath, 2019). This behaviour is even more present in situations where an individual already experiences stress resulting from time pressure. In a crime scene escape attempt, staying on the move decreases the likelihood of an interception between fugitive and police. However, navigation apps like Google Maps have altered the way people navigate traffic. Prior research by Ringhand and Vollrath (2017) and Ringhand and Vollrath (2019) showed that people change their route based on environmental factors such as traffic jams or red traffic lights. However, research suggests that users often prioritise the app's suggested route over observable environmental cues, and keep following the presented route (Mackett, 2021).

Interviews with parcel deliverers were conducted to complement the knowledge gained from the literature review. Appendix F provides a summary and takeaways. It was clear that all the deliverers interviewed experienced high to very high levels of stress during their rounds. Their stress levels increased when unforeseen circumstances arose or when the roads were busy. It is important to note that behaviour depends very much on personal characteristics. Overall, there was a tendency to run a red light when the driver felt safe and the road was quiet. One aspect that emerged in every interview was changing lanes when another direction had a green light and one's own lane had a red light. For the most part, this behaviour only occurred when the person knew that the alternative route would get them to their destination. However, it also sometimes happened when they did not know whether the alternative route would be successful or not. Fear of being further delayed by the detour was the most common reason for not choosing it. There was no real consensus on whether seeing a traffic jam was a reason to choose an alternative route. The people who did not change direction because of a visual traffic jam consulted a navigation app to get information about the duration of the traffic jam before deviating from the planned route.

2.2.4. Rationality in decision-making

The level of rationality is important to take into account when modelling decision-making processes. Therefore, this topic will be studied for both the criminal and route-choice decision-making. There are two levels of rationality: perfect rationality and bounded rationality. In perfect rationality, it is assumed that individuals have access to full information, and strive for utility maximisation. When the cognitive limitations, intrinsic preferences, and information processing capability of humans is taken into account, bounded rationality is considered (Liu, 2022).

Criminal decision-making

There is no consensus in the discussion on how people make decisions, but both levels of rationality are used. When rationality in decision-making is assumed, people choose the option that yields the highest amount of utility. In order to find the optimal choice using this method, the costs and benefits of all options are considered. Rational decision-making is often applied in criminal decision-making. Based on rationality, Becker introduced the economic theory of crime in (1968). This theory uses the analysis of choice, which assumes that a person commits an offense if the expected utility exceeds the utility they could get by using this me and resources at other activities (Becker, 1968), so committing a crime is seen as a problem of maximising utility. According to Becker (1968), an offender maximises the expected utility before committing a crime by making a prediction about the benefits of the crime, and probability and costs of being caught for it.

However, limits of human cognitive capacity for discovering alternatives, computing their consequences under certainty or uncertainty, and making comparisons among them influence the ability to calculate the optimal solution (Simon, 1990). Therefore, the concept of bounded rationality was introduced. This theory relaxes the assumptions used in the subjective expected utility theory, and can therefore be seen as a satisfying strategy instead of an optimal strategy (Simon, 1990). There are different theories that are based on bounded rationality. To be useful in criminal decision-making it should be able to take into account the emotional state of a person. As seen earlier, emotions such as stress and fear play a big role in the choices made by criminals. A theory that satisfies this requirement is the dual process theory (Kempenaar, 2022). The dual process theory suggests that two modes of mental processing operate simultaneously in activities that include solving problems, evaluating risks or deciding between alternative scenarios (van Gelder, 2013). The two modes that can be used simultaneously are controlled versus automatic or reflective versus impulsive (van Gelder, 2013). van Gelder (2013) translates these two modes into a hot (under stimulus control) and cold (cognitive) system when creating the hot-cool framework for criminal decision-making.

Route-choice decision-making

When perfect rationality is used in route-choice decision-making models, the theory of expected utility maximisation is used. Therefore, full knowledge of the road-network and travel time is needed. This rational approach therefore assumes that each driver knows the minimum-cost route in spite of the deterministic or probabilistic (Miyagi & Ishiguro, 2008). Using this approach, one chooses the route with the shortest (perceived) travel-time, travel costs (Liu, 2022), and travel time variability (Katsikopoulos, Duse-Anthony, Fisher, & Duffy, 2000). Rational models are based on situations where a route between a set origin and destination has to be found out of a range of possible routes (Tutuarima, 2023). In those cases, shortest path algorithms are often used, such as Dijkstra's algorithm. Path length, maximum speed and traffic can be taken into account to calculate travel costs (Tutuarima, 2023). However, due to the imperfect and incomplete information available, rationality is bounded (Kottayil, Tsoleridis, Rossa, Connors, & Fox, 2020). Moreover, if drivers all were fully rational, everyone would choose the same road between an origin and destination, as this is the 'optimal' route (Kottayil et al., 2020).

There are a lot of ways to model bounded rationality in route-choice decisions. Those models often incorporate some kind of mental state (Tutuarima, 2023). According to Slovic, Finucane, Peters, and MacGregor (2004), emotions are crucial to make a right decision, as it functions as a risk assessment. A summary of different conceptualisation methods as compiled by Tutuarima (2023) is given. First of all, a calculation of the psychological values can be added to the calculation of costs and benefits. An example is to add road preference to the calculation. Secondly, choosing to use short-term instead of long-term goals and information would lead to a more bounded-rational approach. Emotion can also be modelled by incorporating events triggering emotional response, such as blocked roads, which might result in an agent going from a non-panicked state to a panicked state. Lastly, Tutuarima (2023) mentions a conceptualisation specifically aimed at criminal fugitive escape behaviour by Kempenaar (2022). This conceptualisation divides fugitives in a hot and a cold state based on the dual-process theory by van Gelder (2013), and the state impacts the choice-prioritisation of different route options at intersections. In this conceptualisation, fugitives in the cool state use the shortest-path algorithm, whereas in the hot state the choices are more extensive (Kempenaar, 2022).

A different take on bounded rationality in route choice decision-making is by Miyagi and Ishiguro (2008). They state that each agent does not know the minimum-cost route on the network, and only knows the route information that he or she has experienced. A combination of regret matching and reinforcement learning leads drivers to rational choices in the long run (Miyagi & Ishiguro, 2008). However, this is not backed up by Liu (2022), who states that creating habit in the long run helps to save cognitive resources by searching for less information, which is a characteristic of bounded rationality.

2.3. Police behaviour

As a result of the exceptional position of the police, there are important guidelines they have to follow. As this research focuses on their driving and route choice behaviour, the guidelines related to this topic will be consulted to shape the theoretical background on police behaviour.

The document '*brancherichtlijn politie*' was drawn up to provide drivers of emergency vehicles with guidance on the responsible application of the regulations on the use of optical and audio signalling. The most important take away is that other traffic should never be put at risk. Also included are the rules for switching on signals and the code of conduct. First of all, it is not permitted to use signalling without approval of the control room (Politie, 2023a). This approval is given only when the vehicle is performing an urgent task. An urgent task may be either the provision of assistance in a life-threatening situation, the prevention of a life-threatening situation, or the need for rapid intervention in the event of a serious disturbance of public order.

Priority vehicles are subject to different traffic rules than other vehicles. A police vehicle is a priority vehicle only if it uses both optical and audio signalling. Optical signalling means a flashing blue light, and audio signalling is the two-tone horn (Politie, 2023a). In this case, other road users are asked to cooperate so that the priority vehicle can continue its journey as quickly as possible. However, it is still expected from the police officers to be aware of their special position and corresponding responsibilities. This includes anticipating on the unpredictable behaviour of other vehicles, which can arise because they fail to see the priority vehicle in time. Deviations from general traffic rules and codes of conduct happen restrictive and only made when absolutely necessary (Politie, 2023a). In each situation, the driver weighs up the risk to be taken and the intended purpose.

There are concrete rules that apply when police units choose to deviate from general traffic rules. First of all, approaching and crossing intersections happen at an appropriate speed. When entering the intersection, the driver of the priority vehicle should assume that other road users have not noticed them and might not let them pass (Politie, 2023a). Secondly, ignoring a red traffic light is done at a maximum speed of 20 km/h. Red lights at bridges and railway crossings can never be ignored (Politie, 2023a). Thirdly, roads can not be driven at a higher speed than 40 km/h over the applicable speed limit (Politie, 2023a). In addition, the driving speed on an emergency lane might not exceed 50 km/h (Politie, 2023a). Generally speaking, driving on the lanes of the opposite direction is permitted on non-separated lanes when this leads to a significant gain in time. In the case of separated lanes, where a physical obstacle makes it impossible to return to one's own lane, driving into oncoming traffic is permitted only after authorisation from the control room. The latter does not apply to very short physical separations such as traffic islands (Politie, 2023a). The last concrete guideline in the '*brancherichtlijn politie*' document is the position on the road in case of traffic jams. In these situations, the preference is to drive on the emergency lane. If this is not possible, the option to clear a lane by having the road authority cross off a lane is considered. If both options are not possible to execute, the police car will use the method of driving in between the first and second lane (Politie, 2023a).

2.4. Summary of findings

In this chapter, the relevant theoretical background required to describe the effects of traffic conditions on both criminal fugitive route-choice behaviour and police route-choice behaviour is outlined. This chapter was divided into three topics: traffic, fugitive behaviour and police behaviour.

Firstly, traffic was studied by looking at traffic flow theory and traffic management measures. From flow theory, it was found that the free flow of traffic is disrupted when the flow and density on the road increases. This leads to a lower acceptable speed as headways are reduced. Congestion occurs when the road is saturated with vehicles. For traffic management, two specific measures have been studied in detail: traffic lights and roundabouts. There are four control methods for traffic lights: rigid, vehicle-dependent, semi-rigid and traffic-dependent. While most intersections are controlled using the vehicle-dependent method, it was also found that during peak periods this method behaves more and more like a rigid control as the junction becomes busier. A rigid control system uses fixed cycle, green, yellow and red times. In one cycle, all directions get green exactly once. In order to determine the number of phases and the combinations of directions that get green at the same time, a conflict matrix is composed. As well as controlling a single intersection, it is also possible to link several intersections together to use network control. The most common example of this is green waves, which can be used for two reasons. The first is to improve safety where two intersections with traffic lights are within a short distance of each other. The second reason could be a political decision to minimise congestion or emissions, for example. The chapter on traffic was concluded with a study of roundabouts. They can be seen as a single server system using the first-in-first-out discipline. The waiting time at a roundabout depends on the capacity and intensity of the lane. Up to a waiting time of 50 seconds per car, the roundabout is classified as functioning, which corresponds to a saturation level of less than 80%.

Secondly, escape behaviour was examined, divided into the themes of criminal decision-making, route choice decision-making under stress, and rationality. It was found that there is no specific knowledge about decision-making in escape situations, but that decision-making is strongly influenced by both personal and crime-related characteristics. However, there is no consensus on how exactly these characteristics influence behaviour, which makes it impossible to create behavioural profiles based on these characteristics. Factors that influence route choice decisions include avoidance of traffic and obstacles, route distance and maximum speed, use of navigation devices and familiarity with the area. It was also found that high stress can lead to the avoidance of narrow spaces such as tunnels and bridges. Finally, high stress drivers were found to be more likely to choose alternative routes to avoid being stuck at a red light, even if this meant an increase in travel time and distance. An important consideration in both criminal and route choice decision-making is rationality. Full rationality assumes that people have all available knowledge, which they use to calculate the costs and benefits of all options. They then choose the option that provides the highest utility. However, people have a limited capacity to make all these calculations. Therefore, bounded rationality is introduced, which states that people choose a satisfactory strategy rather than the optimal strategy. In criminal decision-making, the dual-process theory is an example of bounded rationality. This theory suggests that two modes of mental processing operate simultaneously in activities. For example, in a stressful situation such as committing a crime, reflective and impulsive processing might occur at the same time. When deciding on a route, bounded rationality takes into account the emotions that certain circumstances evoke, as well as preferences. In addition, the preference for short-term goals over long-term goals is a classic example of bounded rationality.

Lastly, police behaviour during an interception attempt was studied. This revealed that there are specific guidelines and regulations that govern the driving of police officers, focusing on the use of emergency signals and deviation from standard traffic rules. Police vehicles are only a priority vehicle when both optical and audio signalling is on. If this is the case, deviations from traffic rules are allowed only when absolutely necessary, with concrete rules specifying appropriate speeds at intersections, when ignoring red lights, and when driving on emergency lanes. Furthermore, the position of police units on the road is specified. Driving into oncoming traffic is only permitted when both directions are not physically separated, or at very short physical separations such as traffic islands. In other cases, permission must be obtained from the control room. In cases of traffic jams, preference is given to driving on the emergency lane or clearing a lane with the road authority's assistance. If neither option is feasible, police cars may drive between the first and second lanes.

3

Model

In this chapter, consecutively the conceptualisation and formalisation for the discrete-event simulation model about criminal fugitive route decision-making is developed. This is based on the theoretical background from chapter 2. Both the conceptualisation and formalisation are divided into four sections, each providing insight into a specific topic. Each section first describes the conceptualisation, followed by the formalisation. Section 3.1 covers the implementation of the road network of Rotterdam along with some general concepts. Thereafter, section 3.2 discusses important traffic concepts. Information about fugitive behaviour is presented in section 3.3, and section 3.4 details how police behaviour is implemented in the model. This chapter concludes with an explanation of the model validation in section 3.5.

The model developed for this study can be found via the following link: GitHub Repository: Effects of Traffic on Fugitive Interception

3.1. Road network

In this section, mainly the road network characteristics are presented, The conceptualisation can be found in paragraph 3.1.1, the formalisation in 3.1.2. Besides, some general concepts for a fugitive escape model are introduced.

3.1.1. Conceptualisation of the road network

The model is built for the city of Rotterdam. The road network for this is retrieved from OSMnx, a Python package used to download, model, analyse, and visualise street networks from OpenStreetMap (Boeing, 2017). Only roads that can be used by cars are included.

As a performance metric from figure 4.1 is the percentage of successful interceptions, it is essential what a successful interception entails. Therefore, the concepts of interception and escape need to be covered. A fugitive is successfully intercepted when a police unit and fugitive are located at the same place at the same time. A fugitive escapes when they reach one of the highways surrounding Rotterdam.

Table 3.1: Conceptualisation of general model

Concept	Description
Road Network	The roads of Rotterdam which cars can use, as from the OSMnx-package
Interception	A fugitive is intercepted when a police unit is at the same location as the fugitive at the same time
Escape	A fugitive has successfully escaped when they reach one of the highways from the ring of Rotterdam

Figure 3.1: The road network and ring of Rotterdam. By reaching the ring, one has successfully escaped

3.1.2. Formalisation of the road network

The road network of Rotterdam will be generated using the OSMnx Python package. This package enables the download of spatial data and the visualisation of urban networks (Boeing, 2017). The network will exist out of nodes (intersections) and edges (roads) that connect the nodes. Both nodes and edges have attributes needed for the simulation. Edges contain information on the nodes they connect, their length, maximum speed, travel time, road category, number of lanes, level of congestion, driving speed, whether its a one way road and police travel time. Nodes contain information about their location, which obstacles are present and the delay time on the node. This is visualised in table 3.2. A distinction is made between real data derived from Open Street Map, and data that is based on assumptions as conceptualised in chapter 3.

Table 3.2: Network graph attributes

Edge attributes			
Origin node	Integer	Node ID	Real data
Destination node	Integer	Node ID	Real data
Length	Float	Meters	Real data
Maximum speed	Float	km/h	Real data
One way	Boolean	True/False	Real data
Travel time	Float	Seconds	Real data
Road category	String		Real data
Number of lanes	String		Real data
Police travel time	Float	Seconds	Assumed
Congestion factor	Float	-	Assumed
Travel time with congestion	Float	Seconds	Assumed
Police travel time with congestion	Float	Seconds	Assumed
Node attributes			
Node ID	Integer		Real data
Location of node	Float	Lon, Lat	Real data
Street count	Integer		Real data

3.2. Traffic elements

The components that make up traffic need to be conceptualised and formalised before they can be used in the simulation model. From the theoretical background, it became clear that both congestion and traffic management elements are influential on the amount of time it takes for a fugitive to travel a particular route. This section is divided in three topics: congestion, traffic lights and roundabouts.

3.2.1. Conceptualisation of traffic elements

In this section, the important terms of traffic will be conceptualised. With this, the demarcation of the research is made clear.

Congestion

As can be seen from the literature study, congestion on roads is dependent on the degree of saturation. This is the percentage of the road capacity that is used at a certain moment. The conceptualisation is done based on two concepts both of which cover a part of congestion.

The first concept is time. It has been already established that congestion is the highest during rush hours. However, the level of congestion is not constant but fluctuating over the time period between 16:00 and 18:00. This can be divided into increasing congestion, the peak and declining congestion. In this conceptualisation, the time period where congestion is at its peak is taken into account.

Secondly, the type of road is determinant for the degree of congestion on a road. This is indicated by the fact that the most congested roads are highways, and the least congested are residential roads. This is in line with the hierarchy of the roads, where highways are at the top and residential roads at the bottom of the ladder. It therefore is conceptualised that the type of road, in order of the hierarchy, determines the level of congestion.

Table 3.3: Conceptualisation of congestion

Concept	**Description**
Moment during rush hour	The moment during rush hour at its peak
Type of road	The higher up in hierarchy a road is (highway, trunk, primary, secondary, tertiary or residential road), the higher the congestion is on that road

Traffic lights

The conceptualisation of traffic lights in the model encompasses two main components: the design of individual traffic lights and the design of the traffic light network. During rush hours, it is assumed that all traffic lights operate using a rigid control method, characterised by fixed green, red, and cycle times. However, in reality, these timings vary from one intersection to another. Each intersection is typically managed by a specific controller specifically designed for its unique conditions. Factors influencing traffic light control include the traffic volume an intersection handles and the direction of the main traffic flow. Consequently, even intersections that appear similar may be regulated differently, adding complexity to the modelling process. While numerous assumptions are necessary to simplify the conceptualisation of traffic lights for research purposes, these assumptions are acceptable for addressing the research question. It is important to note that incorporating detailed traffic light designs increases the computational demands of real-time decision-support systems. Therefore, while adding realism improves the accuracy of the model, it is not always an advantage in real-time models.

The total cycle time of a regulated intersection depends on the size of the intersection and the number of different directions possible. However, there is a maximum cycle length to avoid red light negation. This maximum cycle length is longer when an intersection does not include slow-moving traffic, and shorter when it does. The total cycle time is therefore conceptualised as being a random length, with an upper limit. This limit is higher if the intersection does not include tertiary or residential roads, as it is assumed that these are the types of roads where slow-moving traffic is present.

The only aspect that does not require assumptions is the amount of yellow time. For safety reasons, this is strictly defined as a function of the maximum speed on a road.

From the theoretical background, it became clear that the amount of green time is dependent on the intensity of the direction. This means that main directions, directions with the highest intensity, have longer green times compared to less used directions. In some situations a second conceptualisation is possible. This applies to intersections where roads of different hierarchies cross. The length of green light of these intersections can be conceptualised as scaled by hierarchy: the percentage of the total cycle time that a direction is granted green depends on the position in the hierarchy. Specifically, this means that at an intersection where a primary and a secondary road intersect, the primary road is granted green for a greater proportion of the cycle time than the intersecting road. When the total cycle time, and the length of green and yellow are known, the red time can be calculated. The red time is the total cycle time minus the time it shows green and yellow.

With regard to green waves, there are two reasons for their implementation. The first is safety. Drivers don't expect to stop so soon after passing another traffic light, and this would lead to unintentional but dangerous red light negations. The second reason for a green wave is a design decision by the road authority, which can be based on various objectives such as optimising traffic flow or saving fuel. In most cases, green waves are present for the straight ahead direction and not for the turning direction. Green waves can be conceptualised as being implemented when two traffic lights are close together, and that the green wave is only present in the straight ahead direction. As it is unknown on which roads in Rotterdam green waves are implemented, it is assumed here that they are only present on primary roads.

The number of phases is a measure on the tactical level, and is often determined by the number of conflict points an intersection has. By simultaneously granting green to as many conflict-free directions as possible, the intersection is optimally regulated. As the conflict matrices for each intersection are not known, it is very difficult to realistically model an intersection. Therefore, another conceptualisation of the number of phases could be the number of roads meeting at the intersection.

Then, the order of phases has to be conceptualised. The layout of the intersection plays a role in this decision. However, in this research, the order of phases is conceptualised as random. It is important to ensure that in each cycle, each direction gets green.

Finally, it is important to define the waiting time at a traffic light. First of all, the waiting time depends on when one arrives at the intersection. This can be either during the green phase or at any other time in the cycle. There is no waiting time when arriving during the green phase, and a waiting time depending on the cycle length when arriving at any other time. It is assumed that all cars queuing for the traffic light can pass through the intersection within one cycle. Therefore, the waiting time will never exceed the cycle time.

Table 3.4: Conceptualisation of traffic lights

Concept	Description
Control method	Rigid control method, with fixed cycle time and green time for each direction
Cycle time	The time it takes to go through an entire cycle. The length increases with the number of possible directions and when no slow-moving traffic is present at the intersection (CROW, 2022a)
Yellow time	Fixed yellow time dependent on the maximum speed on the road (CROW, 2022a)
Green time	The higher the intensity of a direction, the longer the green time relative to the total cycle time (CROW, 2022a)
Red time	The total cycle time minus the green and yellow times of that specific direction (CROW, 2022a)
Green wave	Only for straight ahead directions and when two traffic lights are critically close to each other
Number of phases	Similar to the number of roads meeting at the intersection
Order of phases	A random order, where each road at the intersection turns green exactly once per cycle
Waiting time	Everyone passes the traffic light within one cycle. Therefore the maximum waiting time is limited to the cycle time.

Roundabouts

The operation of encountering a roundabout can be broken down into several actions. First of all, seeing an approaching roundabout, one reduces speed to be able to react accordingly to the situation ahead. When a car is at the obstacle, there are two options. The first one is that there is no other traffic that has priority over them, and with adjusted speed they can get on the roundabout and choose direction. It is also possible that there are other vehicles with prioritisation that have to be given right of way. This means that the driver in question has to wait until the prioritised flow dries up enough for them to get on the roundabout. On the roundabout itself, one drives with the adjusted speed until the chosen exit road arises. After taking the exit, one accelerates to the normal speed. These different aspects can be conceptualised as follows.

The speed at a roundabout consists of three moments. Before the roundabout one decelerates, on the roundabout itself a lower speed is required for safety reasons, and after the roundabout one accelerates again to the highest possible or allowed speed.

On a roundabout, there often is a main direction. This is the route, a combination of entrance and exit, with the highest traffic flow. Normally this is the direction straight ahead, so here the entrance and exit roads have the same direction. Therefore, it is conceptualised that the main route consists of the two roads that follow the same direction. In roundabouts with four exits, chances are that this way of defining the main direction would result in two perpendicular main routes. This is not realistic, therefore one of the two will randomly be chosen.

The waiting time to enter a roundabout depends on the number of cars in the queue and the amount of traffic coming from the direction to the left. The waiting time due to the number of cars in front can be conceptualised as a function of the degree of saturation and the average waiting time per car. The latter is conceptualised as follows: if a car comes from the main direction, the waiting time will be significantly shorter than if it comes from the road to the left of the main direction. The road to the right of the main direction does not lead to a high waiting time.

The final factor to consider when designing a roundabout is the time taken to drive around the roundabout itself. The choice of exit is very important, as it determines the distance travelled. Secondly, the speed at which the roundabout is taken is important. Combining these two factors, the time it takes to drive around a roundabout from start to finish is calculated from the distance and the speed.

Table 3.5: Conceptualisation of roundabouts

Concept	Description
Speed	Deceleration before the roundabout, on the roundabout a low speed is assumed, where after the car accelerates again
Main direction	The direction with the highest traffic flow. This is the direction that goes straight ahead. In a situation where there are multiple road combinations that go straight, one is chosen as the main direction
Waiting time	How long it takes to enter the roundabout. The longer the queue and the more traffic coming from the left direction, the higher the waiting time
Time to drive roundabout	How much time it takes to drive the roundabout from start to finish, dependent on the driving speed and distance travelled. The distance is determined by the choice of exit

3.2.2. Formalisation of traffic elements

In this section, the important concepts of traffic found in the previous section will be formalised. The exact numbers for implementation in the simulation model are presented in tables.

Congestion

As conceptualised, the level of congestion depends on the type of road. Roads in the network are categorised in one of the following six types: highway, trunk, primary, secondary, tertiary or residential. The relationship between road type and amount of congestion was conceptualised as follows: the higher up in hierarchy a road is, the higher the congestion on that road. This will be implemented by giving each road a congestion factor. This factor only depends on the road type, and not on the number of lanes that road has: this is based on the assumption that the number of lanes is chosen to match the volume of traffic passing through here, making the congestion independent of the number of lanes. However, for trunk, primary and secondary roads with one lane, the choice is made to increase the congestion factor slightly. The values used for implementation can be found in table 3.6.

Table 3.6: Implementation values of congestion

Road type	Congestion factor
Motorway	2 x travel time
Trunk and Primary	1.75 x travel time
Secondary	1.5 x travel time
Tertiary	1.25 x travel time
Residential	1 x travel time
One lane (not for tertiary or residential roads)	value + 0.2

The congestion that is used in the road network of Rotterdam is visualised in figure 3.2. The darker the roads are coloured, the higher the congestion. Figure 3.2 clearly shows the high congestion on the ring of Rotterdam, and the decreasing congestion when going deeper into the network.

Figure 3.2: Congestion on the road network

Under normal circumstances, the travel time on a road is calculated using the road distance and the maximum speed allowed on the road. This leads to a time in seconds that encompasses the amount of time it takes to drive from the start to the end of this road. However, when including congestion, the travel time will increase. This increase is not the same for each road, as can be seen in table 3.6. The travel time with congestion in the model where traffic conditions are taken into account is calculated as follows:

$$\text{travel time with congestion} = \begin{cases} \text{travel time} \times (\text{congestion factor} + \text{one lane factor}) & \text{IF big one lane road} \\ \text{travel time} \times \text{congestion factor} & \text{ELSE} \end{cases} \tag{3.1}$$

Equation 3.1 multiplies the travel time with the chosen congestion factors as in table 3.6. In case a primary or secondary road only has one lane, the travel time increases even more.

Traffic lights

The operation of traffic lights consists of two fundamental components: the phase order and the internal processes within each phase. The first step in regulating a traffic light is to determine whether it is part of a green wave. If this is the case, the regulation of the traffic light is identical to that of its predecessor, but with a short delay depending on the exact distance between the two traffic lights. Otherwise, the traffic light must be configured itself.

In reality, no two intersections in Rotterdam are regulated in the exact same way, and determining the phase order is very complicated. Based on a conflict matrix, the most optimal setting is found for a specific intersection, so that it can handle the local congestion and the distribution of directions as good as possible. As the goal of this thesis is to find a plausible set of fugitive escape routes for the city of Rotterdam, it is not necessary to perfectly implement each intersection.

So, in this simulation model, the conceptual choice is made not to incorporate this way of designing phase orders. Instead, it is decided that traffic lights only calculate their internal state (green or red) when the fugitive crosses this point. This way, the waiting time at the intersection with a traffic light is calculated based on the cycle time and green time. This information combined is used to calculate the probability of arriving during the green time, which results in no waiting time, or else the waiting time until red becomes green. This way of implementing the waiting time at traffic lights avoids the challenge of matching up all traffic lights in Rotterdam. This would mainly get problematic when trying to implement green waves correct. Each component important for the regulation of a traffic light will be elaborated on in the following paragraphs.

Cycle time

The cycle time was conceptualised as increasing with the number of possible directions and when no slow-moving traffic is present at the intersection. In order to arrive at a reasonably realistic cycle time, several intersections were observed (see appendix B). The observation shows that most of the intersections studied have a cycle time between 56 and 63 seconds. This seems to apply to any intersection, no matter what type of roads cross. The only deviation is when a tram uses their priority status to cross the intersection. This increases the cycle time significantly. Therefore, the decision is made to use a longer cycle time for intersections with tram lanes. In these cases, the cycle time uses a triangular distribution of (56,60,240).

Yellow time

Yellow times are regulated by law, and depend on the maximum speed on the road, and on whether or not the lane is going straight ahead. Yellow time increases with the maximum speed, and is higher for ongoing traffic. However, yellow time is not specifically implemented. Some of the red time used in the model would actually be observed as yellow time.

Green time

According to the conceptualisation, the green time of a road depends on the relative intensity of that road compared to the other roads on the intersection. This could be done using the ratio of the number of lanes the specific road has to the total number of lanes the intersection encompasses. For the same reason, the road type could be included to account for the intensity, as roads higher up in hierarchy are more crowded.

However, as a result of the time constraint, the choice is made to simplify the green time calculation. As mentioned before, intersections of different types were observed. From the measurements as in appendix B, the mean green time from the different directions is used. This equates to 20 seconds when the traffic light is part of a green wave or on intersections where a tram is present, as this are almost always big intersections. For all other regulated junctions, a green time of 15 seconds is implemented.

Green wave

A green wave is only implemented when this is required for safety reasons. This is the case when there are traffic lights within 150 metres of each other. Green waves are most common on larger roads. Therefore, the model implements a green wave for traffic lights on primary or trunk roads. For a green wave, blocks of 5 traffic lights are used. When entering a block, there is a probability of having to wait at a red light. After that, when following the road with the green wave, there is no waiting time for the next 4 traffic lights. This is implemented in the model by using an 80% probability of a green light, and 20% probability of a red light at every traffic light on a primary or trunk road. This leads to a different pattern in terms of stop and go, but is similar in terms of delay time on the road.

Red time

When all other times are known, it is possible to calculate the red time for a phase. The red light is shown for the remaining part of the cycle where it is not green or yellow. This relationship can be expressed as follows:

$$\text{red time}_i = \text{cycle time} - \text{green time}_i \tag{3.2}$$

Where:

i = the specific road [-]

Traffic light categories

An overview of the categories, together with the amount of times they occur and how the cycle time and green time is implemented can be seen in table 3.7.

Table 3.7: Overview of the traffic light categories

Category	Implementation
Part of green wave	Cycle time = triangular(56,60,63) Green time = 20
With tram	Cycle time = triangular(56,60,240) Green time = 20
Normal	Cycle time = triangular(56,60,63) Green time = 15

The manner in which traffic lights are regulated is based on a number of assumptions and simplifications. For instance, the yellow time is not taken into consideration. Furthermore, the manner in which green waves are implemented could result in a non-zero wait time more than once within a block in which the green wave is regulated. In reality, upon passing the first traffic light in a block, the remaining traffic lights will be green until entering a new block. Nevertheless, the random factor in determining the cycle time of each traffic light introduces a degree of realism, as each intersection is regulated in a similar manner, but with different parameters.

Roundabouts

In the base model, the maximum speed on a road is used to calculate the travel time. This logic also applies to the travel time on roundabouts. However, the twisty nature of a roundabout means that one cannot drive the roundabout at the set speed limit. During its design and construction, consideration is given to the curve radius. Consequently, the speed on the roundabout itself will be set to 20 km/h below the maximum speed, regardless of the speed limit. This is to allow for the deceleration necessary to navigate the curve safely. This is rewritten in equation 3.3.

$$\text{speed on roundabout} = \text{maximum speed on road} - 20\text{ km/h} \tag{3.3}$$

3.3. Fugitive route choice behaviour

From the literature study, it became apparent that fugitive route choice decision-making can be divided into three sub topics: the fugitive and crime characteristics, fugitive behaviour, and route-choice behaviour. In table 3.10, these two aspects are combined to create two fugitive profiles.

3.3.1. Conceptualisation of fugitive behaviour

In this conceptualisation section, first the characteristics of criminals and the crime scene are discussed. Then, fugitive escape behaviour is conceptualised. From this, two fugitive profiles are created that will be used in the model: the calculating and the distressed criminal.

Characteristics profiles

The different suspect characteristics based on literature as specified in figure 2.1, are hard to translate into suspect profiles. Reason for this is that there are no specific personal characteristics that define a fugitive, and there are very many combinations possible in terms of the different characteristics. Moreover, the correlation between stress sensitivity, risk aversion, level of premeditation, and level of organisation makes it difficult to conceptualise distinguishable fugitive profiles. It therefore is chosen not to conceptualise specific behavioural profiles to reduce the number of assumptions of the fugitives characteristics.

There are three crime characteristics found during the literature study that need to be conceptualized. These are the time of day, the level of impact of the crime and the crime scene location. Regarding the time of day, earlier research already looked into fugitive route choice behaviour during non-rush hour, or even at night. In this conceptualisation therefore, the focus lies on route choice during rush hour, specifically between 16:00 and 18:00. This provides the opportunity to study the effect on route choice of congestion and traffic lights during operating hours.

As for the level of impact of a crime, crimes are categorised in either having low or high impact. However, the difference in suspect behaviour and characteristics between high and low impact crime are not clear. The level of impact does have an effect on the police response. Because of the societal impact of high impact crimes, this conceptualisation will focus on these types of crimes. This will become evident more in the police behaviour than in the fugitive behaviour, as a result of the lack of knowledge on this topic.

Literature showed that there is a relationship between the crime scene location and the type of crime. However, two fixed crime scene locations were selected for this study, chosen to represent contrasting scenarios. The first location is situated in the city center of Rotterdam, providing a complex network of escape routes. This central location was chosen to ensure that fugitives face numerous decision points in order to reach the highway. It is expected that the more limited route options available in the area of the crime scene will result in a higher probability of interception. Therefore, for the second location one of the port docks of Rotterdam is chosen. The road network in this area is significantly different from that of the city centre, with many dead-end roads, different traffic situations and fewer escape route options. By comparing these two distinct locations as starting points for an interception, the study aims to provide a comprehensive understanding of how varying crime scene locations influence fugitive escape strategies and police interception effectiveness.

Table 3.8: Conceptualisation of crime characteristics

Concept	Description
Time of day	During evening rush hour, which is between 16:00 and 18:00
Level of impact of crime	Crimes with high impact on society
Crime scene location	Depends of the type of crime

Fugitive behaviour

Looking at the behavioural factors, these could be divided into criminal behavioural factors and route choice behavioural factors. In terms of the criminal behavioural factors, camera avoidance and the want to be unpredictable were found. For camera avoidance, literature revealed that this is not always a priority for fugitives. However, a planned escape from a high-organised crime has probably taken into account the location of number plate recognition cameras (ANPR) and therefore can avoid them. Non-organised criminals are assumed not to have this knowledge, and therefore do not avoid cameras. The second one, being unpredictable by taking turns at each intersection, is mostly seen in fugitives with high stress.

In figure 2.2, one of the route choice behavioural factors mentioned is the use of a navigation device such as Google Maps. This device calculates the route that has the shortest time to reach the destination based on real time traffic information, which makes the route choice when using navigation arguably predictable. The only difficulty comes from not knowing a fugitive's chosen destination. The combination of the factors being unpredictable and the use of navigation devices is conceptualised by assuming that the fugitive does not use the absolute shortest route from the crime scene location to their destination. In other words, it is assumed that there is a deviation from the proposed route.

In addition to the use of navigation, the level of familiarity with the environment is also important for the ability to choose the best escape route. According to the bounded rationality theory, it is impossible to calculate the shortest route, as information about all travel times is needed. However, the shortest route does not always equal the best escape route. Familiarity is very difficult to incorporate in models about fugitive interception, as the knowledge of the area is both person-specific and environment-specific.

This leads to difficulties in using this factor for police, as it is impossible to know what areas a specific fugitive is familiar with. Familiarity can be conceptualised in different ways, which is dependent on the level of organisation behind the crime. Organised crime can be seen to use full familiarity as a result of the extensive planning. However, non-organised criminals cannot be classified as having no familiarity at all. As it are crimes of opportunity, those offenses often take place in the area where those people live, and where they have some level of familiarity of the direct surrounding area.

Literature showed that drivers under normal circumstances tend to avoid roads with obstacles. Stressed drivers however also avoid spaces that create the feeling of being locked up, which are tunnels and bridges. This is a fairly rational choice for individuals on the run from a crime. Therefore, obstacle avoidance can be conceptualised as a total avoidance of tunnels and the bridges that connect the north and south part of Rotterdam. Moreover, roads with traffic lights and roundabouts are avoided, but not as strictly as those bridges and tunnels. Lastly, roads with a higher number of lanes are preferred. The same avoidance is found for high density traffic. This can be conceptualised as a preference for roads with less traffic.

There is no consensus on the effect of route distance on route choices. In general, the shortest path is preferred. But, there is also evidence for the fact that people are willing to add distance to their route to avoid standing still at a red light. Therefore initially, the effect of route distance is conceptualised as opting for the shortest path, taking travel time into account. This is dependent on both the speed on a road and the length of it. The travel time than accounts for the fact that people do not always go for the shortest distance when this route contains slow moving traffic.

A preference for routes with high maximum speed was found. Reasoning for this is that this brings the suspect as far as possible in a set time. Therefore, roads with a higher speed are preferred over roads with a lower speed.

The destination of fugitives is scoped to be on one of the highways leaving Rotterdam. The choice process to determine the destination can be conceptualised in two ways. Firstly, a fugitive can have a specific destination in mind that they want to reach. This is in line with the way strategic route choices such as the goal are generally made, which is prior to the trip taking place. Secondly, a fugitive may have the destination depend on environmental circumstances, to possibly go to the intended destination later when the police have blown-off the initial search. This is displayed by changing direction constantly as a result of environmental factors. This is different than how destination choice is made in general, and can be classified under the tactical level as presented by Michon (1979). In this conceptualisation, escape attempts have a fixed target that they want to reach. The goal of this research is to study the impact of traffic situations on fugitives' route choice. It is therefore unnecessary to identify the most optimal or precisely correct route, but the generation of plausible routes is sufficient. Even though the destination in this case is immutable, the route to get there is not. Therefore, the erratic driving behaviour can still taken into account.

Finally, the reaction to different situations needs to be conceptualised. This is done in two parts: reaction to intersections with traffic lights, and reaction to congestion. In most cases, the reaction when encountering traffic lights is as expected, which is according to the rules. People choose the lane of the desired direction, then wait for the sign to turn green before crossing the intersection. Yellow and red light trigger the action to stop. However, the interviews show that under high stress, people react differently. The first difference is that a stressed person is more inclined to not obey to the rules, increasing the chance of running a red light. Secondly, under stress, one tends to change direction more often when this direction gets green quicker. This behaviour can be seen in a sudden change of lanes. As a result, the response to a traffic light can be conceptualised twofold, depending on the stress level. A person with a low stress level obeys to the prevailing traffic rules. However, someone with high stress is more likely not to, and will change their direction according to where in the cycle they arrive at the traffic light.

The reaction to congestion also changes according to the stress level, as the interviews revealed. Without any stress, one patiently stays on the congested road. However, someone that is under time pressure has less patience. This translates into the behaviour that when it is possible, this person will leave the road with high congestion, and will turn onto an intersecting road. This is conceptualised as not changing direction for persons with low stress, and changing route when the congestion is higher than the threshold for a stressed person.

Table 3.9: Conceptualisation of behavioural route choice characteristics

Concept	Description
Being unpredictable	Choosing a deviating route from the fastest route as from Google Maps
Level of familiarity	Either full familiarity, in cases of organised crime, or little familiarity in cases of non-organised crime. Than, only familiarity in the direct area of the crime is assumed
Obstacle avoidance	Avoiding tunnels and big bridges, and trying to avoid traffic lights and roundabouts
Traffic avoidance	Avoiding routes with a high congestion chance during rush hour
Route distance	Either minimising the route distance, or route distance is not important because someone deviates from shortest route to avoid standstills (Ringhand & Vollrath, 2017)
Route maximum speed	Preferring roads with a higher average speed to get away as fast as possible (Ringhand & Vollrath, 2019)
Destination choice	Either having a fixed destination in mind, or changing destination according to environmental factors
Emotional state	The fugitive can be classified as being in cool mode or in hot mode (van Gelder, 2013)
Reaction to traffic lights	Without stress, people use traffic lights as the law requires. Under time pressure, they are more likely to ignore a red light and change direction if their preferred direction takes too long to turn green.
Reaction to congestion	Not changing direction for persons with low stress, but changing direction when the congestion is higher than the threshold for a person with high stress

Fugitive profiles

From literature, a clear distinction can be made between short- and long-term goals during route choice. The different goal lengths can be combined with the theory about the control levels, specifically the strategic, tactical and operational level. As previously stated, the strategic level covers the planning stage of driving, which occurs before the trip takes place. This is the control level that is used to set and achieve long-term goals. When planning a route from start to destination, pursuing long-term goals translates into favouring the fastest route possible. Moreover, the strategic level takes into account future circumstances. During planning, it is crucial to consider not only the circumstances at the time of planning, but also to anticipate potential differences at the time of the actual trip. In this conceptualisation, the anticipation of future circumstances is considered to be part of the pursuit of long-term goals. The term future circumstances encompasses traffic patterns and planned roadworks or other scheduled events.

On the other hand, short-term goals require control at the tactical level, which encompasses decisions such as driving speed, lane changes and manoeuvres. Short-term objectives are evident in the preference for routes with a high maximum speed (even when this is at the expense of the quickest or shortest route), and the avoidance of stops, whether at traffic lights, or other obstacles. Short-term thinking can mainly be found when the driver experiences stress.

These two modes of thinking match the hot and cool framework as conceptualised by van Gelder (2013). In line with this conceptualisation, this research uses two fugitive profiles that determine choice behaviour: the calculating fugitive (cool mode) and the distressed fugitive (hot mode). Combining all behavioural factors, table 3.10 can be drawn up. This shows the two different behavioural profiles, and how each of the factors is conceptualised.

Table 3.10: Conceptualisation of the two fugitive profiles

Concept	Calculating criminal	Distressed criminal
Emotional state	Cool mode	Hot mode
Level of organisation	High organisation	No organisation
Goal length	Long term goals • Preference for the fastest route • Anticipating on future circumstances (traffic patterns, planned roadworks or events) during the the planning stage	Short term goals • Preference for roads with high speed • Avoiding standstills at obstacles (traffic lights, roundabouts)
Level of familiarity	Full familiarity	Only familiar with area that is directly surrounding the crime scene location
Destination choice	Fixed destination	Fixed destination
Avoiding narrow spaces	Avoiding tunnels and big bridges	Avoiding tunnels and big bridges
Being unpredictable	Not being unpredictable	Deciding the next step at each intersection, not beforehand
Camera avoidance	Avoiding roads equipped with an ANPR camera	No camera avoidance
Reaction to traffic lights	Dealing with traffic lights in line with the rules (stay on lane, stop at a yellow/red light, drive at a green light)	Possibly changing direction according to the moment in the cycle one arrives at the traffic light
Reaction to congestion	No reaction to the level of congestion	Changing road when traffic gets too congested on the current road

3.3.2. Formalisation of fugitive behaviour

Here, an insight is provided into how the earlier conceptualised behaviour of the different types of fugitives is implemented. From the conceptualisation it became clear that the escape behaviour of a fugitive differs depending on the mental state of the suspect. This led to two criminal profiles: the calculating criminal and the desperate criminal. As the behaviour of these two is different, each will be formalised and implemented separately.

Calculating criminals

First, the behaviour in the cool mode will be formalised. Criminals with a cool processing mode are conceptualised to have organised the crime and subsequent escape in detail. This high level of organisation leads to full familiarity with the planned escape route, obtained either in reality or using maps. Having the opportunity to study the entire network and its road options beforehand, it is assumed to be possible to calculate the 'best' route from the crime scene location to the chosen destination. This implies that calculating criminals follow a pre-planned escape route. To decide what is the 'best' route, it is necessary to understand what requirements the route should meet according to fugitives in cool mode.

From the conceptualisation, the factors that where found for this type of criminal were the following: high organisation, pursuing long-term goals, full familiarity, trying to avoid major tunnels and bridges, as well as avoiding being seen on ANPR-cameras, and being somewhat unpredictable for police. Therefore, a route can be classified as 'best' when long-term objectives are pursued and when foreseeable challenges are avoided. Long-term goals are translated to a preference for the fastest route, in combination with the anticipation of expected circumstances at the time of the escape. This includes traffic patterns and planned roadworks or events. The fastest route can be calculated using Dijkstra's algorithm, using the travel time of roads as the weight. However, this does not take into account the preference to avoid bridges, tunnels and ANPR-cameras. Therefore, a dis-utility factor is included in the perceived travel time. This means that the shortest path is based on the travel time on a road, including the perceived extra time for each obstacle on the road. These perceived dis-utility factors can be found in table 3.11. These factors define how much shorter a route with obstacle has to be in order to be seen as more attractive over a longer route that avoids the same obstacle (van Droffelaar et al., 2024a).

Table 3.11: The perceived dis-utilities of obstacles for calculating criminals

Obstacle	Perceived dis-utility
Bridge	+ 10 s
Tunnel	+ 15 s
Traffic light	+ 30 s
ANPR camera	+ 30 s
Roundabout	+ 5 s

Figure 3.3 shows how the behaviour of calculated criminals is formalised. It shows that after deciding on the route to follow, roads and intersections are crossed in accordance with this pre-planned route. On roads, cool criminals drive in such a way that their behaviour does not stand out. The same goes for crossing intersections, where they follow traffic rules. This means that they will stop at a red light, but cross the intersection when it is green. However, it is assumed that in 2% of the route decisions, a wrong turn is taken. This accounts for human error in decision-making.

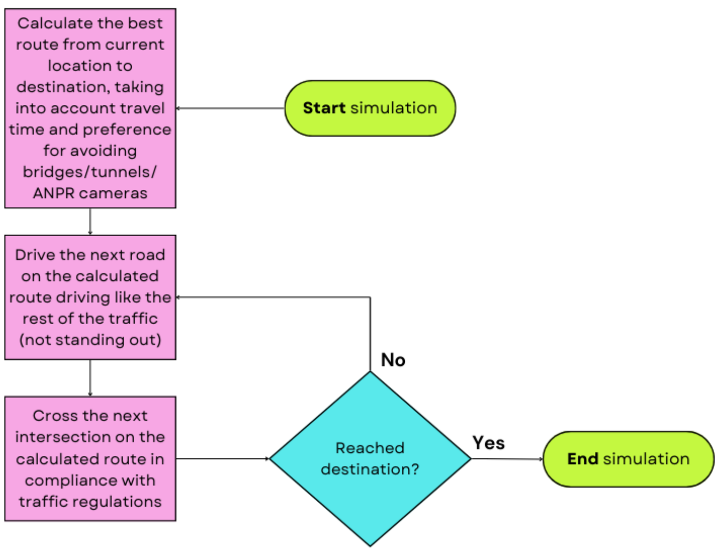

Figure 3.3: Formalisation of the behaviour of the calculating criminal

Distressed criminals

Here, the behaviour in the hot mode will be formalised. Criminals with a hot processing mode are conceptualised to have made no organisation plans about the crime and subsequent escape routes. Given that there is no pre-planned route that can be followed, the decision-making process regarding the route is conducted during the escape. This implies that at each intersection, a directional choice will be made. It is therefore necessary to understand the basis on which these decisions are made for distressed criminals.

It can be assumed that, even with the lack of preparation for the escape route, routes with high congestion are avoided. This can only be decided when the congestion is visually seen. However, this is possible because distressed suspects only decide on their next road when they have the overview of the possibilities. Furthermore, distressed suspects attempt to avoid bridges and tunnels, as these give a sensation of being confined. In contrast to calculating criminals, the ANPR cameras are not avoided, as they are unaware of their locations. These dis-utility factors can be found in table 3.12.

Table 3.12: The perceived dis-utilities of obstacles for distressed criminals

Obstacle	Perceived dis-utility
Bridge	+ 10 s
Tunnel	+ 15 s
Traffic light	+ 30 s
ANPR camera	+ 0 s
Roundabout	+ 5 s

Finally, the reaction to traffic lights as formalised in figure 3.4 requires explanation. As fugitives operating under the hot-mode experience high stress levels, they seek to avoid standstills at traffic obstacles. Moving through the network, even though the distance covered will be higher, provides them with a feeling of control. Therefore, they are not going to patiently wait at a traffic light until they are granted green. It is not uncommon to encounter traffic lights that indicate multiple directions, such as straight ahead, turning left or right. Rather than waiting until the direction becomes green that is in line with the route with the highest speed, suspects will often follow the direction with the least wait time. This is achieved by calculating a threshold value for how long a suspect will wait for the traffic light of their planned direction. If the wait time exceeds this value, they will switch to another direction if possible. The likelihood of this occurring is dependent on the number of lanes the road comprises, as the number of different directions at a traffic light is often related to the number of lanes.

In conclusion, suspects in the hot mode select their route based on the highest achievable speed, which also depends on the level of congestion. However, it is also crucial that they differentiate between this and the situation where the wait time at an obstacle is excessive. In such instances, they attempt to navigate to an alternative route, even if this road is less attractive based on its characteristics. It is important to note that distressed criminals do not operate according to a pre-defined plan. Instead, they select the optimal option at each intersection based on the delay time and characteristics of the neighbouring roads. Here, just like with calculating criminals, a factor of 2% is used to simulate human error. Even though distressed suspects do not operate according to a plan, this error could for example be present in choosing a dead-end street.

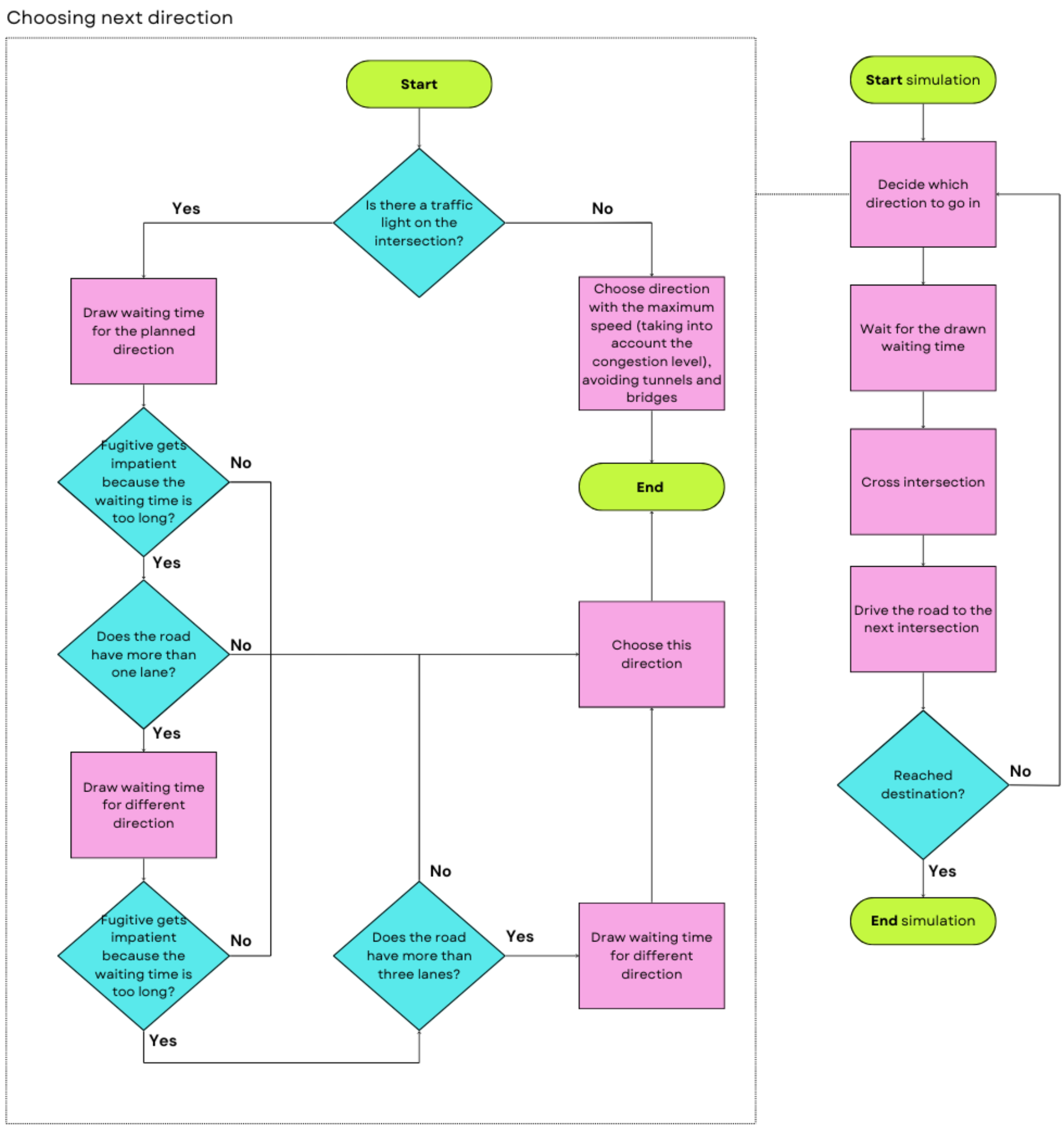

Figure 3.4: Formalisation of the behaviour of the distressed criminal

3.4. Police behaviour

In addition to the fugitives playing a big role in the interception model, the police behaviour is also important. The theoretical background indicated that there are specific guidelines for police officers when driving a priority vehicle. The concepts needed for police driving behaviour will be explained here, and are presented in table 3.13. Lastly, these concepts are translated to quantifiable metrics in order to be implemented in the discrete-event model.

3.4.1. Conceptualisation of police behaviour

First of all, it is important to classify where the police units start an interception. In this conceptualisation, each unit starts from one of the police stations in Rotterdam, which are presented in appendix C. Secondly, the number of units working together in an interception attempt is important, as this influences the interception probability. Each police station sends a maximum of one unit to react to a crime. As the crime is conceptualised to be a high-impact crime, police will utilise their signals in order to be classified as a priority vehicle.

It became evident that police officers in a priority vehicle seek out locations on the road with the greatest available space. This leads to the conceptualisation of a preference for bus lanes when they are present, as these are typically empty. Moreover, video analysis of police driving behaviour revealed that not only the level of saturation, but also the speed of traffic on a road and the number of lanes impact the ease with which the police unit can pass along stretches of road. The combination of those factors can be seen as the road resistance. Road resistance increases with decreasing speed and number of lanes. The same logic applies to traffic signals, where it is easier to pass queuing traffic when the intersection has lanes reserved for right- and left-turning traffic.

The guidelines for driving a priority vehicle as in section 3.2 are very specific in terms of speed, as it should be safe at all times. Despite the fact that the normal maximum speed does not apply to these vehicles, they are still subject to a maximum speed that they cannot exceed. Furthermore, vehicles should be operated at an appropriate speed when running a red light, crossing an intersection or using emergency lanes, in order to ensure safety. Consequently, the travel speed of a police unit may be conceptualised as being higher than the maximum speed, but in special situations, the speed is reduced considerably.

Table 3.13: Conceptualisation of police behaviour

Concept	Description
Police starting points	A unit starts the interception attempt from one of the police stations as in appendix C
Number of police units	The number of units that work together to intercept the fugitive
Use of signalling (siren)	Police drives with siren on
Use of bus-lanes	Bus-lanes are preferred over other roads
Road resistance	How easy it is for police vehicle to pass traffic. The resistance increases when a road has fewer lanes, and when the traffic speed on the road decreases
Travel speed	The driving speed is chosen according to the situation. This means driving above the maximum speed in normal conditions, but at special situations such as intersections, the speed is reduced considerably

3.4.2. Formalisation of police behaviour

The driving behaviour of police consists of three main actions: the planning of the route, followed by driving the roads and crossing the intersections. As a result of the vast experience of police agents driving in Rotterdam, it is assumed that they are able to calculate the best route. They do not deviate from this. Driving on roads and crossing intersections in the model is done based on the branch guidelines as specified in chapter 3. In reality and according to the guidelines different behaviour can be seen under different circumstances.

However, due to time constraints, the police behaviour has not been implemented in accordance with the conceptualisation. Compared to the conceptualisation, the use of bus-lanes is not included. The same goes for the reduced speed at intersections, which is not implemented in the model. Instead, the travel speed of units is set at 1.1 times the maximum speed on roads with one lane and 1.3 times the maximum speed on the rest of the roads. This factor is designed to reflect the fact that the crossing of intersections requires a lower speed than driving on a road. The factors have therefore been set slightly below the prescribed speed for priority vehicles, which is a maximum of 40 km/h above the speed limit. This approach allows for an average approximation to be taken into account. It has to be noted that there is a discrepancy between these guidelines and the actual implementation. In the model, the police use the same roads as the suspects, so no emergency lanes or bus lanes are taken into account. When the road is congested, the factor for police speed is used over the travel time with congestion to ensure that police use the same congestion levels as criminals.

In the model, the travel time for a police unit is based on the general travel time, as in equation 3.4.

$$\text{police travel time} = \frac{\text{travel time}}{\text{police speed factor}} \tag{3.4}$$

The police speed factor used can be found in table 3.14.

Table 3.14: The speed factor used to calculate the police travel time

Situation	Police speed factor
One lane	1.1
More than one lane	1.3

An intersection can either be non-regulated or regulated with traffic lights. In the case of the latter, the police is still permitted to drive even when it is red. In the model, this is formalised in such a way that the police always drives through red lights.

3.5. Validation and verification of the model

When constructing a model, it is crucial to validate both its structural design and outcomes. In this section, the validation of the structural design is conducted. The validation of the results will be presented in section 6.1. Validity refers to the degree to which the real-life system aligns with the modelled system. Due to the limited data available on fugitive interceptions, this proves challenging. Obtaining representative data on these interceptions is nearly impossible, as it mainly is extremely hard to gather information about fugitives who escaped. The model is not validated by experts but is an expansion of earlier research by van Droffelaar et al. (2024a). Since that research was conducted in close cooperation with the police, it is assumed that no significant errors are present in the model.

Even though both fugitive and police behaviour are modelled in a simplified manner, excluding a large proportion of possible behaviours, this does not necessarily invalidate the model. The goal of this research was to determine whether incorporating traffic into the optimisation models adds value in finding robust police positions. As the reactions to traffic for the two actors are modelled different from each other, the exact behaviour is not essential for achieving this objective.

Moreover, a high level of transparency is required to enhance the verification of the model. This report achieves this by thoroughly explaining the conceptualisation, formalisation, and implementation methods. This ensures that the steps taken to arrive at the results are clear and comprehensible.

4

Experimental design

After the implementation of the discrete-event model, the experimental set up for the escape model is discussed in this chapter. The experimental design explains how the model is used to generate the data that will be needed for the analysis. The chapter starts with a presentation of the input parameters that will be varied, complemented with the output variables of interest.

4.1. XLRM framework

The XLRM framework is a commonly used framework for structuring information in model-based decision support (Jafino, Kwakkel, & Taebi, 2021) (Lempert, 2003). It consists of four elements: external factors (X), levers (L), relationships in the model (R) and performance metrics (M). Each of these elements will be discussed, where after they will be applied to the case of fugitive escape modelling. This framework will be used as a base for the experimental set-up. The goal of the simulation model is to evaluate the effect of the levers on the performance metrics, while controlling for the external factors. The framework for this case is presented in figure 4.1.

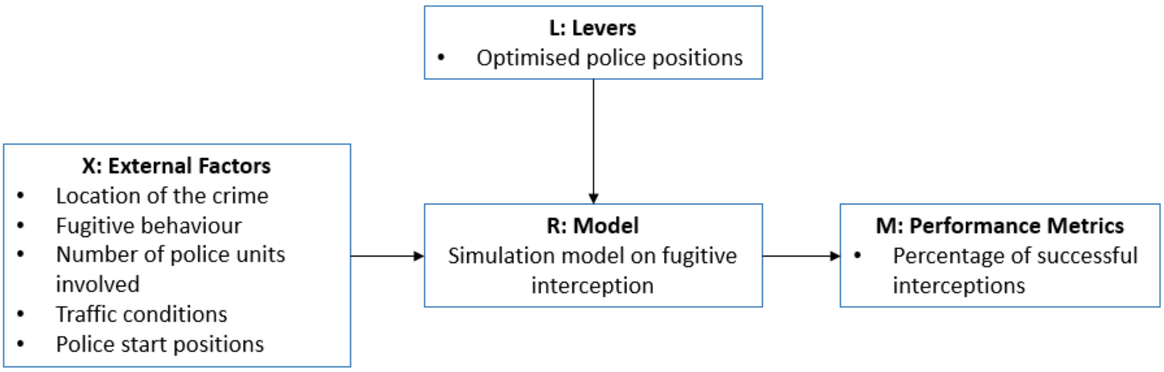

Figure 4.1: XLRM-framework for the simulation model

External factors (X)

An uncertainty that affects the system but cannot be controlled is classified as an external factor. Most variables in the XLRM framework fall into this category. For example, the location of the crime is an external factor as it is determined by the offender and significantly influences the pursuit. Similarly, the fugitive's behaviour is uncontrollable, including their mental state and any behavioural rules associated with it. Additionally, the number of police units and their starting positions, as well as the traffic conditions, are also considered external factors, as they are used in the experiments. The external factor of greatest interest in this study are the traffic conditions, as the research question specifically focuses on this aspect.

Levers (L)
Lempert (2003) describes the L as policy levers. In this context, the levers are treated as input variables whose effects are examined. The objective of this thesis is to assess the added value of incorporating traffic into the effectiveness of police strategies. This strategy encompasses both the number of deployed units and their positions. The optimised positions are the results of the optimisation model. Moreover, the effectiveness will be evaluated based on these positions.

Performance metrics (M)
The performance metrics (M) are the outcome variables to be observed. The primary metric of interest is the percentage of successful interceptions. This metric will be calculated for each combination of input variables in the experimental setup. Additionally, the robustness of the optimised police positions under varying circumstances will be analysed, based on the interception percentage. Thus, the percentage of successful interceptions is classified as the principal performance metric.

Relationships in the model (R)
The relationships in the system (R) refer to model structure and features. It entails the ways in which the external factors, levers and performance metrics are tied together and relate to each other. This is the actual simulation model, which was conceptualised and formalised in the previous chapter.

4.2. Experimental set-up
To be able to draw conclusions, the effects of the independent (input) variables on the dependent (output) variables have to be studied. Therefore, both the external variables and the levers from the XLRM framework have to be varied. In accordance with this diagram, the effects on the performance metrics of the crime scene location, fugitive behaviour, number of police units involved, and the traffic conditions have to be studied. These include the fugitive routes, the police routes, and the percentage of successful interceptions. The factors that will be varied in the experimental set-up and their values will be explained in this paragraph.

Location of the crime
The first external factor is the location of the crime. Realistically, a crime can take place anywhere in Rotterdam. However, this uncertainty is reduced to only two locations. Therefore, two locations with very different characteristics are chosen. The first location is in the centre of Rotterdam. This area is characterised by a large number of traffic lights, intensive use of public transport and a functional layout of the road network that allows easy access to the motorways. The second location is a harbour dock. This is an industrial area where the circumstances are most different from the city centre. The industrial area is known for its dead ends. Also, the escape route from this location is fairly predictable, as there is only one direction that leads away from the dock. After leaving the industrial area, it is likely that the suspect will not take the only road leading to the motorway, so as not to be too predictable. In this case, the only other possible route is through an area with village-like streets. This makes these two locations interesting to include in the experiments. The two locations are shown in figure 4.2

Figure 4.2: Overview of the two crime scene locations

Mental mode
As conceptualised, fugitives can either be calculating or distressed. This is in line with the dual process theory, and more specifically the cool and hot mental mode. The differences between the route choice decision making between the two is an important factor in understanding the success of an interception. In the experimental set-up, the mental mode can take two values: the cool and hot mode.

Traffic conditions
The aim of this research is to understand the effect of including realistic traffic conditions in a fugitive interception model. Therefore, it is very useful to see the difference in results between the model with and without traffic conditions such as traffic lights and congestion. By comparing the performance metrics derived from the experiments, statements can be made about the effects of traffic. The traffic situations can be split into several parts to study the effect of each part separately, but due to time constraints it is decided that each scenario is run either with all traffic situations or without any at all. Without traffic situations included, it means that both fugitive and police drive each road with the maximum speed, and that no waiting time is used when encountering obstacles. Table 4.1 summarises the differences between the model where traffic conditions are included and where not.

Number of police vehicles
The number of police vehicles used in an interception attempt is influential on the success rate. Therefore, this variable is also included in the experimental design. The number of police vehicles used in an interception is also a direct translation of the severity of the crime. Because the scope of this thesis is a high impact crime, the minimum number of vehicles used is 2. The outcomes will be compared to the interception with 4 vehicles. As conceptualised, police units start at a police station. The overview of the starting locations of the scenarios with four and two units can be found in C.

4.3. Experimental design
Having worked out these four factors, they are now combined in such a way as to create an experimental design. This is a full-factorial design. It is shown in table 4.2.

Table 4.1: The differences in the model with and without traffic included

Concept	Without traffic conditions	With traffic conditions
Road availability	All roads accessible for cars in the network (as from Open Street Map) are available.	All roads accessible for cars in the network (as from Open Street Map) are available.
Travel speed	Both fugitive and police move with the applicable maximum speed of that road.	In general, congestion is influential on the speed. For fugitives, the travel speed depends on the level of congestion in combination with the prevailing maximum speed. On roundabouts, the speed is 20 km/h lower than the set maximum speed, as a result of the sharp turns that have to be taken. For police, the travel speed is a factor higher than that of the fugitives.
Wait time	No wait time at intersections	Implemented wait time at intersections with traffic lights for suspects. Moreover, the police has no wait times at intersections as a result of being a priority vehicle.

Table 4.2: Experimental design

Scenario	Crime scene location	Mental mode	Traffic conditions	Number of police units
1	City center	Cool	Not included	2
2	City center	Cool	Not included	4
3	City center	Cool	included	2
4	City center	Cool	included	4
5	City center	Hot	Not included	2
6	City center	Hot	Not included	4
7	City center	Hot	included	2
8	City center	Hot	included	4
9	Port dock	Cool	Not included	2
10	Port dock	Cool	Not included	4
11	Port dock	Cool	included	2
12	Port dock	Cool	included	4
13	Port dock	Hot	Not included	2
14	Port dock	Hot	Not included	4
15	Port dock	Hot	included	2
16	Port dock	Hot	included	4

Running the model using the design as in 4.2, the results can be analysed. The run outputs that will be analysed are the following:

Fugitive routes: the routes taken by fugitives will be presented using figures of the map of Rotterdam and all its roads. On this map, 1000 possible fugitive routes will be plotted. This generates insight into what routes are used to calculate the interception percentage.

Percentage of successful interceptions: this metric shows the percentage of the 1000 generated escape routes that could be intercepted using the starting positions of the police units. This metric is presented in a table, showing the percentage of interceptions in each experiment.

Robustness of optimised positions: the model generates a set of optimised police positions. These positions and the fugitive escape routes are imported to evaluate their relative robustness. This means how well a strategy performs on a different set of routes, that is generated using a different scenario. This will be presented using heat maps, that show how well a certain strategy works under different circumstances.

4.4. Number of runs

The model uses probabilistic distributions in multiple places in the model. To make sure that the generated results are not coincidentally based on extreme values, it is not enough to generate only one route from the crime scene location to destination. Therefore, the model generates 1000 routes based on the input parameters. Moreover, because the goal is to generate plausible escape routes, it is also convenient to generate multiple routes whose likelihood of use can be estimated. Each scenario as in 4.2 is run only once, and consists of 1000 possible escape routes. By generating 1000 routes per scenario, the routes generated show enough overlap to form a pattern. This makes it possible to interpret the similarities and differences between the escape routes chosen in the scenarios.

4.5. Evaluation of effectiveness optimised positions

To address the research question, it is also necessary to examine the effectiveness of the optimised positions when a scenario different from the expected situation occurs. This will provide insight into whether including more realistic traffic conditions is important for the location of the optimal police positions. To evaluate the relative robustness of the optimised police positions and interception routes, these positions and routes are imported and analysed in comparison with a set of routes generated using a different profile. A profile includes a mental mode and a combination of traffic conditions. This will be done following the set-up as shown in figure 4.3.

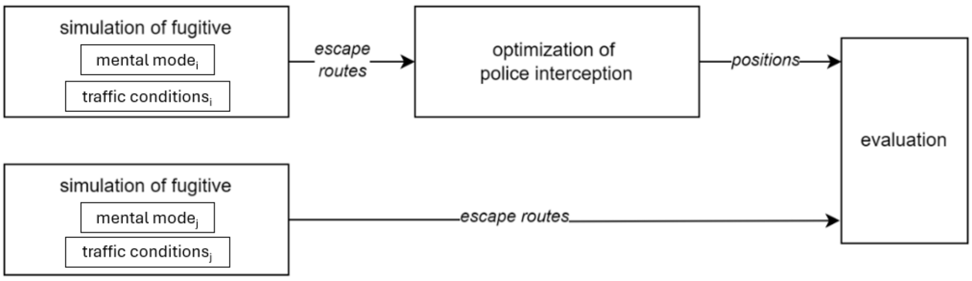

Figure 4.3: Set-up of the robustness evaluation (adapted from van Droffelaar et al. (2024b))

Summarised, this figure shows that the police positions will be optimised on the escape routes from profile i. These resulting positions will thereafter be evaluated on the escape routes from profile j, in order to understand how well the positions would function when the profile is different than expected.

5
Results

In this chapter, the results from the experiments are presented. Paragraph 7.1, presents the results of the generated fugitive escape routes with and without traffic conditions. In section 7.2, an overview of the interception probabilities in the different scenarios is shown. This is followed up by the found optimised positions in section 7.3. Section 7.4 looks into the robustness of the optimised positions for routes where traffic is taken into account, by performing an evaluation. These results are used in order to find an answer to the research question. This section ends with a short summary on the results in paragraph 7.5.

5.1. Generated fugitive routes

This section presents the escape routes generated for two crime scene locations in Rotterdam. The routes are shown on the city's road network. When the suspect reaches a highway, they have successfully escaped. An interception therefore only takes place within the ring of Rotterdam. The red dots on the maps visualise the escape points. The fugitive routes presented in table 5.1 vary in the used mental mode, crime scene location and which traffic conditions are included. The routes are compared by means of a visual inspection, so without metrics. In a small proportion of choices, the suspect will choose an unplanned road. This results in a route pattern arising around the optimal paths. As presented earlier, there are two types of criminals for which the routes are generated: calculating and distressed criminals.

In the model, calculating suspects are classified as cool, and do not deviate from their planned route. The planned route is based on the shortest path between the crime scene and their destination on the ring of Rotterdam. During the route planning process, they try to avoid roads that are equipped with ANPR cameras, bridges and tunnels. However, in some cases, the planned route is not taken as a result of the noise, where after the shortest route to destination is calculated again.

Distressed suspects are classified as hot, and are modelled to decide their escape route at each intersection. This means that they do not follow a planned route. However, the decision at an intersection is based on the maximum speed and number of lanes from the possible route choices. Moreover, their route choice at regulated intersections are driven by the observed wait time.

The results of the escape routes under different circumstances are presented in table 5.1. For two crime scene locations (center and port), and with or without traffic included, the routes are generated for a fugitive in hot and in cool mode. The darker the road is drawn, the more of the generated possible routes use this traffic artery. It is important to note that the route decisions are based on the perceived network. For the calculating criminal, the perceived network includes the travel time with or without congestion and a dis-utility for each obstacle. This stems from the conceptualisation that said that criminals in the cool-mode consider all foreseeable situations when planning their escape route, which includes congestion. This also means that including a wait time at intersections with a traffic light does not influence the route choice, as the perceived dis-utility factor of a traffic light does not change. The differences between the routes in the scenario where suspects move through the network with the

Table 5.1: Fugitive escape routes in the different models

Model	Cool	Hot
Center, without traffic		
Center, with traffic		
Port, without traffic		
Port, with traffic		

maximum speed and the routes that are chosen when traffic conditions are included can be attributed entirely to the congestion factor. This is because the perceived aversion of traffic lights and other obstacles does not change.

However, this is not the case for escape attempts by a distressed criminal. When a fugitive experiences high stress, their routes are impacted by traffic lights. This is the result of the modelling choice that people under time pressure do not patiently wait until their direction gets a green light, but choose the direction where the wait time is satisfactory. This also means that the routes generated for distressed criminals are influenced by both congestion and delays caused by obstacles, and not only by the perceived dis-utility of those traffic obstacles.

First of all, the results in table 5.1 show that the generated routes do not differ a lot between calculated and distressed criminals when traffic is not taken into account. This finding holds true for both the crime scene in the city center and the port, and is therefore independent of the location of the crime scene. However, it is clear that the routes generated based on suspects in cool mode vary more between roads, while the routes found for suspects in hot mode seem to use fewer different roads.

In contrast to the results of the model without realistic traffic, which showed no significant difference between hot and cool modes, including realistic traffic reveals distinct differences in the generated routes for hot and cool modes. Escaping from a crime scene in the city center in cool mode leads to generated routes in the north-east of Rotterdam. This residential road is preferred, despite its longer distance. This could be attributed to the fact that there is no congestion on this road, while the nearby roads are congested. For fugitives in hot mode, according to the model results, this route is not expected to be taken. Instead, a route straight north from the crime scene is found, that was not found for calculating fugitives. The differences for escape routes in the hot and cool modes are not extreme when a crime takes place in the center of Rotterdam. Contrarily, escapes from the port location show a more significant difference. Calculating criminals use both the Maastunnel and Erasmusbrug in order to cross the Maas. Distressed criminals almost never use the Erasmusbrug, preferring to use the Maastunnel to get from the south to the north of Rotterdam. When traffic is not included, the Erasmusbrug is not used in either mental mode. An explanation for this could be that there is more congestion in the Maastunnel than on the bridge, which leads to more routes using the Erasmusbrug. In general, the generated routes from the model with traffic included show a more diverse pattern than from the model without traffic included.

To summarise these results, the route pattern is more spread out over the city of Rotterdam when the offender operates in the cool mode, and as a result of the inclusion of traffic jams and delays at traffic lights. This difference appears to be greater when the crime scene is located in the port docks rather than in the city center.

5.2. Percentage of successful interceptions

After generating approximately 1000 possible routes for each scenario as shown in table 5.1, the interception percentage will be calculated. This is the percentage of the generated routes that can be intercepted by one of the police units starting from a police station. Table 5.2 shows the differences in interception percentage between the experiments without and with congestion and traffic lights.

First of all, the location of the crime scene has a very strong impact on the interception probability, independent of the traffic conditions. Someone who commits a crime at the port dock always has a higher probability of being caught in any scenario. An explanation for this difference could be that an escape from the dock initially has little route options, as a result of the dead-end characteristics of the port. This limits the number of potential routes, and with that the unpredictability, making it easier to be intercepted in the early stages of the escape.

Secondly, the number of police units involved in an interception attempt significantly impacts the outcome. An increase is observed between attempts with respectively 2 and 4 police units, where the more police cars used in an interception, the higher the interception percentages will be. This pattern can be observed for both crime scene locations used in this research. Even though the absolute and relative increase in percentage are not exactly the same, the same pattern is found. Each unit is capable of intercepting fugitives within a specific radius. Consequently, the greater the number of units

Table 5.2: An overview of the change in interception percentages between the scenarios with and without traffic conditions

Mental mode	Location	Police units	Int. without traffic	Int. with traffic
Cool	City center	2	38%	45%
Cool	City center	4	45%	61%
Cool	Port dock	2	83%	84%
Cool	Port dock	4	84%	85%
Hot	City center	2	43%	42%
Hot	City center	4	50%	52%
Hot	Port dock	2	82%	83%
Hot	Port dock	4	85%	89%

working together, the larger the radius in which suspects can be intercepted. The exact start positions are also important for this.

Thirdly, the results show that, independent of the other variables, the interception percentages for fugitives in cool mode are higher than for fugitives in hot mode. The main difference between the two mental modes is that distressed criminals don't follow a strategy, but decide their next route choice based on the environmental characteristics at each intersection. Calculated criminals, on the other hand, are assumed to take the shortest route. Therefore, suspects in hot mode could be classified as being more unpredictable. The results could therefore be interpreted to mean that the more predictable an escape attempt is, the higher the probability of interception. This effect is more clear for a crime scene in the center of Rotterdam.

Lastly, the inclusion of traffic conditions impacts the interception percentages found. Regardless of the number of police units used during an interception attempt, including congestion and delays in the model leads to an increased interception probability compared to the results from the model without traffic. However, for most scenarios, the difference between the models is insignificant. The only exception for this is the scenarios where the suspect operates in cool mode and the crime scene location is in the city center. Here, a significant increase in the interception rate is found.

The exact percentages as presented in 5.2 should not be interpreted as the absolute truth. This can be concluded from the sensitivity analysis that is done on the used model seed. Using a different seed to run the model results in a slightly different outcome. The complete overview of these results can be found in appendix I. However, independent of the seed that is used to run the discrete event simulation, the same general results are found. The effect of including traffic is still the biggest in scenarios where the fugitive operates in the cool mode and the crime scene takes place in the city center. The fact that the extremely slight decreases in interception percentage when including traffic are found in different scenarios when another seed is used, implies that this is not a result to which importance should be attached. The overall pattern is more important. Therefore it can be stated that the crime scene location, the fugitives' mental mode, the inclusion of traffic, and the number of police units used all have effect on the interception percentage, independent of the seed that is used. The interception probability increases when the fugitive is classified as calculating, when the number of police units increases, when the crime scene location yields less route possibilities, and when traffic is included in the model.

Besides, the sensitivity of the outcomes to the congestion factor is analysed, of which the results are also shown in appendix I. Running the model with doubled congestion factors relative to the original model leads to very different results. It remains true that increasing the number of police units in an interception attempt and having more possible escape routes lead to a higher interception percentage. However, using these factors, the finding that criminals in the cool mode are more likely to be caught no longer applies. It is also not observed that more extreme traffic conditions lead to a higher interception probability.

In order to be able to make statements about the effects of specific traffic conditions, congestion and delays at regulated intersections are studied separately. However, this is only done for the scenarios where the inclusion of traffic made a significant difference in terms of interception percentage. From figure 5.2 follows that there are two scenarios that meet this criteria: a fugitive in cool mode that committed a crime in the city center, and where either 2 or 4 police units are deployed. The results of this analysis can be found in appendix H. However, there are no unambiguous conclusions to be drawn from these results, other than that the interception percentages for a model including only traffic light delays and not congestion are similar to those found for the model including both traffic conditions.

5.3. Optimised positions

The police positions are optimised based on the generated escape routes. By visually comparing the outcomes of the optimised positions between the scenarios with and without more realistic traffic included, the effects of traffic on the optimal police positions can be studied. In tables 5.3 and 5.4, the figures of different models are presented, showing which routes can and cannot be intercepted, including the police starting (light blue) and ending (dark blue) positions. A route drawn in orange means the fugitive escapes when using this route, green indicates that this route can be intercepted, and blue shows the route the police vehicles need to take to their end position in order to intercept the indicated routes. However, it is important to note that the optimised positions are found based on a heuristic model, which means that the result shown is not necessarily the sole optimal solution for the police unit positions.

In table 5.3, the escape routes from a crime scene location in the city center are depicted. When comparing the results of the optimal police positions between the hot and cool models, generally similar positions are found. It is worth noting that this is based on a visual inspection without the use of quantitative KPIs. The most similar positions between the two mental modes are found in the models where only 2 police units are deployed. The results show that the optimised positions are not strongly dependent on the mental mode used in the model. However, they are not exactly the same in both experiments. This could be partly due to the heuristics, but is probably a result of the difference in the generated routes. The main finding is that the directions of the positions are similar, although the exact positions are slightly different.

Second and most important, the effect of the inclusion of traffic conditions on the optimal police positions can be seen from the results in table 5.3. In the scenarios where 2 police units are used during an interception, there is almost no difference found in the optimised positions for the models with and without traffic included. When the police deploys 4 units, the contrary is true, as the positions do not seem to be in the same locations. Moreover, the impact of traffic conditions on the distance between the crime scene and the optimized police positions varies: when 2 police units are used, this distance increases with traffic conditions included; however, when the number of police units is doubled to 4, the distance decreases under the same traffic conditions.

Lastly, the routes that are used by caught and escaped fugitives can be seen in the figures in table 5.3, respectively in green and orange. The geographical distribution between caught and escaped are heavily dependent on the police positions. Therefore, not a lot of weight has to be put onto this. The positions are optimised to capture the most generated routes as possible, and no importance should be placed on the specific routes.

In table 5.4, the escape routes from a crime scene location in the city center are depicted. At first glance, a striking difference with table 5.4 is that here the main colour is green, which indicates that most of the routes can be intercepted. This is in line with the interception percentages found as presented in section 7.2.

Corresponding to what was found for a crime scene in the city centre, there also is an effect visible of traffic on the optimised positions for a crime scene in the docks. The marked position shown in figure 5.1 is consistently located in nearly the same spot across all experiments. This position is very close to the crime scene, allowing for the interception of many of the generated routes. Consequently, there are fewer routes left for the other units to cover, causing these additional units to serve primarily as backup, intercepting some of the remaining routes. The uncovered routes span various directions throughout Rotterdam, making the assignment of these modelled police units appear somewhat random. Due to this randomness and the very high interception percentage achieved, no better explanation for the effect has been found beyond its apparent randomness.

Table 5.3: Fugitive escape routes in different models for the crime scene in the city center

Model	Cool	Hot
Without traffic, 2 units		
With traffic, 2 units		
Without traffic, 4 units		
With traffic, 4 units		

Table 5.4: Fugitive escape routes in different models for the crime scene location in the port dock

Model	Cool	Hot
Without traffic, 2 units		
With traffic, 2 units		
Without traffic, 4 units		
With traffic, 4 units		

Figure 5.1: The optimised position that is similar in all experiments

The results also show that when the model deploys 4 police units, most of the positions found are on the south side of the river De Maas. Furthermore, the optimisation model finds positions that are very close to each other when there are 4 units available. The reason for this could be that the route choices are predictable, so that the interception can take place early in the escape attempt. From the results it becomes clear that a crime scene in the port docks leads to a completely different outcome than when a crime is committed in the center of the city.

5.4. Robustness evaluation

With the results on the robustness of the optimised position, this section provides an answer for the research question *What is the added value of taking more realistic traffic into account in the optimal positioning of police units for fugitive interception?* In the previous paragraphs, the optimised police positions for each scenario have been found. It was found that the location of the optimal police positions were mainly dependent on the number of police units cooperating in an interception, and the location of the crime. It was already found that using more realistic traffic conditions in the interception model leads to a slightly increased interception probability.

The evaluation analyses the success of optimised police positions, determined based on a specific profile and corresponding set of routes, compared to routes generated with different profiles. These profiles consist of a combination of a mental mode and traffic conditions. The results are presented in figures 5.2 and 5.3 for a crime scene location in the city center with 2 and 4 police units involved, and in appendix G for a crime scene in the port docks. The scores represent the row-normative values, with lower scores indicating a lower probability of interception. It needs to be noted that the police travel speed used for the evaluation deviates from the speed used in the determination of the interception probability and the optimal positions. For the scenarios where congestion was not taken into account, the modelled police speed was only based on the maximum speed on a road. However, in scenarios were congestion was present, the police speed was based both on the road maximum speed and its level of congestion. In the evaluation, the average of those two speeds was used. This could potentially lead to an overestimation of the police speed in scenarios with congestion, and an underestimation in the scenarios without.

An interception attempt involves many uncertainties. Assumed that the crime scene location and the number of deployed police units are known, the model incorporates uncertainty in the fugitive's mental state and the traffic conditions at the time of escape. The results are displayed using a heat-map, which can be interpreted as follows: on the y-axis, the optimisation model is shown. This represents the model used by the police to determine their optimal positions, taking into account the scenario for the interception attempt that they expect. On the x-axis, the evaluation model is depicted, representing the realistic circumstances. For example, the third cell in 5.2 (-0.9) illustrates the impact of a situation where the police expect the fugitive to operate in a cool mode and anticipate non-congested traffic conditions, but in reality, the fugitive's behavior is classified as hot and the traffic is not busy. The -0.9 is a normalised score and can be interpreted as a 90% decrease in the amount of routes that can be intercepted when the situation would have been estimated correctly.

In general, three types of errors can occur between the estimation (optimisation model) and reality (evaluation model). First, a mismatch can happen in the mental mode. This occurs either when the suspect acts more distressed than expected or when they behave more calculated than anticipated. Additionally, errors can occur if the traffic situation is wrongly estimated, while the fugitive's mental mode has been accurately predicted. Lastly, a completely incorrect estimation can arise when both the mental mode and the traffic situation differ from what was expected.

It is important to know whether it is possible for these errors to occur outside the model world. If, after all, they are unrealistic, there is no need to interpret them. The first option is that route pattern is more fanned-out than expected, which happens when a cool mental mode is wrongly assumed. Contrarily it is possible that the routes are less spread out than expected, when a fugitive is wrongly classified as operating in hot mode. Both of these errors are easily made, as the estimation of fugitive behaviour is extremely challenging. Secondly, an estimation error can happen on the traffic situation in Rotterdam at the time of the escape. The incorrect assumption of no traffic leads to an overestimation of the time it takes for a fugitive to escape. Moreover, congestion and traffic light delays disproportionately affect the fugitive's speed compared to the police, whose speed is relatively less impacted by these factors. This could result in the fugitive reaching the highway earlier than anticipated, causing a significant shift in the interception points and leading to the optimised positions performing poorly. On the other hand, presuming traffic when the city is actually empty leads to an underestimation of the time needed to escape. This could result in sub-optimal positions being used, which could have been better located if the police knew they would have extra time before the suspect arrived at a certain position. However, this type of error is less likely to be made, as traffic is less unpredictable than the mental mode of a fugitive.

The descending diagonal is 0 in all cells, serving as the reference value where the x and y-axes represent the same profile. The ascending diagonal illustrates the performance in scenarios where the difference between the profiles of the optimisation and evaluation models differ the most extreme, meaning that both the mental mode and traffic conditions are different from what was expected.

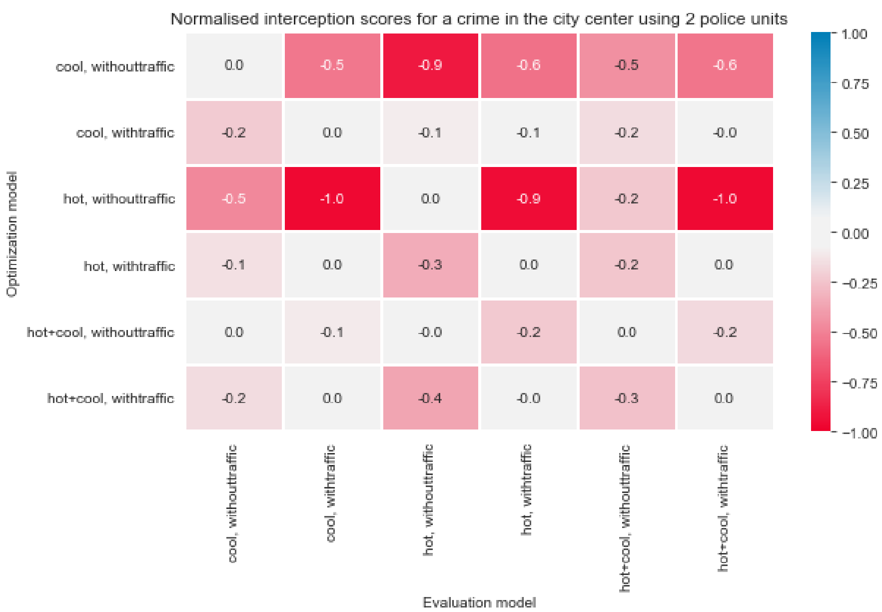

Figure 5.2: Results of the robustness evaluation of different profiles with 2 police units used for interception for a crime scene location in the center

Figure 5.2 shows the results for the situation where 2 police units are used to intercept a fugitive after a crime scene location in the city center of Rotterdam. The worst possible error, according to the results, is to presume the circumstances of the escape to be without traffic while the fugitive is distressed (hot), when in reality the fugitive acts very calculated (cool) or partly calculated (hot+cool) in a city that is highly congested, and where fugitives are delayed at traffic lights. This shows a 100% decrease in intercepted routes relative to the number of routes intercepted when the same profile is used in both the optimisation and evaluation models. This result could be classified as logical, as both the mental mode and traffic situation are (partly) wrongly estimated. Accordingly, a low score would be expected in each of the cells on the ascending diagonal. However, a similar low result is only found in the first row, where cool and without traffic is expected, while hot with traffic better describes the realistic situation. For the other two cells on this diagonal only a 10% decrease is found when the optimisation and evaluation models use completely opposite profiles. From this, it can be concluded that assuming no traffic leads to worse effectiveness in the completely opposite profile, while wrongly assuming traffic when there is none has only a minimal effect. Contrarily, this straightforward effect is not found for the possible errors in the mental mode. So, in general it seems to be important for the performance of optimised police positions to use the correct traffic situation.

This is in line with the results when routes from both hot and cool modes are used combined to calculate the optimal positions. They show a score of 0 in all cells where the included traffic conditions are the same in the optimisation and evaluation models. However, when there is a mismatch in the used traffic situations, the interception scores decrease between -50% and -10%. This shows again that using the correct traffic conditions in the optimisation model play a pivotal role in the performance of the position outcomes. Using the routes from both hot and cool mental modes offer a reliable approach when mode of behaviour is unknown, scoring not extremely negative on any of the sets of routes.

Also interesting are the very red-coloured cells that are not located on a diagonal. This includes the two unexpected -0.9 values in the first and third row of figure 5.2. The first value arises when the fugitive behaves more stressed than expected when traffic is not included in the model. In terms of escape routes, the results have shown that this leads to a more fanned-out pattern. An explanation for the negative values could be that the routes for a fugitive in hot mode differ to such an extent that the calculated police positions can only intercept a small fraction of the routes. This aligns with the routes and police positions shown in the first row of figure 5.3, where the comparison can be made for cool and hot modes when traffic is not considered. These figures show that one of the positions is placed on the opposite side of the crime scene. Additionally, it can be seen that in the scenario with a suspect in hot mode, a smaller portion of the routes is generated to the east side of Rotterdam, potentially leading to a low number of intercepted routes. The second -90% value in the heat-map results from estimating that the suspect in hot mode does not suffer from traffic, while in reality, they do. This type of error means the police have more time for an interception than anticipated. This is because, as modelled, the police suffer less from included traffic conditions than criminals. While fugitives suffer from both congestion delays and delays at regulated intersections, the police only face congestion but drives through red lights. Therefore, the speed difference between the two actors increases, giving the police more time to intercept a fugitive before they can escape at one of the highways. The fact that the positions are determined based on a scenario where the police estimated having less time than they would if the scenario were estimated better means the positions are in sub-optimal places. If the extra time had been considered, the positions could be timed better. However, the first and third rows in figure 5.2 show that having traffic when this is not expected does not make up enough for mismatch between the optimisation and evaluation models when the police uses 2 units in the interception.

Lastly, the two models without traffic (in both cool and hot mode) seem to perform poorly on all other sets of routes. An explanation could be that these modes generate distinctly different routes than the rest of the scenarios. However, this is hard to verify visually from the figures in table 5.3. It seems to be a small bit worse to wrongly assume that the fugitive operates in cool mode, than to wrongly estimate them under hot mode.

A distinct difference between the heat-maps in figure 5.2, and 5.3 that arises when the police doubles the police deployment to 4 units, is the diminished level of redness visible. This indicates that, in general, the police have a higher success rate in intercepting suspects when more units are deployed. Correspondingly, the deviations from the descending diagonal (where simulation model = evaluation model) are smaller, meaning a wrong estimation of reality does not result in the same decrease in interception probability as observed with the deployment of 2 police units.

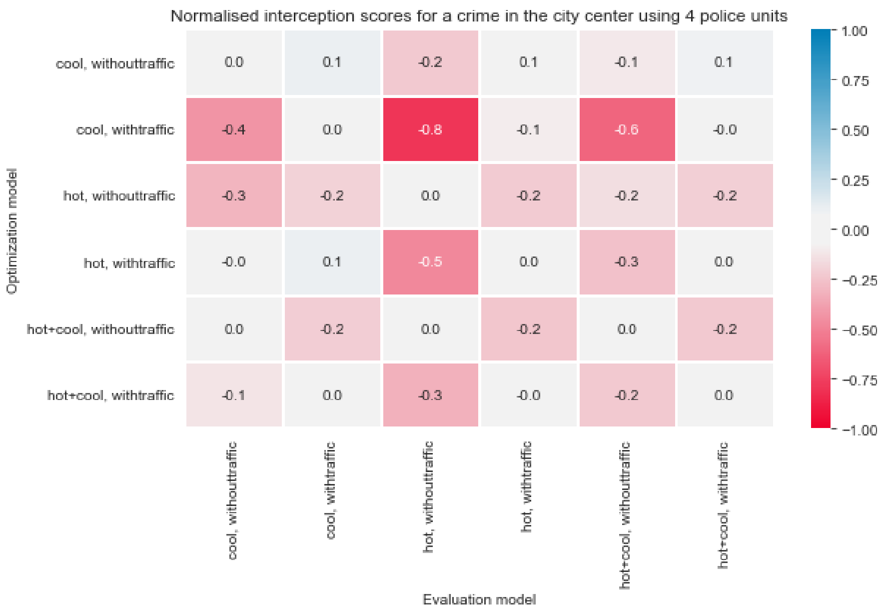

Figure 5.3: Results of the robustness evaluation of different profiles with 4 police units used for interception for a crime scene location in the city center

The negative values of -0.8 and -0.4 can be explained based on a visual inspection of the figures in table 5.3, which shows that some of the positions are quiet different between the scenarios. This could indicate that the underlying routes differ to such an extent that the optimal police positions are not able to perform well on the other set of routes. This is in line with the difference in the interception percentages as presented in table 5.2.

Contrary to what was found for scenarios with only 2 police units, slight positive values of 0.1 are observed here. This means that the positions resulting from the optimisation model perform better in another scenario than its own. This might indicate that the routes of that evaluation model are less spread out over the network than those from the optimisation model. The routes are less spread out over Rotterdam for suspects in cool mode compared to fugitives in hot mode when traffic conditions remain unchanged. This can be explained by the fact that distressed criminals are less predictable, leading to more random route choices. However, the other positive value is harder to explain. While in both models the fugitive is in cool mode, the results say that including traffic would lead to a less spread out pattern. This would mean that congestion causes fugitives to choose more similar routes.

It is remarkable that the optimisation model with the overall worst performance differs from the one seen in figure 5.2. In that figure, the optimisation model based on the routes of a fugitive in hot mode and a city without traffic performed the worst. However, with 4 units, the worst performance shifts to the optimisation model where a fugitive behaves in cool mode and the city is congested, resulting in the most negative performance in terms of added scores. However, the results in this row again show that it is important to take the right traffic conditions into account, as the cells with a mismatch in traffic conditions have significantly more negative scores than those where the traffic situation is the same in the optimisation and evaluation model.

Heat-maps are also created for an escape from the port docks, which are presented in appendix G. In sections 5.1 and 5.2, it was already observed that, regardless of the traffic conditions included and the mental mode used to generate routes, the interception percentages were very high. This is due to the port docks being a distinct location in Rotterdam, with a dominant escape strategy of using the S101 to reach the A15 motorway. The same results are found in the robustness evaluation. For the port location, all optimised positions are robust under all evaluation models. This implies that the considerations about which optimisation model to use are not important in finding robust optimal positions for a crime at this location.

In summary, for a crime scene in Rotterdam, the optimised police positions are only robust when the set of routes in the evaluation model is generated based on the same traffic conditions as those used in the model to find the optimal positions. If there is a mismatch between the traffic conditions in the optimisation and evaluation models, the optimised positions are not robust. This correlation was not observed with the mental mode of the suspect during an escape, which was another uncertainty accounted for in the model. The results suggest that incorporating accurate traffic conditions into the optimisation model is more crucial than accounting for the suspect's mental state. It is important to note that traffic impacts more than just congestion and traffic lights; it fundamentally affects the timing of an interception. This impact is twofold: on one hand, accurate traffic estimates may provide the police with more time before the suspect escapes, while on the other hand, incorrect traffic estimates could reduce the time available. Both scenarios could result in fewer interceptions—either the positions might be optimised better with a longer time frame, or the suspect might escape before the police reach their position if the suspect moves through the network faster than anticipated. In contrast, understanding the suspect's mental state focuses on predicting their likely escape routes. To summarise, traffic affects the timing of an interception, whereas the suspect's mental state influences the potential location of an interception.

6 Discussion

This chapter discusses in turn the opportunities of including traffic in real-time decision support in 6.1, the ability to estimate traffic correct will be discussed in 6.2, a discussion of the effects of the simplified behaviours as mentioned in the limitations can be found in 6.3, where after the verification and validation of the results is presented in 6.4, the limitations of methods are discussed in 6.5.1, the assumptions and limitations of traffic implementations in 6.5.2, the limitations of fugitive behaviour are explained in 6.5.3, and finally in 6.5.4, the limitations of police behaviour are analysed.

6.1. Ability to estimate traffic

One of the future applications of AI in police work is supporting the decision-making of control room operators. To this end, the Politielab AI is developing an Intelligent Geographical Control Room Assistant (IGMA) to aid control room operators in managing various police units on the street. By predicting the most likely escape routes based on crime and criminal characteristics, the positioning of each unit can be optimises to increase the chances of catching criminals red-handed. Current research in this area aims to understand the effect of different behavioural profiles on the robustness of these optimised positions. Similar to this research, they formalised the dual-process theory, categorising criminals into cool and hot modes. Previous studies indicated that network topology significantly influences the effectiveness of police interception positions. However, no significant difference was found in the robustness of positions based on the behavioural profile used. They concluded that using a super set, which combines routes from all profiles to find optimal positions, provides a reliable approach when the behavioural mode is unknown. This finding raises the question of how accurately the mode of behaviour can be estimated.

Based on the information provided during the report to the control room, the operator can classify the offender's behaviour as either cool or hot. However, there are situations where the report lacks details about the suspect's behaviour, or where the suspect does not fit neatly into either category. Using both behavioural modes in the AI application provides a robust solution, but the challenge of accurately classifying behavior remains. This research highlights the added value of including traffic conditions in the model used to predict escape routes. Unlike behaviour classification, estimating traffic at the time of the escape is less challenging. For example, there is a clear difference between traffic congestion on a Sunday night and a Tuesday afternoon. Additionally, the results showed that merely including delays at traffic lights closely mirrors the broader set of traffic conditions (delays at traffic lights and congestion). Traffic light regulations are predictable during peak times, such as rush hours, due to their rigid control. Outside of rush hours, predicting delays at traffic lights is slightly more complex but still manageable. This makes including traffic an interesting addition in the models used as control room assistant.

6.2. Real-time decision support

Even when it seems feasible to estimate traffic accurately for use in optimisation models, it's crucial to remember that these models need to run very quickly. From the moment a call comes in, there is only a short window of time before police units need to be notified of their deployment locations. Therefore, the model must generate these positions within 30 seconds to 1 minute. Each additional piece of information inputted into the model increases its run time. Therefore, it is important to make sensible abstractions: what additions significantly improve position accuracy enough to justify a more computationally demanding model? The findings showed that, regardless of the behavioural mode included, positions optimised with traffic considerations are more robust than those without. Therefore, it can be stated that it seems important to equip the model with a certain traffic option. However, this leads to the question: what level of traffic realism is important to include in the models? It is essential to balance the detail and accuracy of inputs with the computational efficiency required for timely decision-making.

In this research, congestion was implemented with a static factor based on the road type, even though realistically, congestion is dynamic and always changing. This approach already showed an improvement, indicating that efforts toward more realism in traffic conditions are beneficial. The expectation is that including a speed-delaying factor across the city network will not significantly increase the run time. However, incorporating delays at traffic lights is more complex, as it involves considering multiple factors: the time at which the fugitive arrives at the intersection, the colour of the light at that moment, and the type of intersection. Even without trying to create a digital twin of Rotterdam's traffic, the model's calculations would increase more significantly than when adding congestion. This makes it less feasible for practical implementation.

The question of whether it is worth including both delays resulting from congestion and traffic lights should be answered positively, based on the results of this thesis. Every opportunity to increase the number of arrests should be pursued. As computers continue to advance in their capabilities, it is very possible that this will become feasible in the near future.

6.3. Verification and validation of the results

First, verification of the model is needed to check whether the results are in line with the expectations and hypotheses. The compiled hypothesis was that introducing more realistic traffic conditions would results in an increased interception percentage when police stations are used as starting positions. Reasoning for this was that the police experiences less difficulty from the included congestion and delays at traffic lights than suspects. This is in line with the outcomes: the interception percentages increased when the traffic conditions were included. This was found to be true for both crime scene locations used. It was expected that the interception percentage would be higher for crimes in the port in comparison to those committed in the city center, as the possibilities for escape routes is a lot smaller there. This results in a more predictable escape pattern, making it easier to intercept the suspect. This is also in line with the results: the interception percentage in the port dock is almost twice as high than the percentages under the same conditions for an escape from the city center.

Validation is the process of comparing model results with real world data to determine the accuracy of the results. In this context, however, direct validation is challenging due to the lack of available empirical data. It would be impossible to carry out the experiments in real life, as any knowledge of how the experiment would be carried out would lead to very different behaviour by the suspect. Furthermore, there is no empirical data on the effectiveness of police positions. The success rate depends on many circumstances, which makes it impossible to obtain this data. Furthermore, the escape routes chosen by criminals are unknown. Therefore, validity of this part of the research can not be ensured.

Even though it is not possible to compare the model results with real-world data, performing a sensitivity analysis on the model parameters can increase validity. This analysis helps in understanding how changes in input parameters affect the results. The seed sensitivity analysis demonstrated that while the model results varied, the overall conclusions remained consistent. Similarly, the analysis of using an extreme congestion factor showed that, except for an extreme case where 100% of escape attempts in the port docks could be intercepted, the results were stable. For the city center, no notable differences were observed, which enhances the validity of the results.

6.4. Limitations and mitigation

The model is based on many different assumptions. These assumptions lead to limitations in the study and in the results. First, the methodological limitations are briefly discussed, and then the conceptual limitations are mentioned, including how they might affect the findings.

6.4.1. Methods

This research uses a combination of literature review, interviews, and discrete-event simulation modelling. Each method has inherent limitations, that will be discussed in the following paragraphs. However, using multiple methods combined helps to provide a more comprehensive understanding of the research problem and enhancing the robustness of the findings.

The literature review faced a shortage of scientific articles on police behaviour, necessitating reliance on government documents and YouTube videos. Although these sources are not ideal, efforts were made to use credible channels managed by the Dutch Police to enhance accuracy.

Interviews were limited to three participants, which in general is not a sufficient sample size for robust conclusions. Moreover, these interviews were drawn from a personal network, introducing potential bias. A larger, more diverse sample would provide more reliable insights into stress-induced route choice behaviour. Despite these limitations, the interviews provided valuable initial insights into the topic. Because they were used to shape the background knowledge, three interviews offered enough information to use in the simulation model.

The simulation model is based on several assumptions, which are detailed in the following sections about traffic conditions, fugitive and police behaviour. While these assumptions may affect the model's precision, they are necessary to simplify the complex real-world phenomena into a model. When the assumptions are considered when drawing conclusions on the outcomes of the model, the effects of the assumptions stay limited.

6.4.2. Traffic conditions

The included traffic conditions consist of the delays at intersections and the congestion on the roads. The intersections themselves can be divided into two categories: those with traffic lights and those without. For the controlled intersections, the delay time is included using the cycle time and a random arrival time within that cycle. The arrival time determines whether someone has no waiting time, or how long the waiting time is until the traffic light is green again. This is calculated by drawing a random number. This, in combination with the cycle time, which is based on a triangular distribution, tries to capture the diversity in the regulation of the intersection.

Realistically, a traffic light also includes yellow light and clearance times, which are not considered in the model. However, because only the green time and cycle time are modelled, the yellow and clearance times can be seen as part of the red times in the model. No big difference in behaviour is expected when including yellow time, so this assumption is reasonable. The green time used in the model is based on observations from various intersections, with an average calculated for all directions. This means each traffic light category (with tram, part of green wave, normal) has a fixed green time, regardless of whether the vehicle is following the main road or turning. In reality, green times for turning traffic are shorter for safety reasons. Calculated criminals patiently wait for green lights, so their routes are unaffected. However, distressed criminals are expected to alter their planned routes based on observed waiting times, ideally staying on the main road to minimise waiting time. Since the model does not differentiate green times, distressed criminals in the simulation turn as often as they go straight, potentially creating more dispersed escape routes than in reality. This discrepancy is challenging to confirm due to limited knowledge of actual escape routes.

For intersections without traffic lights, the model does not account for any waiting time. This is unrealistic, as factors such as parked cars, minivans, rubbish trucks, and the need to give priority to traffic from the right can cause delays in residential areas. Consequently, the model may overestimate travel speed and time in these areas. Including wait times at unregulated intersections would lower the average travel speed, increasing the time needed to reach the ring of Rotterdam. This reduction in speed differences between fugitives and police could potentially increase the interception percentage. However, even with reduced speed differences, the overall pattern of results is expected to remain consistent. Moreover, the route pattern is not expected to differ with or without delays in residential areas, as route decisions are made to avoid traffic lights rather than based on expected delays.

Regarding congestion, the model currently bases congestion factors solely on road type and whether a road is a one-lane road. While it is generally true that roads higher in the hierarchy tend to have more traffic, this relationship is not absolute. The number of lanes on a road is often determined by traffic intensity. Therefore, not all roads within the same hierarchical level experience the same congestion volume. This discrepancy can impact the preferred escape routes, as roads with higher actual congestion might be less attractive to fugitives than the model suggests. Including more detailed congestion data could improve the model's accuracy in representing realistic escape routes. The goal of this research, however, is not to predict and present the best police positions, but to understand whether adding traffic would have added value for the optimisation. Therefore, it is not possible to model the congestion level of each road exactly correct.

6.4.3. Fugitive behaviour

This research primarily adopts the fugitive behaviour patterns used in previous studies, which apply the dual-process theory of hot and cool mental modes. Although dividing all criminals into two behavioural profiles is not entirely realistic, it does not significantly impact the outcomes of this research. The main objective was to evaluate the effect of incorporating traffic into the performance assessment of police positions under different behavioural profiles. The two mental modes serve as a means to validate the results, ensuring that the observed effects can be generalised across different types of fugitive behaviour. This approach ensures that the conclusions drawn about the impact of traffic conditions on police strategy remain robust, regardless of the specific nuances in criminal behaviour.

However, assuming that all escapes are car-based could impact the outcomes of the model. In reality, there are various escape behaviors, such as changing vehicles, using pavements and cycle paths instead of roads, hiding until the initial search is abandoned, or opting for a different mode of escape like a motorbike. Each of these behaviors would likely necessitate distinct police strategies. In a congested road situation, the likelihood of going off-road may increase. It's uncertain whether including traffic would produce the same effects if the escape behaviors vary significantly.

6.4.4. Police behaviour

The model currently only accounts for the higher speed of police vehicles compared to suspects but fails to capture the complexity of real-world police travel. As discussed in Chapter 2, police can use bus and emergency lanes when classified as priority vehicles and must adjust their speed in certain situations. These factors are not reflected in the discrete-event simulation model, which simplifies police travel to a constant high speed. Ignoring these nuances in the model likely leads to an overestimation of police speed and, consequently, interception probabilities. This discrepancy could make it seem that police are more effective at intercepting suspects than is realistically possible.

Therefore, the interception percentages should not be heavily emphasised. Instead, the focus should shift to the robustness evaluation results. As mentioned earlier, omitting delays in residential areas for fugitives has led to an overestimation of their travel speed, and a similar overestimation is present for police speed. The fact that both fugitives and police speeds are overestimated is advantageous, as it avoids the problem of comparing an underestimated speed of one actor with an overestimated speed of the other, which would skew results more. This still allows a accurate study of how traffic affects the robustness of police positions, so that the results could still be interpreted.

7 Conclusion

In this chapter, the conclusions that follow from the results will be covered. This will be done by first providing an answer for each of the four sub-questions in sections 7.1 to 7.4. Thereafter, an answer for the overarching research question will be formulated in 7.5. In 7.6, the possibilities for generalisation of the results will be presented. This section continues by mentioning the implications of the study in section 7.7, the recommended future research in 7.8, and finalises with some recommendations for the police in 7.9.

7.1. Sub question 1: describing traffic conditions

How can realistic traffic conditions in fugitive interception be described?

Knowledge about traffic conditions can be extracted from two research domains: traffic flow theory and traffic management. From the traffic flow theory, it was found that the variables flow, space mean speed and density are important. These three make up the fundamental flow relationship, that states that the traffic flow is equal to the density multiplied by the space mean speed. When the traffic flow and density are low, free flow conditions are present. Each vehicle then has enough road space to drive with the desired speed. At times where traffic flow and density increase, the speed will get reduced, as a reduction in available road space results in a smaller gap between two vehicles. In order to ensure safety, the speed has to be reduced. This is what happens when congestion is formed during rush hour. The higher the flow and density, the lower the average speed will be, until this is so low that a traffic jam has formed. This starts to happen when the degree of saturation on a road exceeds 80% of the roads capacity.

Traffic management is the deliberate manipulation of traffic flows in order to optimise them. This can be used in daily situations and in situation where a disruption of normal situations occurs. Examples of traffic management tools are Dynamic Message Signs (*DRIP*s in Dutch) that could convey a change in maximum speed or warn for an open bridge, static signs, traffic lights, roundabouts and parallel roads. Traffic lights can be regulated using one of the following four methods: rigid, vehicle-dependent, semi-rigid or traffic-dependent. In The Netherlands, the vehicle-dependent control method is by far the most used. However, with an increasing intersection load, the green times of a vehicle-dependent control are increasingly bounded by the maximum green times as used in a rigid control, which is the case during rush hour. In a rigid control, there are five important attributes: the location of the traffic light, the lanes or directions it corresponds to, the green, yellow and cycle time for the traffic light under study. Moreover, the number of phases within a cycle is important when arranging a rigid control system. Besides regulating each intersection individually, it is also possible to optimise a group of regulated intersections. This is known as network regulation, from which the most well-known application is the so-called green wave.

7.2. Sub question 2: reaction to traffic

How do the different actors in a fugitive escape attempt react to traffic conditions?

From the literature study, it was found that criminal decision-making can be divided into three overarching themes: suspect characteristics, crime characteristics, and criminal behaviour characteristics. For general route-choice decision-making, it was found that factor such as obstacle and camera avoidance, route distance and maximum speed, the use of a navigation device and the familiarity with the area play a role. Stress also plays an important role in escape attempts, as increased stress is experienced when there is a discrepancy between desired actions and what can realistically be achieved within the time constraints. This is the case when a criminal wants to escape before being caught by the police. The influence of stress on driving behaviour was found to be as follows. Risky behaviour is more likely to occur, such as speeding or running a red light. Another behaviour found in stressed people is to avoid the feeling of being locked up and unable to escape, which is the case in tunnels, on bridges and in heavy traffic. Stress is found to be an important reason for the willingness to choose an alternative route to avoid being stuck at a red light, for example, even if it means extra travel time and distance. In other words, distressed fugitives highly value free-flowing traffic, which underlines the unwillingness to endure the inconvenience of waiting at traffic obstacles. All in all, traffic conditions influence the choice behaviour of refugees mainly when delays are high. In such cases, a deviation from the planned route is more likely, even if the planned route is the shortest. Interviews with parcel deliverers, who often work under a lot of stress, revealed that they are prone to change their planned direction at a traffic light when they become impatient and that they avoid congestion by choosing alternative routes when congestion is observed. This behaviour aligns with findings from the literature review on drivers under time pressure.

The document *brancherichtlijn politie* was consulted for the behaviour of the police during an interception attempt. This document has been drawn up to give drivers of emergency vehicles a code of conduct for driving a priority vehicle. This is only the case when both visual and audible signals are used. In all situations, it is important that the driver always weighs the risks against the intended purpose. The guidelines state that approaching and crossing an intersection must be done at an appropriate speed. The speed for running a red light should not exceed 20 km/h, but may not be ignored on bridges and railway crossings. In general, the speed used may not exceed the applicable speed limit by more than 40 km/h. If an emergency lane is used to overtake queuing traffic, the speed must be less than 50 km/h. In certain circumstances, it is permitted to use the road of oncoming traffic, but only if it is possible to return to one's own lane. Finally, if a police unit has to pass a congested road, it will do so by driving between the first and second lanes, when no emergency lane is present.

7.3. Sub question 3: effect of traffic on interception probability

What is the effect of including realistic traffic on the calculated interception probability of fugitive suspects?

The effect of several factors on the probability of intercepting a fugitive was studied. These factors included the location of the crime scene in Rotterdam (either the port docks or the city centre), the mental state of the fugitive (hot or cool), the number of police units involved in the interception attempt (2 or 4), and the presence or absence of traffic delays in the model. The higher the percentage found, the greater the number of generated routes from that profile the police were able to intercept. The findings revealed that a key factor in successfully intercepting a fugitive is the predictability of their escape routes. Predictability increases when a fugitive is well-prepared and follows the shortest route to escape the city, as opposed to a distressed criminal who decides their direction at each intersection based on the situation. It was found that 'cool' fugitives were intercepted more frequently than those in hot mode. Additionally, the predictability of escape routes also depends on the location of the crime. When a dominant escape strategy was present, meaning a route that is chosen relatively often, the interception percentage was significantly higher. The third variable in the model was the number of police units deployed in the interception attempt. The results showed that increasing the number of units improved the effectiveness of the police.

Of primary interest is the effect of including traffic in the model on the resulting interception percentages. Generally, the results showed that when delays due to congestion and traffic lights are included, the interception percentages increase. However, this effect was most convincing for escapes from the city centre by fugitives in cool mode. In situations with higher traffic during the escape and interception attempt, resistance through the network increases for both the fugitive and the police. However, the results seem to point to the conclusion that the police is less affected by this than the fugitives, resulting in a higher interception score. Thus, it can be concluded that traffic delays in the city work to the advantage of intercepting offenders.

When the set of traffic conditions used in the model is divided into congestion and delays caused by traffic lights, the findings showed that the interception percentages obtained with only traffic lights included were more consistent with the percentages found for the entire set of traffic conditions than when the model was run with only congestion included. This leads to the conclusion that the effect of traffic lights on interception percentages is greater than that of congestion.

7.4. Sub question 4: effect of traffic on police positioning

What is the effect of including more realistic traffic on the optimal police positions in order to maximise the interception probability?

Similar to the interception percentage calculations, the police positions were optimised based on profiles comprising a combination of variables: the crime scene location, the number of police units involved, the mental mode describing fugitive behaviour, and whether or not traffic conditions were included. The model optimises the positions to jointly maximise the probability of intercepting fugitive routes. Due to the lack of suitable metrics, the comparison of the effects of these variables on the positioning of police units was performed visually.

First of all, no difference was found between the optimised positions for fugitives in hot and cool modes. This indicated that, even when escape routes are generated based on different behavioural profiles, the optimised positions are not located in significantly distinct locations. This similarity was more pronounced when an interception attempt with 2 police units was modelled, compared to four units. However, the difference was still minimal with more police units. Therefore, it can be concluded that the optimised positions are not strongly dependent on the behavioural profile of the fugitives.

The results indicate that including traffic delays in the model does not significantly change police positions when the crime scene location provides a certain level of unpredictability in terms of route options. So, this conclusion does not hold for a crime scene in the port dock area, where the route options are predictable. In every scenario for the port docks, the police interception attempts proved very effective, making it challenging to draw definitive conclusions about the impact of traffic or other variables. However for a crime scene in the city center, it was found that including traffic in the model where only 2 police units were deployed led to an increased distance between their positions and the crime scene location. For four units, this distance decreased. This suggests that intercepting with only two units is more challenging than with four units, as expected. Consequently, the time needed to reach an effective interception point increases with fewer units, leading to positions farther from the crime scene. Conversely, the more police units deployed, the less distance and time needed to find an optimal position. This outcome is highly dependent on the starting positions of the units, which, in this research, were selected from various police stations in Rotterdam. In conclusion, traffic delays provide police with more time to intercept a fleeing suspect, an advantage that becomes more clear with additional units.

Although both the interception percentages and police positions did not differ significantly between the experiments with and without traffic included, the robustness evaluation, which assessed the effectiveness of the optimised positions on a set of routes from a different profile, found that the positions calculated with traffic included were more robust. The scores were generally less negative across all profiles. This indicates that, even though there might not appear to be a substantial visual difference in the optimised positions, a difference does exist. The exact differences between the positions with and without traffic remains unclear due to a lack of specific metrics. However, the robustness analysis demonstrated that positions taking traffic into account are more reliable if the traffic situation during an escape and interception attempt is wrongly estimated. This suggests that traffic has a significant and important impact on interception positions, and leads to an advantage when it is considered in the optimisation models.

7.5. Research question: added value of including traffic

What is the added value of taking more realistic traffic into account in the optimal positioning of police units for fugitive interception?

Firstly, the effects of incorporating more realistic traffic conditions into the model on interception probability were examined. A minor relationship was found between the inclusion of congestion and traffic lights and the interception probability, which increased when realistic traffic conditions were included in the model. However, a stronger relationship was identified between the crime scene location and the number of police units deployed and the success of an interception attempt. The more police units deployed in an interception attempt, and the less predictable the fugitive's route choices, the higher the interception probability. The results indicate that in scenarios where both congestion and regulated intersections cause delays in the escape, the success rate of police interceptions increases. This finding is logical. Police units move through the network at a higher speed than the suspects, regardless of the level of congestion. Moreover, delays caused by traffic lights are not accounted for in the modelled police agents. Fugitives are more affected by traffic than the police. This results in an extended time window to intercept a fugitive, as the difference in speed increases due to traffic delays. Consequently, the time before the fugitive can reach one of the highways of Rotterdam increases, creating more opportunities for the police to intercept them before they escape.

Most importantly, the effectiveness of the optimised positions under different circumstances was investigated. The optimised positions for each profile were evaluated for their effectiveness if the profile changed. Would these positions still work effectively if the generated escape routes differed? A clear conclusion emerged from this evaluation: independent of the fugitive's mental mode, the inclusion of traffic delays in the optimisation model significantly improved robustness. However, the most robust positions were found when the correct traffic conditions were estimated. Traffic often follows a pattern, making it somewhat predictable, in contrast to the mental mode which is harder to predict. The mental mode determines the specific positions where a fugitive might be located, while traffic conditions influence the timing of those positions. Timing appears more crucial in finding robust police positions than knowing the fugitive's exact location. However, this effect seems to decrease when more units are deployed in an interception attempt. This suggests that the extra time obtained from traffic delays does not compensate for non-robust optimised positions when only two units are deployed. When four units are deployed, the time gained from traffic delays helps the police overcome the use of sub-optimal positions.

For the second crime scene location, the port docks of Rotterdam, these effects are not observed. The interception percentage is consistently high, making it challenging to determine the impact of traffic on this probability. However, the evaluation indicated that the robustness of the positions for this location is not influenced by the profile used in the optimisation model, probably due to the predictability of the escape routes. This suggests that, in highly predictable environments like the port docks, the inclusion of traffic conditions does not significantly affect the robustness of the police positions.

Therefore, it can be concluded that the optimised positions when congestion and traffic light delays are not considered are not capable of intercepting escape routes found with more realistic traffic conditions with a similar interception percentage, and vice versa. This indicates that accounting for realistic traffic conditions improves the robustness and effectiveness of the police positions in more complex urban environments.

Summarising, the added value of incorporating realistic traffic conditions into the optimal positioning of police units is that the positions identified will be more relevant than they would be without considering traffic. The model that is currently being developed assumes an empty city, allowing agents to move around the city network at maximum road speed. While this may reflect the situation on a Sunday night, it is often not feasible to drive at maximum speed during rush hour. Therefore, incorporating realistic traffic into the model would yield outcomes more aligned with reality. The results of this study also demonstrated that positions determined without accounting for traffic are not robust for escape routes generated when fugitives decide their path based on traffic conditions. However, the opposite was not found to be true: police positions optimised for scenarios where traffic is considered remain effective, although to a lesser extent, even when traffic is absent. This implies that optimising positions for an interception attempt during rush hour on a weekday remains effective if the escape and interception occur on a Sunday night, while the reverse is not true. Thus, it can be concluded that considering traffic is crucial for identifying the most optimal positions.

7.6. Generalisation of results

In chapter 5, it was found that both the interception probability and the location of police positions were highly sensitive to the location of the crime scene. This was found for the two crime scene locations in Rotterdam of the port dock and the city center. Those locations have very different characteristics in terms of escape possibilities. Therefore, it may be difficult to generalise the outcomes on interception probabilities for different locations in Rotterdam, let alone in other geographical locations. It might be possible to generalise the outcomes for crime scene locations with similar (un)predictability levels in terms of escape possibilities in other cities.

However, the finding that the effectiveness and robustness of the optimised police positions seem to increase when these positions are based on the escape routes with more realistic traffic conditions is a result that can be generalised. It is important to consider the degree of similarity between the city and Rotterdam, because it is possible that suspects will behave differently if the road network is laid out differently. Rotterdam has a very functional network, which facilitates the flow of traffic to larger roads. The routes, and therefore the interception success and police positions, may show significant differences when an escape and interception attempt is simulated in a village or a city with an old centre. It is therefore expected that the results can be generalised to other cities that have a similar road network to Rotterdam. These are likely to be cities built after the Second World War.

7.7. Implications of research

The implications of this research are divided into theoretical and practical implications. Theoretical implications are broader and might suggest changes to existing theories of models of the world, and can be found in section 7.7.1. Practical implications focus on real-world applications and could improve policies and practices, and are mentioned in 7.7.2.

7.7.1. Theoretical implications

As described in chapter 1, the goal of this thesis was to determine whether including realistic traffic conditions in the simulation model for fugitive interception would affect the optimal police strategy. This aims to narrow down the range of possible fugitive interception points and to relax the assumptions currently used in such simulations.

This thesis provides knowledge for the field of criminal fugitive route-choice behaviour, highlighting the critical role of incorporating traffic into optimisation models for fugitive interception. The research demonstrates that models based on empty city scenarios fail to accurately reflect the complexities introduced by traffic, which can significantly affect travel times and interception success. The findings show that optimised police positions derived from traffic-free models are not robust when the city is congested, emphasising the necessity of including traffic dynamics in such models. By integrating traffic, this study challenges the assumption that traffic does not impact fugitive interception, offering a more nuanced understanding of how traffic conditions influence police strategy effectiveness. The research reveals that ignoring traffic can lead to the use of sub-optimal strategies, thereby providing valuable insights for refining police interception strategies.

7.7.2. Practical implications

The finding that including traffic conditions positively affects the effectiveness and robustness of police positions for interceptions will assist in determining optimal positions after a crime has been committed. When the crime location is known, the optimisation model can swiftly identify police positions that maximise the interception probability.

The conclusions also suggest that the optimal interception positions identified without traffic considerations are less effective when escape routes are based on more realistic traffic conditions, such as waiting times at traffic lights and congestion. This implies that in the police decision support system it is important to incorporate the realistic traffic situation at the time of the crime. However, this conclusion comes with challenges, as incorporating traffic into the base model increases run time.

By guiding the police in developing this decision support system, this thesis contributes to creating a safer society. The overall aim is to find the optimal balance between accuracy and the required computational power and information in the models, enabling the police to enhance their strategy for catching criminals red-handed. More red-handed arrests will lead to a higher prosecution rate and, consequently, fewer unsolved crimes.

7.8. Future research

This thesis tried to find the effects of different traffic conditions on the optimal police positions. The outcomes increase knowledge on the importance of including traffic in the optimisation models, so that the police positions coming from the developing decision support system are more effective in real life situations. Due to system boundaries, time limitations, and lack of knowledge, many simplifications have been made. The limitations from chapter 6 lie at the heart of the recommended future directions for this research, which will be discussed in this chapter. The future research can be divided into three research domains: traffic, fugitive behaviour and police behaviour.

Regarding the way traffic has been included in the network, the following future research is recommended:

- **Delay times at unregulated intersections:** at this moment, only delay times at regulated intersections have been considered. However, other factors in residential areas, such as giving right of way to vehicles from the right, parked cars and other local circumstances, can also cause delays. Including these factors would reduce the speed at which fugitives move through the city, potentially affecting their preferred escape routes. It is worthwhile to study whether this results in significantly different optimal positions and probability of interception. It is important to know if this information should be included in the decision support model, which is the case if this reveals that including these delays leads to very different outcomes.
- **Out-of-pattern traffic events:** the research currently only considers congestion and delays caused by traffic lights, which are relatively predictable aspects of traffic. Traffic generally follows a weekly pattern, and traffic light regulations are also partly following this pattern when regulated vehicle-dependent. However, there are circumstances that can disrupt these patterns, such as bridge openings and accidents. These situations could significantly impact the decision-making of fugitives and pose additional challenges for both the police and suspects in reaching the location. Such unpredictable events make the interception attempt more complex and less straightforward.
- **Traffic light regulations:** the traffic lights included in the current model are regulated based on a triangular distributed cycle time and the same green time for both straight and turning traffic. However, in reality, there is a significant difference in green times between different directions, where that of turning traffic is significantly shorter. This discrepancy is expected to impact the chosen escape routes, particularly for distressed criminals who decide their next direction based on the length of the delay time. The decision to turn off a road will be made less frequent. Therefore, future research should diversify the green times per direction to reflect more realistic traffic conditions. It is crucial to investigate whether this change in green times leads to different escape routes, potentially making previously optimised police positions less effective.
- **More realistic and dynamic congestion levels:** currently, the model uses a static congestion level, where values depend on the hierarchical level of the road. However, this approach does not always reflect reality, as the importance of a road in the network does not necessarily correlate with higher congestion. Therefore, it is recommended to use more realistic congestion levels based on real observations. Data from traffic counters can be utilised for this purpose, allowing the actual used capacity of a road to determine its congestion level. As previously mentioned, the current model incorporates static congestion. It is also advisable to study the effects of dynamically increasing or decreasing congestion during an escape attempt. This would help to reflect on the conditions during the formation or decline of rush hour, providing a more accurate representation.

On the subject of fugitive behaviour, a lot of extra research is needed in order to be able to capture all facets.

- **Other methods of escaping:** the current model only considers car-based escapes. However, criminals can employ various strategies, such as using alternative modes of transportation, hiding until the initial search is called off, or changing vehicles mid-escape. Future studies should investigate these diverse strategies and their impact on the effectiveness of interception attempts. In particular, the use of different vehicle modes is pertinent to this study. For instance, motorcyclists have more options when encountering congestion compared to car drivers. Additionally, individuals trying to escape from a congested city might be more inclined to violate traffic rules. The interaction between traffic conditions and fugitive behaviour needs further study to understand the choices made by fugitives under different circumstances. Such research would provide a more comprehensive understanding of escape strategies, enabling the development of more robust and effective interception models that account for a broader range of scenarios and behaviours.
- **Diversity in fugitive profiles:** now, the fugitives have been classified in two profiles: calculating and distressed criminals. However, this is nowhere near enough variance to capture all possible behaviours. Future research can help to better conceptualise and include these behaviours. By investigating the effects of personal characteristics on specific behaviours, more specific predictions can be made about the routes. If some characteristics are known when a crime is committed, this information could be used to find even less random escape routes. This could increase the probabilities of interception.

Lastly, the future research directions that is recommended on the topic of police behaviour is the following:

- **More realistic behaviour:** police units have to follow specific guidelines when driving a priority vehicle, including maximum speeds in various situations and specific positions on the road. However, the current model simplifies this by using an increased average speed for police units compared to the maximum speed, which does not account for speed reductions at intersections or on busy roads. Moreover, the extra resistance encountered at traffic lights is not at all taken into account. This could result in an underestimation of the time police needs to reach their positions, and could potentially skew the outcomes of the model. To address this, additional research should be conducted to increase the realism of police behaviour in the model. By accurately reflecting the reduced speeds at intersections and on congested roads, it can be determined if the current model overestimates police speed and how this affects interception opportunities and strategies. This refinement could lead to more accurate and effective police positioning.

Lastly, it would be valuable to study the escape routes and interception probabilities from various other crime scene locations, as the location of the crime seems to significantly influence both the optimised positions and the success of interceptions. Future research should explore different crime scene locations, selected based on their characteristics and escape possibilities. When the crime location is known to the police, with this knowledge, the escape routes can be predicted with greater accuracy, allowing police strategies to be more effectively tailored to the specific circumstances of each situation. This approach could enhance the likelihood of successful interceptions and improve overall crime response efficacy.

7.9. Recommendations for police

The findings indicate that incorporating traffic into optimisation models for fugitive interception enhances the robustness of the identified positions. This suggests that errors in positioning are reduced when traffic conditions are considered, while also aligning the model outcomes more closely with real-world scenarios where traffic and traffic lights create delays. Consequently, it is recommended to integrate traffic into the models to improve their accuracy. While the extent of integration is ultimately up to the police, the significant role of traffic presented in this thesis justifies its inclusion.

If a choice must be made regarding which traffic aspects to focus on, the results suggest that traffic light delays are particularly influential. Therefore, initial efforts should prioritise incorporating traffic light delays into the models. Implementing traffic lights within a rigid-regulation framework could be a starting point, with potential for increased realism as computational capabilities allow. Congestion, while also important, should be considered secondary to traffic light delays. Initially, congestion can be modelled using a factor that adjusts travel times based on the differences in speed between police and fugitives.

Broader implications of these findings reveal that timing plays a more critical role in interception success than knowledge of the precise location of the fugitive. Inaccurate estimations of the fugitive's speed through the city can significantly impact interception outcomes. Therefore, it is advisable for the police to experiment with varying escape speeds in their models to ensure that optimised positions remain effective under different timing scenarios.

By following these recommendations, the effectiveness of interceptions is likely to improve. Successfully apprehending offenders shortly after a crime is committed is the most effective way to ensure proper prosecution. This approach contributes to enhancing the resolution rates of crimes, currently at 25% overall and 45% for violent crimes, and ultimately supports the goal of a safer society for Dutch citizens.

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Zhao, Y., Li, M., & Guo, C. (2020). Developing patrol strategies for the cooperative opportunistic criminals. In *Lecture notes in computer science* (p. 454–467). Springer International Publishing. doi: 10.1007/978-3-030-38991-8_30

A

Literature study

The following search queries were used for the theoretical background and were generated through the search engine Scopus. The only exception is that this search engine is not used for the subject of traffic control, as information from CROW was all inclusive for the situation in The Netherlands.

In the column 'papers found', the total number of results from Scopus is noted. In the rightmost column, the filtered results are shown. The filtering is done by checking the relevance of the articles on the applicability to fugitive route-choice decision-making.

Table A.1: Literature search

Topic	Search query	Papers found	Relevant papers
Traffic flow theory	traffic AND flow AND theory AND fundamentals	3	(Guerrieri & Mauro, 2021)
Traffic control	Verkeersmanagement AND verkeerslichtenregeling in Kennisbank CROW)	2	(CROW, 2014) (CROW, 2022a) (CROW, 2022b) (Fortuijn, 2011) (Fortuijn, 2013)
Criminal decision-making	criminal AND behaviour AND (escape OR capture) AND (modeling OR simulation)	17	(Escobar, Cuevas, Toski, Ramirez, & Pérez-Cisneros, 2023) (Zhao et al., 2020) (Zhang et al., 2016)
Route-choice decision-making	(route-choice OR route-seeking OR wayfinding OR pathfinding) AND car AND (modeling OR simulation OR model) AND ”decision making”	16	(Alizadeh, Bourbonnais, Morency, Farooq, & Saunier, 2018) (Katsikopoulos et al., 2000) (Katsikopoulos, Duse-Anthony, Fisher, & Duffy, 2002) (Liu, 2022) (Miyagi & Ishiguro, 2008) (Saxena et al., 2018) (Hochmair, 2005)
Stressed behaviour in traffic	congestion AND stress AND NOT (automated OR autonomous) AND NOT (cycling OR pedestrian OR bus)	37	(Cœugnet et al., 2013) (Pawar & Velaga, 2020) (Hennessy & Wiesenthal, 1999) (Emo et al., 2016) (Ratering et al., 2024) (Mackett, 2021) (Ringhand & Vollrath, 2019) (Ringhand & Vollrath, 2017)
Police route-choice decision-making	(’police AND behaviour’) AND (’escape’ OR ’capture’) AND (’modeling’ OR ’simulation’)	18	(Escobar et al., 2023) (Zhao et al., 2020) (Zhang et al., 2016)

B

Observation of intersections

In this appendix, the results of intersection observations are published. Its goal was to discover the order of magnitude of cycle and green times for different intersections. Therefore, three intersections from different types have been studied. Roads can be of different types: primary, secondary, tertiary or residential. This is used in the classification of intersections. The observations were done during either morning or evening rush hour. However, at the time, it was 'Meivakantie', which might have resulted in a distortion of normal traffic density. In the figures of the following sections, dashed lines represent bike lanes, and the grey lines represent tram lanes. Arrows on a road indicate the direction of the lane, which are accompanied by the corresponding green times for that direction.

B.1. Maasboulevard/Geldersekade

Figure B.1 shows the situation where the Maasboulevard and Geldersekade (Rotterdam) cross, At this intersection, two secondary roads cross. This observation was made on Tuesday May 7th between 09:15 and 09:30.

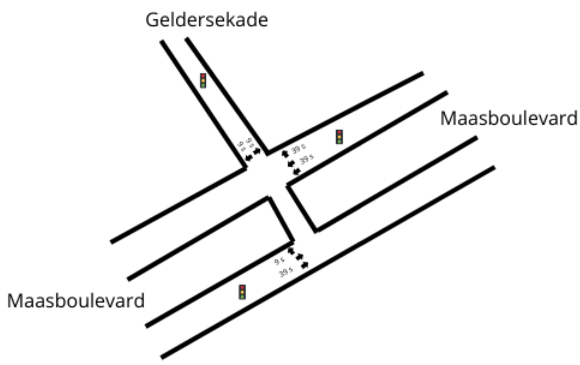

Figure B.1: The observed green and cycle times at the intersection between the Maasboulevard and Geldersekade

B.2. Erasmusbrug/Nieuwe Leuvenbrug

Figure B.2 depicts the roads Schiedamsedijk, Vasteland, Erasmusbrug and Nieuwe Leuvenbrug. This observation was made on Tuesday May 7th between 16:05 and 16:40. This intersection crosses two secondary roads. The intersection was very crowded, with traffic coming on most directions. It has to be noted that during the measurement of the cycle time, two trams were allowed to cross the intersection. This probably increased the cycle time drastically.

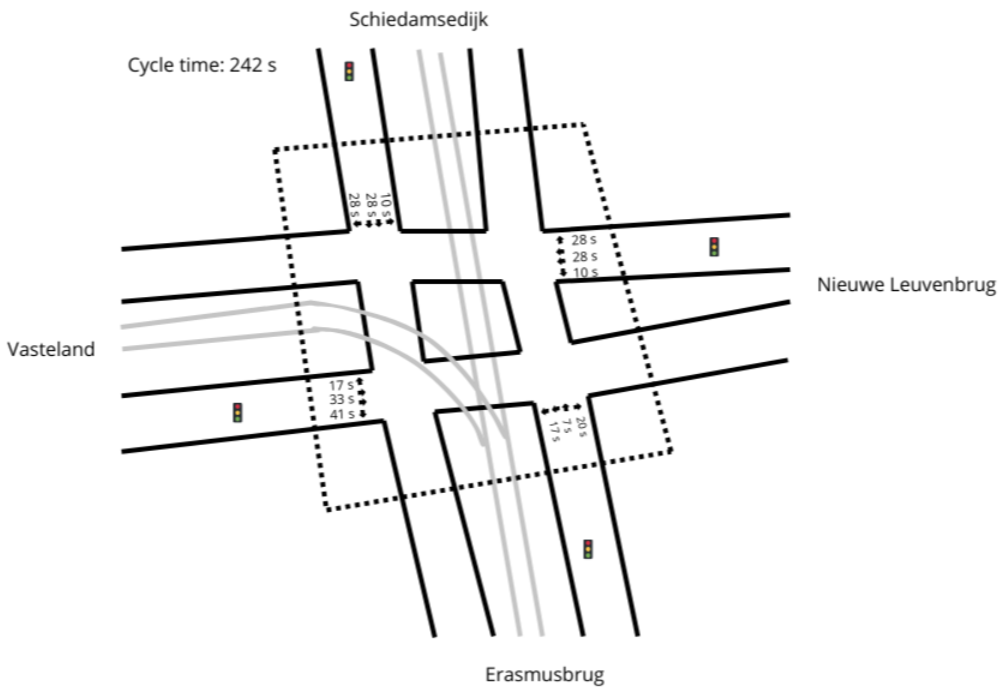

Figure B.2: The observed green and cycle times at the intersection between the Erasmusbrug and Nieuwe Leuvenbrug

B.3. Van der Louwbrug/Willemsbrug

Figure B.3 shows the situation on the location where traffic from the André van der Louwbrug and Boompjes/Willemsbrug cross. This situation is classified as a three-way crossing of secondary roads. This observation took place on Tuesday May 7th at 9:10. All directions were observed to be used when the intersection was medium busy.

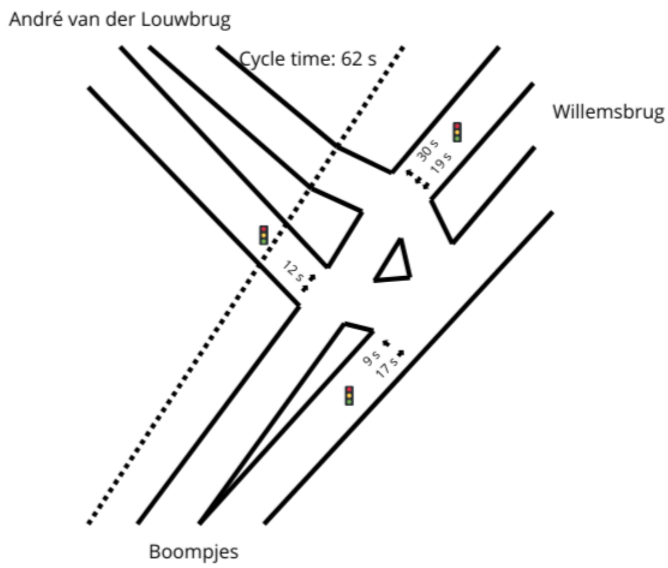

Figure B.3: The observed green and cycle times at the intersection between the André van der Louwbrug and Willemsbrug

B.4. Weena/Henegouwerlaan

The intersection from figure B.4 shows a crossing between secondary and tertiary roads. The observation was made on Tuesday May 7th at 17:00. It was quiet busy from all directions.

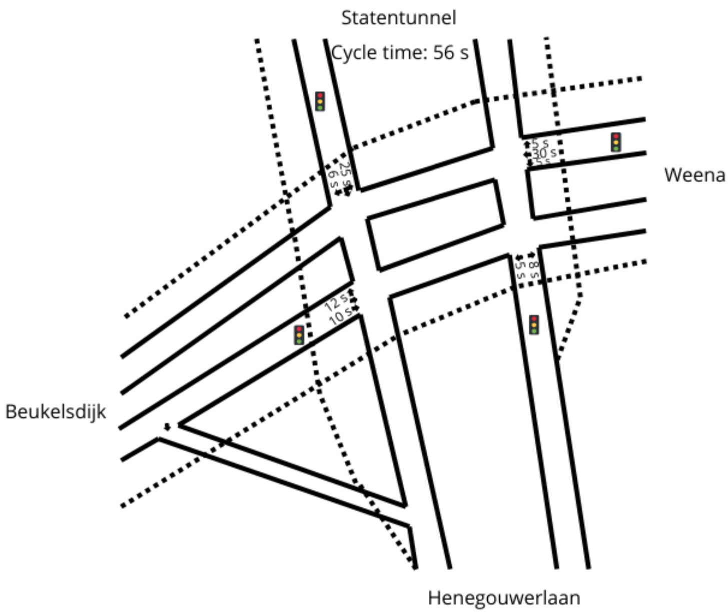

Figure B.4: The observed green and cycle times at the intersection between the Beukelsdijk and the Henegouwerlaan

B.5. Voorhofdreef/J.J. Slauerhofflaan

Figure B.5 shows the situation at an intersection between a residential and tertiary road. For convenience purposes, this observation was made in Delft.

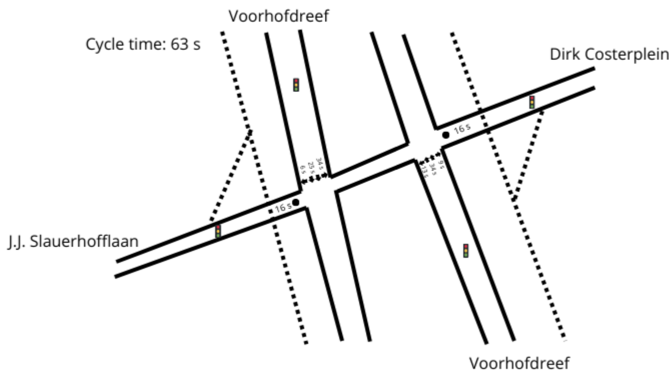

Figure B.5: The observed green and cycle times at the intersection between the Voorhofdreef and the J.J.Slauerhofflaan/Dirk Costerplein

B.6. Conclusion

From these figures it can be concluded that all controlled junctions have a cycle time of around 60 seconds. This is independent of the type of road crossing. An exception to this cycle time length is when tram lanes cross the intersection. Here the cycle time is much longer (up to 240 seconds). The green time between the different road types however is different.

C
Police stations

A list of the police stations included in the model. Although there are a more than four police stations in Rotterdam, the choice is made not to model them all. In the decision on which police stations to include, the goal was to have stations in different areas of the city.

- Politie Eenheid Rotterdam, Doelwater 5, 3011 AH Rotterdam, 51.92399, 4.48020 (Centrum)
- Politiebureau Rotterdam-Maashaven, Maashaven Noordzijde 5, 3072 AE Rotterdam, 51.90194, 4.49594 (Maashaven)
- Politiebureau J.J.P. Oudsingel, Doctor J.J.P. Oudsingel 1, 3067 EG Rotterdam, 51.88815, 4.54668 (Oost)
- Politiebureau Slinge, Slinge 162, 3085 EW Rotterdam, 51.87564, 4.482000 (Zuid)

Figure C.1: Overview of the locations of all four police stations in Rotterdam

The locations of the 4 police stations in Rotterdam will be used in the maximum scenario. Their placements on the map of Rotterdam can be seen in figure C.1.

For the experiments, the minimum number of police units is set on 2. The locations are chosen to be in the centre and south of the city. The locations are visualised in figure C.2.

Figure C.2: Overview of the locations of two police stations in Rotterdam

D

YouTube videos on police driving behaviour

This appendix describes five videos of the YouTube channel of *Politieacademie rijopleiding*. In the videos, coaching on how to drive a priority vehicle is performed. From this, police behaviour during driving with signalling can be extracted.

Instructierit optische en geluidssignalen Parkkade/Koperstraat Rotterdam

This ride was not during rush hour, and the traffic conditions appeared to be calm. The normal time to complete this route during a calm period is between 20 and 35 minutes (according to Google Maps, checked at 12 PM on a Monday). The time they took to complete the route was just over 12 minutes.

- 0:57 ”The gain is not necessarily in speed but in being able to keep moving.”
- The vehicle predominantly stays in the left lane.
- Even when there is a clear passage at a red light, the speed is always reduced for better visibility and safety.
- At busy moments, such as at 6:04 where many people are spread across multiple lanes at a traffic light, it is difficult to pass through. They proceed through the middle but at a very low speed.
- 7:30: ”I am not taking the bus lane because I am familiar with this area.” Later in the video, it is shown that the bus lane turns off to another direction without a possibility to return to the main road.
- They accelerate on roads and slow down at points where roads merge or cross.
- 8:50 They do use the bus lane.
- 9:23 - 9:52 On a single-lane road, it is much harder to pass preceding cars, so the speed is significantly reduced here.

Instructive Ride with Optical and Acoustic Signals Rotterdam 17/09/2020

They took the exit Charlois/Euromast around 11:15 AM as indicated by the clock at 5:20. The normal time to complete this route is between 16 and 28 minutes (according to Google Maps). Their time was 7 minutes.

- By keeping a distance and not driving too close to other cars, they make themselves visible (otherwise, the flashing lights are less noticeable).
- 5:40 Passing through the Maastunnel went smoothly, as all cars moved to the right, and there was space on the left.
- In complex situations like the roundabout at 6:42, where the signs need to be read carefully, the speed is reduced.

Instructive Ride with Optical and Acoustic Signals Rotterdam 14/02/19

- The siren is activated at moments when no one would be startled and do anything reckless (for example, just after an intersection).
- To go straight at traffic lights, the lanes for left and right turns are also used because there is usually less traffic.
- 2:00 If the traffic light just turned red or is amber, the speed is significantly less reduced.
- 4:48: On a 50 km/h road, "using 70-80 km/h makes the best use of your speed. This way, you do not suddenly appear at an intersection, giving people the chance to make room."
- 6:10: At a two-lane traffic light with a queue of cars, it takes a while for drivers to make room between the two lanes.
- Explanation given in comments: Even when the light is green, speed is adjusted to account for other people just making it through on red.

Instructive Ride with Optical and Acoustic Signals From De Kuip to Groene Kruisweg Rotterdam

The normal duration of this route is around 13 minutes. They completed it in 8 minutes.

- 0:32 On a 50 km/h road, the driving instructor states that the speed should absolutely not exceed 90 km/h.
- When there is a bus lane and the regular lanes are occupied, the bus lane is used.

Footage of Instructive Ride with Optical and Acoustic Signals 11/04/17. Parkkade /Koperstraat Rotterdam.

In this video, it is mentioned that a malfunction of the Erasmus Bridge has caused traffic on the mainland to be gridlocked. Thus, this video most closely resembles rush hour conditions.

The normal time is approximately 20 minutes. Their time was about 13 minutes. Another video with the same start and end points but less traffic took 12 minutes.

- Straight-ahead lanes at a traffic light are much more congested than turning lanes. Therefore, they often use the left/right-turning directions to bypass the straight-ahead traffic.
- To prevent blind spot accidents, it is better to choose the left side rather than the right (7:03).
- 3:20 "When weaving through stationary/slow-moving traffic, the speed is always kept low."
- On a two-lane road, they often go between the lanes at a traffic light. After the traffic light, there is usually more space, and they can accelerate until the next intersection.
- In this video, it is very clear that traffic builds up in front of traffic lights and thins out afterward (e.g., at 4:00).
- 5:22: "Maximum speeds can be exceeded by 40 km/h when driving with optical and acoustic signals" –> the police traffic guideline is the leading directive here.
- 8:09 shows how to maneuver around a busy spot.
- 8:45 Speed on bus lanes is much higher than on the regular road.
- It takes a while for people to make room at a traffic light, so the police car often has to almost come to a stop, for example, at 11:42.

E

Questions interview

- Can you tell me about your experience as a delivery driver? Where did you work, what did you deliver, and how did this process work?
- How familiar were you with the area where you made deliveries? (specifically with a car, not by bike)
- How did you initially determine the route you would follow to visit all addresses?
- How much stress or time pressure did you experience during deliveries? Can you rate it on a scale from 1 (no stress) to 5 (maximum stress)? Were there specific situations or circumstances that increased this stress? If someone indicates they did not experience stress, ask: Imagine you were experiencing a lot of stress, how would your behavior differ?
- I will now describe a few situations, can you indicate how you would respond as a delivery driver, and why you made that choice? (emphasize that all answers are equally valid)
  - Traffic lights
    - Suppose you arrive at a traffic light, and you see that the direction you want to go just turned red (you know you have to wait for a whole cycle), what do you do?
    - Suppose you feel like you have been waiting at a traffic light to turn right for a long time, but the straight-ahead direction is green and there are no more cars going that way. What do you do? Why?
    - Are there any other situations related to traffic lights that influence your choices?
  - Traffic congestion
    - Suppose you want to turn, but you see that the road is completely congested. What do you do?
    - Suppose you are on a road that is moving very slowly. You cross another road that is less busy. What do you do? Why?
    - Have you ever experienced this yourself? If so, what did you do and why?
  - Open bridge
    - Suppose you see from a distance the lights flashing that a bridge is opening or is open. What do you do?
    - Have you ever experienced this yourself? If so, what did you do and why?

F

Interviews

In this appendix, the interviews are summarised. Thereafter, the take-away points are listed and explained.

F.1. Person 1: medicine delivery driver

Person 1 has experience of delivering medicines for a pharmacy. This delivery took place during the weekday evening rush hour. The delivery area covered two medium-sized villages with which the delivery person was reasonably familiar. The addresses had not been sequenced by the pharmacy. At the beginning of the shift, person 1 sorted the addresses by neighbourhood. Then the route for each neighbourhood was driven using Google Maps. In general, the stress level during the delivery was rated as a 2 on a scale of 1-5, but there were times when it reached a 4. Higher stress levels were caused by crowds on the street, but even more so by other appointments later in the evening.

In these stressful situations, person 1 behaved as follows:

- They did not always wait for a green light at intersections with traffic lights known to be sub optimal
- When they saw that the preferred direction just turned red, they sometimes chose another direction that would turn green more quickly
- Deviating from the predetermined route (not the order of addresses, but the way to get to the next address) was also triggered by visual congestion
- At signals that a bridge was closing, the decision was still made not to stop until the barriers were closed.
- If a bridge was already closed, an alternative route to the next address was chosen, as it was possible to cross another bridge in these villages. However, this involved increasing speed to avoid this bridge also closing.

There were also two interesting comments made by Person 1. First, it was mentioned that the decision to deviate from the route suggested by Google Maps depended on familiarity with the area. If he did not know whether another route would get him closer to his destination, he would choose not to deviate from Google Maps for fear of wasting time. Second, Person 1 indicated that a motivating factor behind the decision to deviate from the route was to keep moving. Standing still gave a sense of powerlessness, and taking a different route actually gave a sense of control.

F.2. Person 2: supermarket deliverer

Person 2 did delivery for a supermarket in a medium-sized city. This city was the place they grew up in, so they were familiar with the area to a certain level of detail. In two-hour time slots, 10 to 12 addresses had to be visited. According to person 2, this was too tightly planned and it was generally impossible to achieve this in the time available. This led to a very high level of stress, which on average was rated at a 4 on a scale of 1-5. This could also become a 5 in situations that were described as unexpected, such as the next orders not being ready when they arrived at the supermarket or the bus suddenly not being at the agreed place. The order in which the addresses were visited also had to be determined within the time slot. Person 2 always did this in the first 15 minutes, filling in all the addresses on Google Maps and then dragging the order until it looked visually like the best route had been found. However, there was a caveat to this, as there were places where Google Maps said the road was closed, but an exception for delivery drivers was in place. Therefore, this method still required some knowledge of the area.

Under stressful circumstances, person 2 behaved as follows:

- When seeing that the traffic light just turned red, they sometimes ignored this. But only if possible, at intersections that were not too busy
- At intersections that they knew, they used this knowledge to bypass sub optimal traffic lights, by going in another direction
- When feeling like the traffic lights were red for no reason, they sometimes chose to follow the green direction, even though they did not know whether this would work better
- The main factor in deciding whether or not to deviate from the route as from Google Maps was familiarity, in fear of needing extra time when the deviating route did not work
- Something person 2 had found to be good for speed was following public transport vehicles or the direction of tram rails. This was because they often seemed to turn green faster than other vehicles. Therefore, they sometimes stayed longer behind a bus when they actually had to change direction, because this felt like it saved time
- Rather than responding to actual stimuli of congestion (seeing that there was a traffic jam in front of you), they responded more to the colour codes on Google Maps, as this could be used to estimate how long the delay would be. Therefore, no impulsive decisions were made: ”information wins time”
- They did not often differentiate from the Google Maps route when they saw traffic jams, as they genuinely believed that Google Maps knew the quickest route to their destination
- In the situation of an open bridge, they just waited until it opened again. This was done because he felt there was no alternative route

F.3. Person 3: driver for a transport company

Person 3 works for a transport company that distributes packages within Europe. They specifically drive the routes within the ’Randstad’ area of The Netherlands. How well they know the area varies greatly, as the route can consist of both returning and new addresses. The order between addresses is planned in advance, taking into account road congestion at specific times, but more importantly the distance between addresses. The apps they use are a combination of Google Maps, Apple Maps, Flitsmeister and Wayz, as those can have significant time differences. The stress level during the deliveries is generally rated as a 3, but can rise to a 4. It rises when clients have strict time demands that are not possible in terms of distance, when they get into unexpected traffic jams, or when the day already starts with a time delay.

In stressful situations, person 3 shows the following behaviour:

- Driving through an orange light but certainly stopping at a red light, to reduce the risk of getting extra delay time due to an accident
- They would change lanes to a lane that has green, to avoid long waits at traffic lights. This behaviour does not only occur in familiar situations, but is also executed at random, which might lead to extra travel time
- During congestion, they only change direction after an inspection of the map. Most of the time, they stay on the lane, because of the feeling that the congestion could not last forever and will resolve itself
- They would be less likely to turn onto a congested road, in which case the the road on which traffic does move would be preferred

- Open bridges would not trigger the rerouting response, as they believed that finding another way over the water would increase travel time as well

F.4. Conclusion from interviews

Each of the deliverers that were interviewed report fairly to highly stress levels. Combining the three interviews, it is clear that the tendency to run a red light is common, but varies from person to person. None of the interviewees drove through a red light when they considered the situation to be dangerous. One aspect that emerged in every interview was changing lanes when another direction had a green light and one's own lane had a red light. An important reason for this behaviour was the feeling of knowing an alternative route after changing direction in the hope that it would be faster. However, this behaviour less frequently occurred when the interviewee did not know whether this route would work. The fear of being further delayed by the reroute was the biggest reason not to opt for this often.

A contradiction that emerged from the interviews is that person 1 says that seeing traffic jams is a reason to choose another road, while person 2 says that seeing traffic jams does not actually trigger this behaviour. Person 2 reacts more to seeing congestion on the navigation app. This is in line with person 3, who also looks at an app to decide whether to take a different road.

Although there is no complete consensus, it is unlikely that open bridges would be a trigger for choosing a different route. The difference between person 1, who said they changed their route when there was an open bridge, and the other two, who said they did not, could be the difference between driving in a village and in a city.

From the interviews, the following factors are included for distressed criminals:

- Changing direction at a traffic light when planned direction takes too long
- Avoiding congestion by not turning into a road when this one is too congested, or get off a congested road for a less crowded one

G

Scores of the evaluation

In this appendix, the resulting matrices from the evaluation are presented. For the center crime scene location, only the scores are presented, as the heatmap on the normalised scores are already shown in the main text. For the port location, both the scores and normalised scores are presented here. For the normalised scores, each number indicates the number of routes that a certain optimisation model can intercept on the routes from the evaluation model. The total number of routes generated is 1020. The numbers are normalised per row.

G.1. Center crime scene location

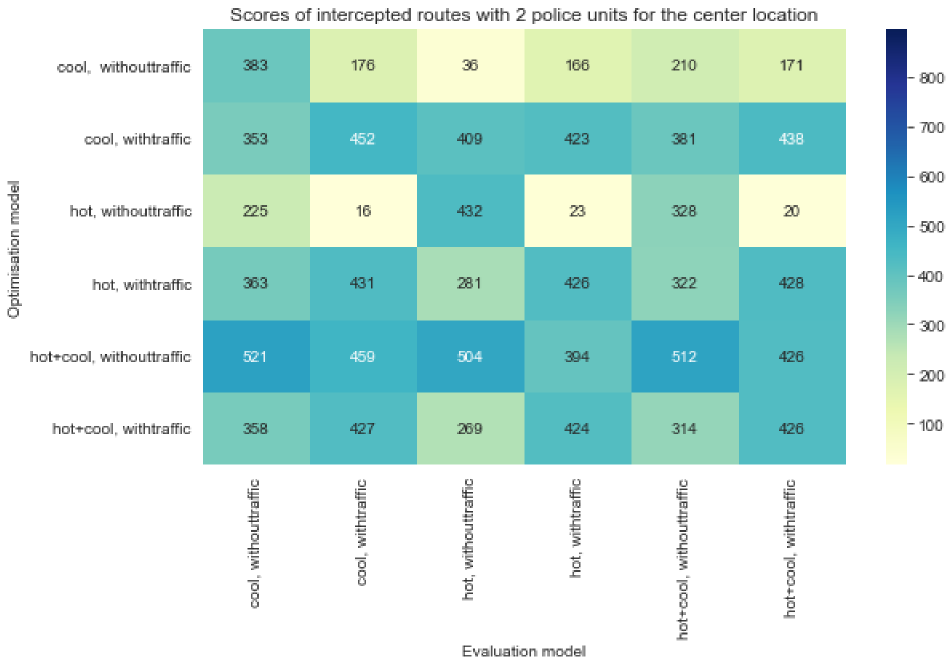

Figure G.1: The number of intercepted routes in the evaluation with 2 police units for the center location

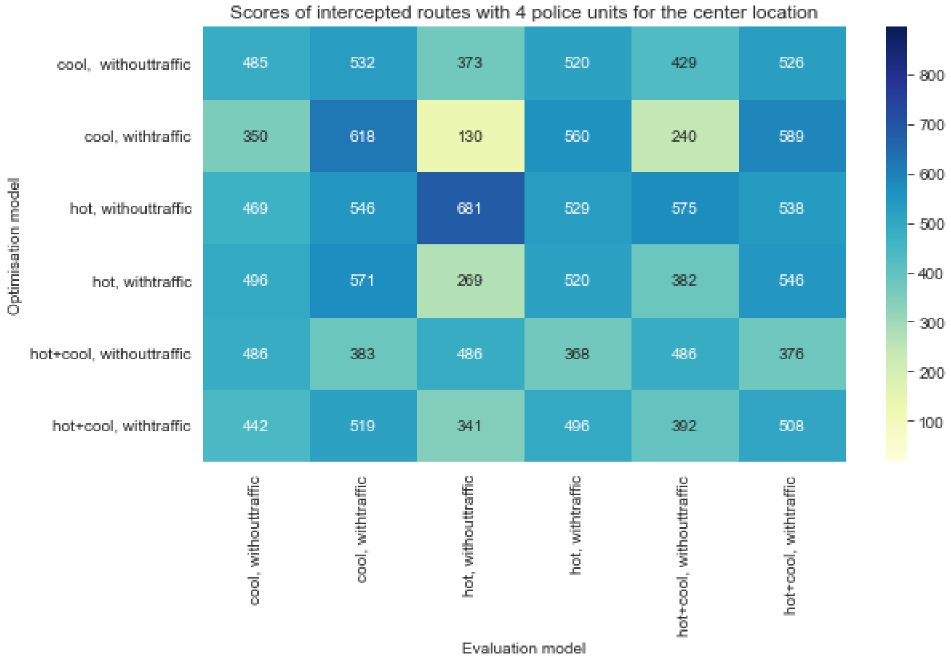

Figure G.2: The number of intercepted routes in the evaluation with 4 police units for the center location

G.2. Port crime scene location

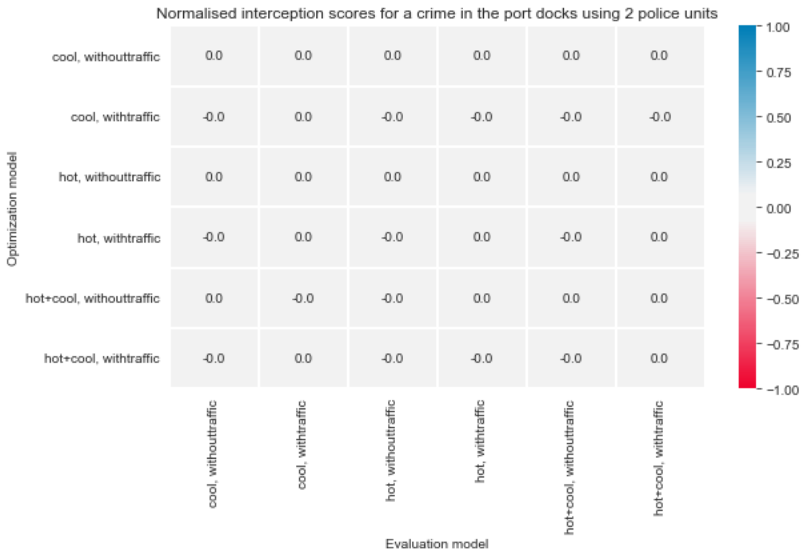

Figure G.3: Results of the robustness evaluation of different profiles with 2 police units used for interception for a crime scene location in the port dock

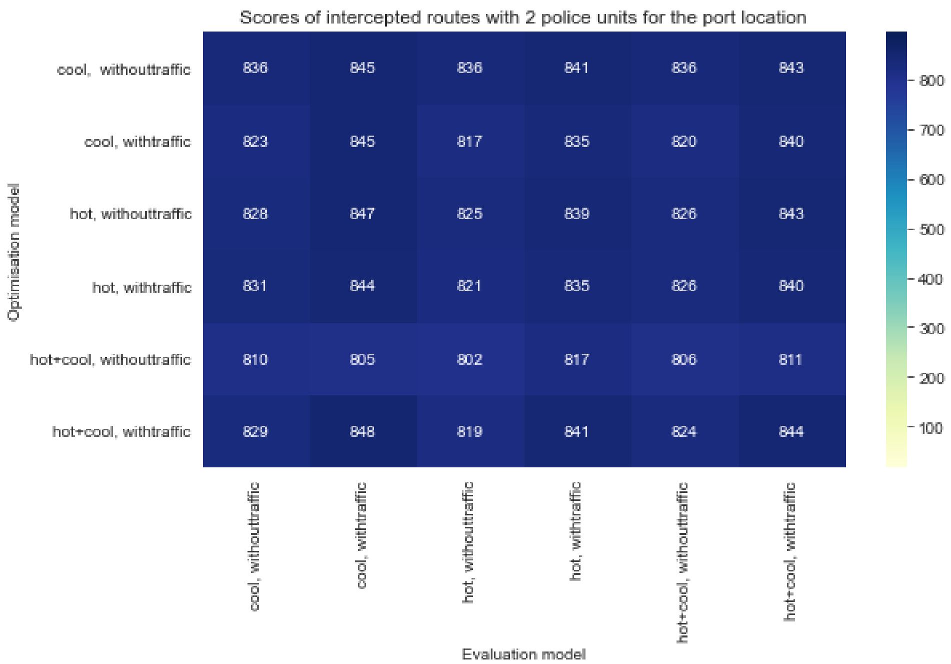

Figure G.4: The number of intercepted routes in the evaluation with 2 police units for the port location

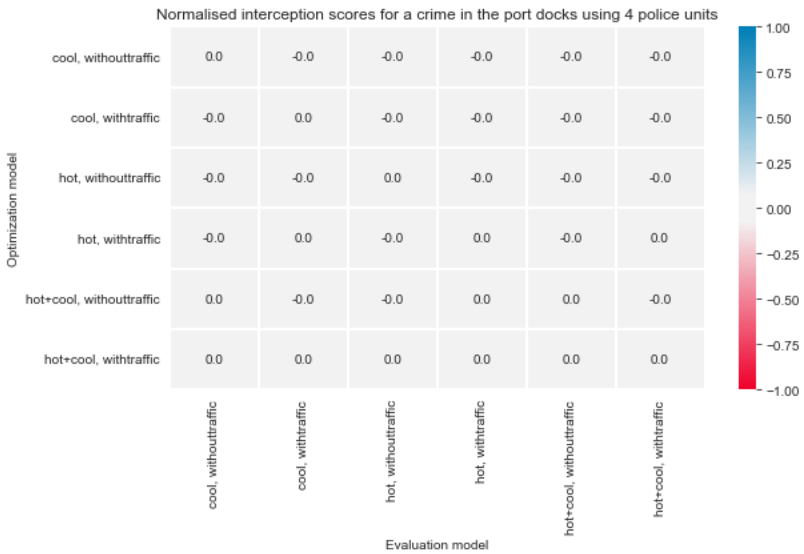

Figure G.5: Results of the robustness evaluation of different profiles with 4 police units used for interception for a crime scene location in the port dock

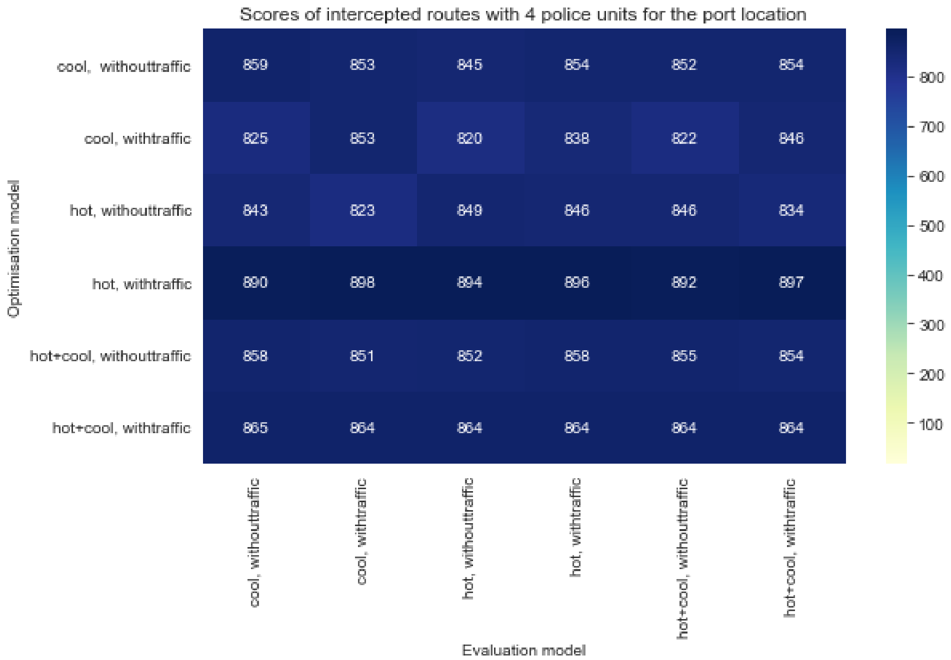

Figure G.6: The number of intercepted routes in the evaluation with 4 police units for the port location

H
Dis-aggregated traffic conditions

In this appendix, the results from the model for the dis-aggregated traffic conditions are presented. In general, traffic conditions entail the combination of congestion and traffic lights. However, it is interesting to study the effects of both these components separately. The results of the interception probabilities and robustness evaluation are presented in this appendix.

It is important to note that the separation of traffic lights and congestion is only examined for those experiments that showed significant interception probability differences between the model with and without traffic. These were the experiments where the fugitive operates in cool mode, and where the crime took place in the city center of Rotterdam.

First of all, the interception probabilities of separated traffic conditions are presented, in table H.1

Table H.1: An overview of the change in interception percentages between the scenarios with and without traffic conditions

Mental mode	Location	Units	With traffic	Only congestion	Only traffic lights
Cool	City center	2	45%	50%	43%
Cool	City center	4	61%	49%	65%

Table H.1 shows that the interception probabilities found in the experiments where only traffic lights are taken into account are quiet similar to the probabilities found in the experiments where the combination of traffic is used. If only congestion is taken into account, this is not the case. However, it can be concluded that the probabilities found for the dis-aggregated traffic experiments are in the same order of magnitude.

Secondly, the robustness is studied. This is interesting because it provides insight into the importance of including the separate traffic factors in the decision-support system.

The evaluation results in figures H.1 and H.2 show that the circumstances where only congestion is taken into account perform well on an evaluation model where traffic is not taken into account. On the other hand, the optimised positions from the profile that only considers traffic lights perform well on the evaluation models where traffic is included. Therefore, it can be concluded that the situation resulting from including delays at traffic lights is closer to the entire set of traffic conditions in terms of the resulting optimised positions. Following earlier results that including the right traffic conditions is significant in finding robust positions, this shows that it is more important to implement traffic lights into the optimisation model, than it is to include the congestion at the time of the escape.

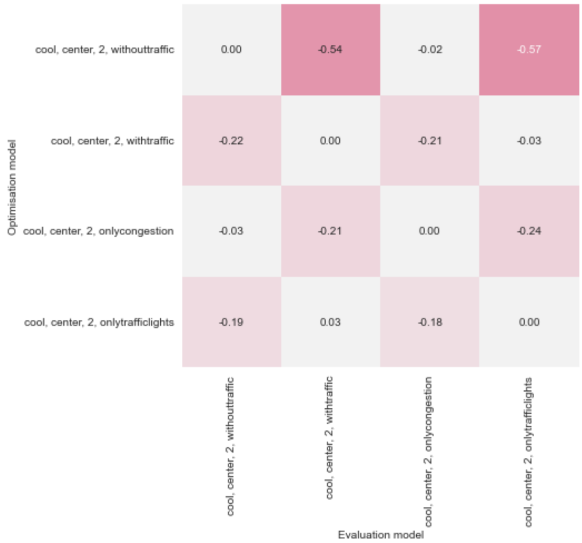

Figure H.1: Results of the robustness evaluation of the dis-aggregated traffic conditions for a crime scene location in the city center, where the fugitive behaves according to the cool mental-model, and the police dispatches 2 units

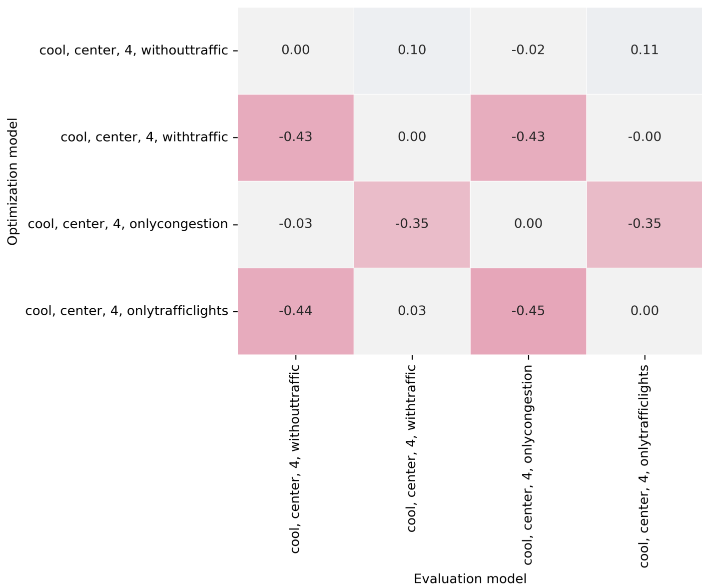

Figure H.2: Results of the robustness evaluation of the dis-aggregated traffic conditions for a crime scene location in the city center, where the fugitive behaves according to the cool mental-model, and the police dispatches 4 units

I

Sensitivity analysis

The sensitivity of the results is tested on two factors: the used seed, and the congestion factor. The results of this analysis are presented in this appendix.

I.1. Sensitivity on used seed

First, the sensitivity of the results to the seed used is analysed. This is done by running the model with a different seed. These results are shown in blue in table I.1. The numbers in black present the percentages from the seed that was used in the first place.

Table I.1: An overview of the change in interception percentages between the scenarios with and without traffic conditions using a different seed

Mental mode	Location	Police units	Int. without traffic	Int. with traffic
Cool	City center	2	38% → 51%	45% → 56%
Cool	City center	4	45% → 54%	61% → 62%
Cool	Port dock	2	83% → 83%	84% → 84%
Cool	Port dock	4	84% → 86%	85% → 85%
Hot	City center	2	43% → 42%	42% → 48%
Hot	City center	4	50% → 53%	52% → 54%
Hot	Port dock	2	82% → 83%	83% → 83%
Hot	Port dock	4	85% → 85%	89% → 84%

From table I.1, it becomes clear that there is a minimal difference between the outcomes from the two seeds. This difference is the most present in the experiments where the fugitive behaviour can be classified in the cool mode, and the crime scene occurs in the city center. In those cases, the percentages from runs with the changed seed are significantly higher than the results from the model with the original seed. However, the two outcomes are not different to the extent where the drawn conclusions from the results are different. With the changed seed, the results still show that the inclusion of traffic has a positive effect on the interception chance, when an effect is found. This positive effect is found the greatest in experiments where the suspect behaves according to the cool mode, and the crime takes place in the city center of Rotterdam.

I.2. Sensitivity on used congestion factor

Secondly, the effect of using an extreme congestion factor on the interception percentages was studied. For the extreme value, numbers twice as high were used as in the normal model. The difference is shown in table I.2, where the normal value is shown in black, and the extreme value in blue.

Table I.2: Implementation values of congestion under normal and extreme conditions

Road type	Congestion factor extreme
Motorway	2 → 4
Trunk and Primary	1.75 → 3.5
Secondary	1.5 → 3
Tertiary	1.25 → 2.5
Residential	1
One lane (not for tertiary or residential roads)	value + 0.2 → value + 0.4

The effect of the changes presented in table I.2 on the interception percentages is shown in table I.3. The interception percentages found under normal circumstances are shown in black, while the percentages under extreme congestion levels are shown in blue. Note that this table only shows the percentages for runs with traffic included, as extreme traffic is only compared to normal traffic and not to situations with no traffic at all.

Table I.3: An overview of the change in interception percentages between the scenarios with and without traffic conditions

Mental mode	Location	Police units	Int. with traffic	Int. with extreme traffic
Cool	City center	2	45%	51%
Cool	City center	4	61%	49%
Cool	Port dock	2	84%	100%
Cool	Port dock	4	85%	100%
Hot	City center	2	42%	60%
Hot	City center	4	52%	53%
Hot	Port dock	2	83%	100%
Hot	Port dock	4	89%	100%

Here, the main difference can be found in the experiments where the crime scene is located in the port dock. Using extreme congestion factors lead to an interception probability of 100% in all experiments where the crime scene location is in the port docks. For the other experiments, table I.3 shows that the probabilities slightly increase. This is as expected, as police are less affected by congestion than fugitives are. Therefore, the more traffic, the higher the interception probability. This increasing effect is more obvious for interceptions attempts with 2 police units, as there is more room for improvement when looking at the percentages.

J

Informed Consent

U bent uitgenodigd om deel te nemen aan een master scriptie onderzoek naar routekeuzes onder tijdsdruk. Deze studie wordt uitgevoerd door Veerle Zuurdeeg, MSc student Engineering and Policy Analysis aan de Technische Universiteit Delft.

Het doel van dit onderzoek is het verkrijgen van inzichten in hoe stress en tijdsdruk invloed heeft op routekeuzes. Uw ervaringen en antwoorden worden gebruikt om de kennis hierover uit te breiden en te valideren. De verkregen informatie wordt anoniem gebruikt voor kennis input van de theoretische basis van het simulatiemodel. Het interview zal bestaan uit open vragen met betrekking tot routekeuzegedrag in verschillende verkeerssituaties. Ieder antwoord op een open vraag is goed. Het doel van open vragen is om zoveel mogelijk te leren over het onderwerp.

Uw identiteit zal vertrouwelijk zijn. Interview transcripties, notities, email gesprekken en meeting samenvattingen zullen veilig en anoniem worden opgeslagen, alleen toegankelijk voor de onderzoeker. De uiteindelijke MSc thesis zal publiek beschikbaar zijn en geen verbanden naar uw identiteit bevatten. Uw deelname aan deze studie is volledig vrijwillig en u kunt op elk moment besluiten te stoppen met de deelname. U bent vrij om vragen niet te beantwoorden.

In het geval van een online gesprek zult u gevraagd worden om expliciet akkoord te gaan met de inhoud van dit formulier door dit online te ondertekenen en terug te mailen. Daarnaast zal de eerste vraag zijn of u akkoord gaat met de voorwaarden.

Voor vragen kunt u mij of mijn afstudeerbegeleider Ir.Irene van Droffelaar aan de Technische Universiteit Delft benaderen. Door dit doc-ument te ondertekenen bevestigt u dat u dit document heeft gelezen en toestemt met de hierboven beschreven voorwaarden.

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